Measuring the Impacts of Climate Variables on Electric Consumption:

A Look at the U.S. Residential Sector

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Abstract Sudden temperature changes because of short-term weather shocks and long-term climate extremes are difficult to forecast. Further volatility in these extremes leads to a response in household electricity consumption that overwhelms the capabilities of electric providers to generate and distribute electricity to the residential sector. The demand for electricity in this paper is explained by annual residential price (cents/kW h), personal income per capita, and the distribution of extreme climate variables across each of the lower 48 states. Given the pre-determined macroeconomic variables of price and income, the Arellano Bond estimator is used to correct implied endogeneity with the outcome variable of residential electric consumption. These estimates are then used to analyze long term effects of climate extremes on annual state-level residential electric consumption from 1990-2019. Extremes in average low temperature, high temperature, and 1-day precipitation are found to have significant effects on household consumption. This is weighed in consideration to long-term household responses through capital purchases and climate expectations. Further policy implications for electric infrastructure regarding increases weather resistance and generation capacity for volatile energy demand are explored.

1. Introduction

For the electricity sector in the United States, production follows demand. Yesterday's consumption informs providers how much to produce today. This also includes historical consumption data for the past week, month, and year to account for seasonality in behavior. Forecasting using this information is done to determine electricity generation and production given average expectations of daily weather in the short-run and climate in the long-run. Climate is also described the long run average of weather itself. However, because of climate change, climate extremes in the form of natural disasters and atmospheric behavior over time have increased. These climate extremes are defined as the deviation of climate from the historical average over a sustained period. This is different from weather, which is the day-to-day temperature and variations. For example, a snowstorm in the Northeastern United States that lasts longer or is colder than previous snowstorms on average may be an outlier. Once the frequency of these extreme snowstorms increases in a year-to-year period, it is then they are classified as climate extremes. This would also apply to droughts, heat waves, and torrential rain. In climate data, the instances of these events are not captured. Rather their impacts on general climate variables of annual temperature highs/lows and precipitation are measured.

While climate change does impact the frequency and intensity of extreme climate events, its effects are not significant enough to be considered an influence on residential electric consumption over a handful of decades. Climate variables, price, and income are the only factors represented in the aggregate household panel data used. Climate variables are separated into two categories: annual climate normals and annual extremes. Annual climate normals include average temperature, minimum temperature, maximum, temperature and total precipitation. Annual extremes are measured across 9 specific regions as defined by the National Oceanic and Atmospheric Administration[1] (see Fig. 1). Each of the states within a region shares a similar climate to each other. An estimate for an extreme in a given year would represent the value for all states within that region. Unfortunately, more extensive data on differences across individual state-level climate variables is not available. However, with the currently obtainable data it is still possible to analyze spatial variation between climate variables to determine their impact on households.

Traditional energy demand theory has established that short-term weather shocks in the form of hotter and colder outside temperatures lead to increase heating and cooling usage within households, referred to as the intensive margin effect. Despite this, the difficulty in predicting these extremes in the long-run leave electric providers with demand that greatly outweighs their capacity to generate and distribute power across the entire residential sector as evidenced by blackouts in California during the 2020 summer. Not only do these extremes strain existing power grids, but they also can lead to the depreciation and collapse of infrastructure sensitive to flooding and hot or cold temperatures. In Texas during the winter season in 2021, pipeline freezes prevented oil and petroleum from fueling power generation. While Texas is the only power grid in the US that does not borrow power from nearby grids during blackouts (see Fig.2), costs are still felt in other states through permanent damage to facilities. This can be avoided by refurbishing infrastructure to be more resistant to extreme temperature changes both hot and cold.

Using aggregated climate data at the state level, this paper attempts to measure how these climate extremes impact residential electric consumption responses by households over a 30-year period. This analysis is conducted using the Arellano Bond estimator for dynamic panel data to control for two potential issues. The first is the potential omitted variable bias that is corrected by taking the first difference of the model to remove the time invariant components. Next is the endogeneity problem created by including macroeconomic variables of price and income which are weakly exogenous in relation to consumption. This is resolved by using further lags of these 3 variables as instrumental variables. By understanding how different climate extremes contribute to residential electricity consumption, it is then possible to make policy changes to correct infrastructure and production. In addition to this, these results are also compared to the extensive margin effects, where households respond in the long run through methods other than by increasing their electric consumption.

Including this introduction, the paper is separated into seven sections. The second section of this paper looks at existing literature explaining the role of weather and climate in relation to electricity consumption using cross-sectional and panel-data models. The third section aims to give the reader a background on household energy expenditure theory and utility maximization in response to a changing climate. The fourth section explains the parameters chosen in the model specification, and potential impacts on the outcome variable of residential electricity consumption. Sections 5 and 6 then describe the panel data collected and methodology in choosing the appropriate model. Finally, the seventh section of this paper discusses the relevance of these results in consideration of long-term household responses and policy.

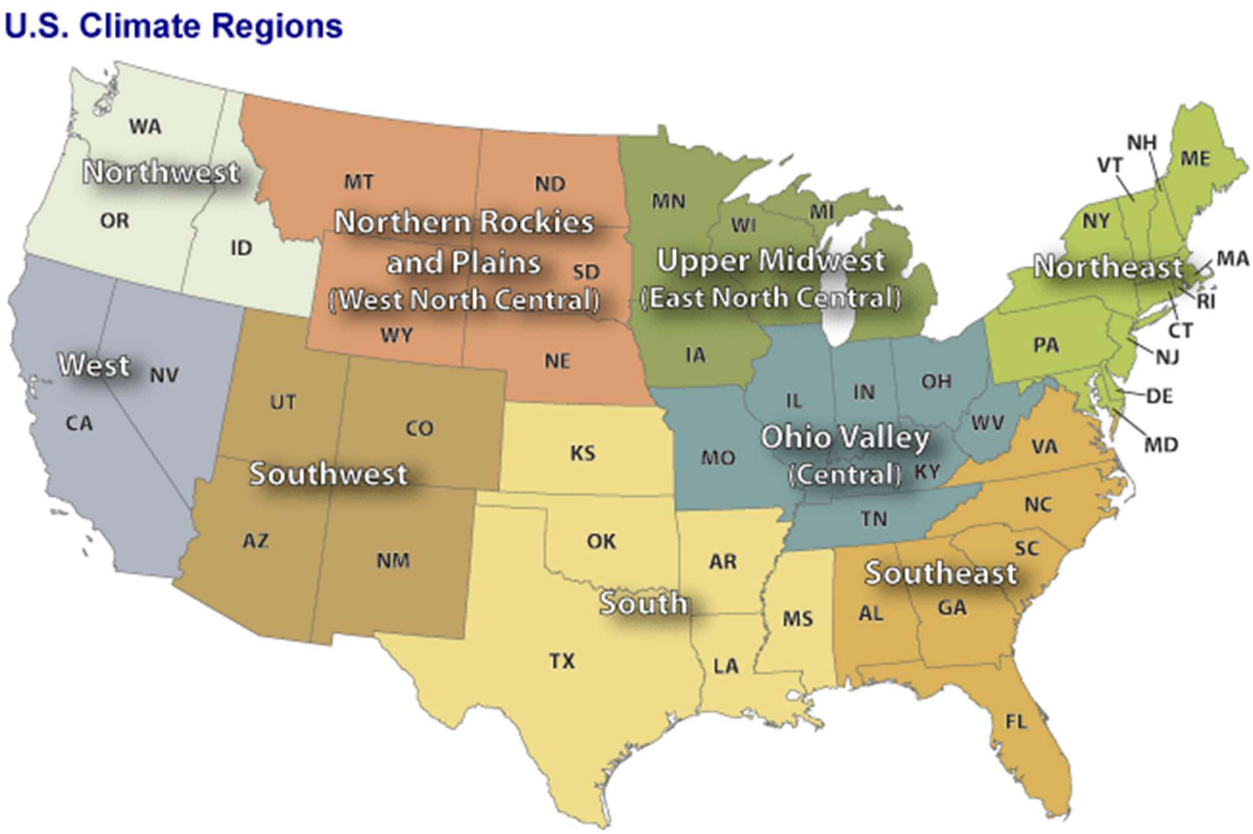

Figure 1: Regional climate divisions as defined by the NOAA

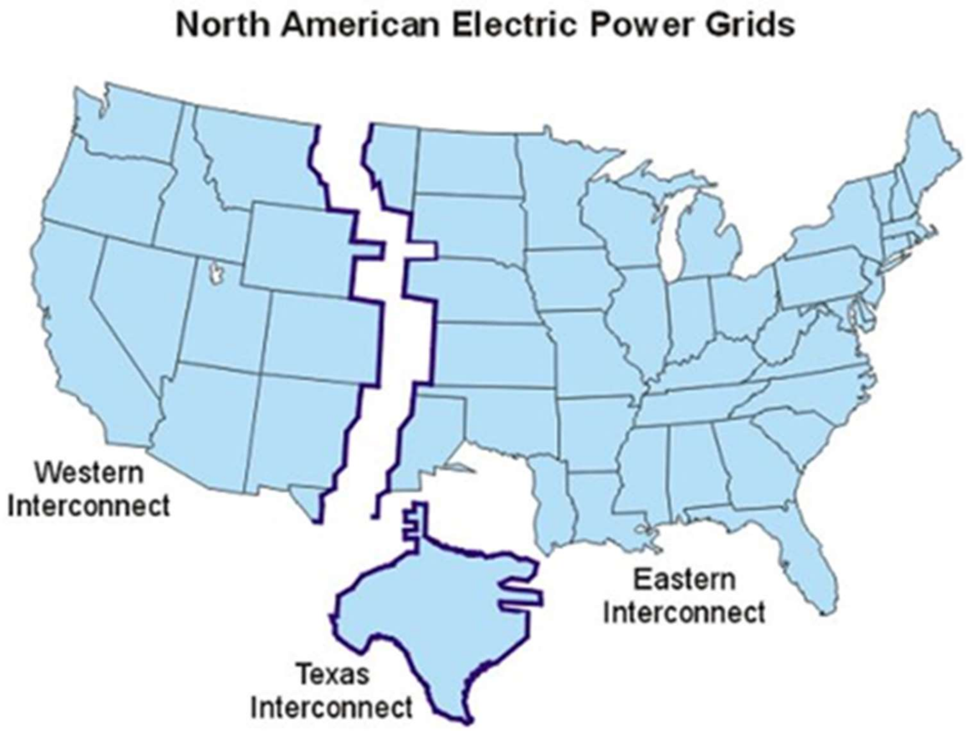

Figure 2: U.S electricity grid and markets

2. Relevant Literature

Existing literature has reinforced the impacts of short-term weather shocks on household responses in heating and cooling. In 1994, Peirson and Henley[3] first analyzed the effects of extreme temperatures on households and England. Using panel data, they found that extreme temperatures increase electric consumption as previous theory dictates. Households were also found to be both insensitive to changes in price if temperature rises and less sensitive to temperature changes. This implies that if households change their expectations towards the frequency of weather shocks over time, eventually becoming climate extremes, then they may not consume as much electricity in response. Instead of focusing on short time periods as they did in England, this paper looks at the long-run responses considering those same general economic intuition of increased demand in response to shocks. Past literature also mentions long-run responses such as defense expenditures in the form of insulation and more efficient AC and heating units[4]. However, these responses are not further explored in their analysis. This paper attempts to resolve that in the discussion of the results by considering the potential for these responses to reduce consumption estimates through capital purchases and changing expectations.

Past papers implement the fixed-effects model to analyze climate variables found in the panel data. Outside of climate, other variables such as income and price have been considered, and in some instances found to have a larger impact on future residential consumption than climate extremes would[5]. However, given that price and income are macroeconomic variables, there is a potential endogeneity issue that the fixed-effects model alone cannot resolve. Instruments proposed by other papers use the added tax rate for electricity prices and total value added tax as variables to correct the endogeneity present in models that include macroeconomic variables. Other papers attempt to fix this through using the Arellano Bond estimator[6] for dynamic panel data, where the lags of weakly exogenous variables are used as instrumental variables in the regression. This used specifically for household income and energy prices, as the two are endogenous in the model specification of other papers. In this paper the Arellano Bond method is used to lag personal household income per capita and average annual electricity prices.

The main contribution of this paper towards the existing literature is to measure the impact climate extremes in a long-term horizon using panel data consisting of both climate and macroeconomic variables. To correct for the endogeneity problems between consumption and the predetermined variables of income and price, I utilize the Arellano Bond estimator to try and build on existing literature through a different model selection. In addition to this, contributions to exploring other long-term responses outside of electric consumption changes are also made. Past literature has not explored how household expectations change with increased frequency of extremes. This is not without limitations however, due to a lack of household level panel data versus existing aggregated data for the entire residential sector. Because of this, even with the use of instrumental variables, omitted variable bias is difficult to avoid over long periods of time. This framework is applied to state-level panel data for the United States whereas past models utilize data across countries or within specific regions. This accounts for spatial variation of climate that past papers control for by looking at regions with a uniform climate. Furthermore, the inclusion of drought measures in the form of precipitation estimates expand on previous climate variables used which focused only on temperature related estimates.

3. Economic Background

The underlying economic theory for this paper follows concepts established in energy economics. The following equations are borrowed from the section on economic theory in Aufhammer's 2014 exploration of relevant literature of climatic impacts on energy consumption[4]. The relation between temperature and household response is described through the household energy expenditure theory Eq. (1).

$$U = U(E^{\rightarrow}, D^{\rightarrow}, Y; F_0(t)) \tag{1}$$

In this model, a household's utility is determined by the combination of goods given the distribution of outside temperature at that moment in time by $F_0(t)$. E represents a vector for the different sources of energy a household consumes in their response. For heating demand the sources of energy include coal, gas, and electricity, whereas cooling demand just uses electricity. D represents a vector for different durable goods that affect the marginal utility of energy use such as refrigerators, HVAC systems, and central heating[4]. Y is a composite or numeraire good. In this paper, the assumption is that most US households use electricity for heating and cooling. Durable goods are also considered in the discussion of results, however their impacts on consumption are not represented in the data, so they are excluded from the statistical analysis. Outside temperature is represented by a variety of climate variables ranging from temperature averages, extremes, and precipitation totals.

The maximization of a household's utility given choices of durable goods and energy sources with respect to outside temperature is subject to prices and temperature. This is represented by the model Eq. (2)[4] where the household is constrained by its income I, price of energy sources P_E, and price of durable goods P_D. In this paper's model specification, price and income are represented in the data to incorporate this economic theory and serve as explanatory variables for the residential sector's consumption in a year. A house derives utility directly from Eq. (3)[4]:

$$\max_{E^{\rightarrow},D^{\rightarrow},Y} U(.\,;F_0)\,\mathrm{s.t.} = \mathrm{P}_{\mathrm{E}}^{\rightarrow} E^{\rightarrow} + \mathrm{P}_{\mathrm{D}}^{\rightarrow} D^{\rightarrow} + Y \leq \mathrm{I} \tag{2}$$

$$E = E(|t_{in}\text{-}t|,\, D) \tag{3}$$

where $|t_{in}\text{-}t|$ is the absolute value of the difference of the interior temperature and exterior temperature. This difference is the temperature change mitigated by the household given a set of durables that determine the energy required to control the interior temperature. There are specific assumptions made with the maximization of utility theory that are also upheld in this paper. The first is that while prices of energy and durables may respond to climate change, they are assumed to not be significant unless the time span of the analysis is over several decades. Second, the discounting of costs as households transition their energy consumption is not considered in this paper. However, the larger effects of household transition and adaptation are explored in the discussion of the results.

4. Model Specification

The model specification for the paper contains three sets of independent variables: general climate averages and totals, climate extremes, and macroeconomic. Each of these regressors and the outcome variable of residential electric consumption are categorized by year *t* and state *i* and thus is represented by a general panel data model provided below in Eq. 4[7]. One exception to note is temperature-related climate extremes, as a single estimate in a year represents the same value for multiple states within that region. In this model, they are treated as individual estimates for each state.

$$\mathrm{Y}_{\mathrm{i,t}} = \beta_0 + \beta_1 \mathrm{X}_{\mathrm{i,t}} + \beta_2 \mathrm{X}_{\mathrm{i,t}} + \ldots \beta_{10} \mathrm{X}_{\mathrm{i,t}} + \mu_{\mathrm{i,t}} \tag{4}$$

The general climate averages and totals include: the state's annual maximum temperature, minimum temperature, average temperature, and total precipitation (inches). I included the temperature estimates as variables in the model to follow the previously established economic theory on energy demand. The justification for using minimum and maximum was because the extreme climate variables reflect extremes both below and above the minimum of maximum for a year. For example, extremes in minimum include both occurrences when it is much colder than the minimum on average and when it is much hotter than the minimum on average. The same applies to maximum temperatures. Total annual precipitation was also included to see if rainfall would be associated with individuals in a household staying inside, therefore increasing energy consumption. This also serves as a measure of drought, as areas with less precipitation are associated with a greater likelihood of drought caused by higher temperatures. Other models use humidity and air pressure as additional non-temperature specific climate variables, but there was no data available on annual measures in each state.

Climate extremes include: extremes below and above the average maximum and minimum temperatures in a year and extremes in 1-day precipitation. The temperature-related extremes are divided into 4 different variables (extremes below minimum, extremes above minimum, extremes below maximum, and extremes above maximum). The specification of these extremes as being higher or lower is a necessary distinction because minimum temperature warmer than usual and maximum temperature colder than usual are assumed to have a negative effect on electric consumption. This is because while they are categorized as extremes, their values approach the range of temperatures from 69-79 degrees Fahrenheit, where neither the cooling or heating effect applies (see Fig. 3)[8]. Precipitation extremes over 1 day are necessary to evaluate how short-term

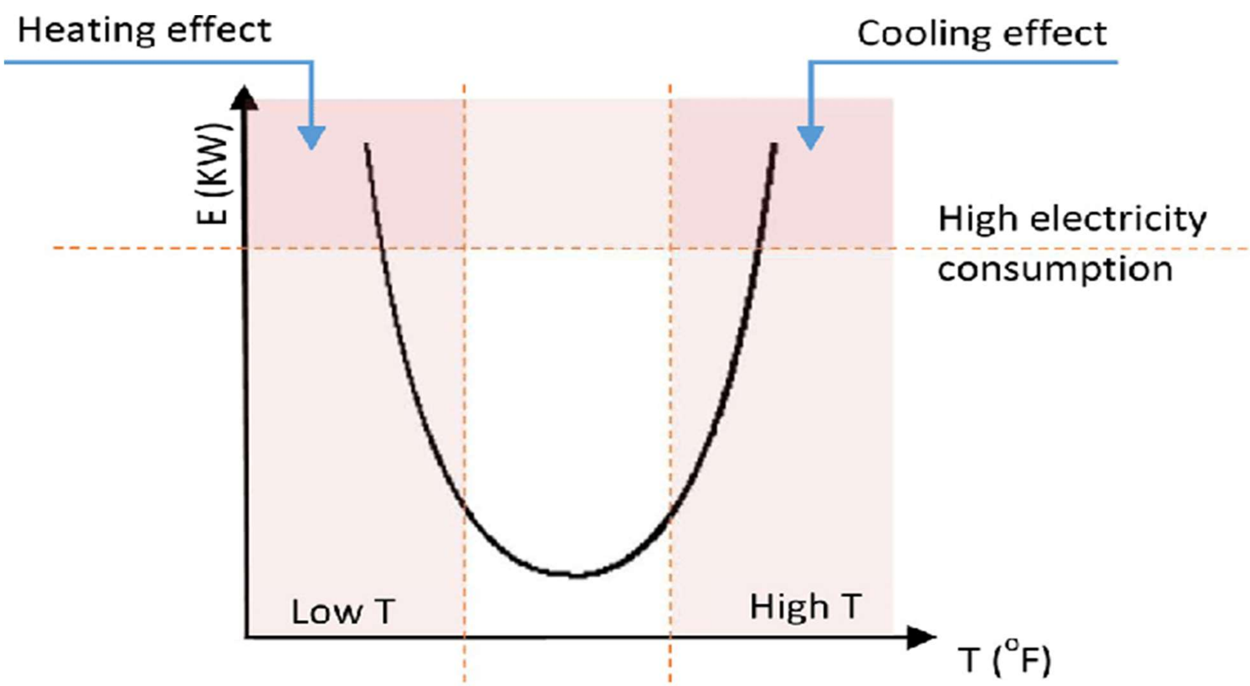

Figure 3: Heating and cooling effects

torrential rain affects electric consumption in contrast to total rainfall. While total rainfall may be greater in some regions than others, this does not account for how it is spread out over the course of a year. Precipitation in a state for a year may come through intense rainfall over a few weeks, while for other states rainfall is spread out through the entire year in sparse amounts. Extremes help capture these responses that cannot be measured through climate normals alone.

Finally the macroeconomic variables included are average annual electric prices measured in cents/KwH and annual personal income per capita for each state. Income and prices are essential to the model as the underlying theory and previous literature[5] have taken into account the budget constraint of a household's energy demand given energy prices and cost of durable goods. The income effect plays a role in allowing households to consume more electricity, and it is assumed that this will occur in the empirical results as historically, US GDP has risen around 3.14% on average (trading economics). In this model, the prices of durable goods are not considered due to the lack of household level panel data detailing the specific capital purchases made by households each year. Therefore, the budget constraint only includes the prices of electricity in relation to available income. Personal income is included instead of disposable income, as changing tax laws for rebates, income tax, and grants across states would be too complex to account for in the model without further data. The price effect is assumed to negatively affect household consumption at a greater rate than the income effect. Since price is directly related to a single good, it would have direct effects on consumption. The assumption is that increases in income would lead to multiple smaller increases in consumption of different goods depending on the household's preferences. Some households may decide to spend their extra income on investments, nutrition, or leisure.

5. Data

The data used for the model comes from several government agencies who provide downloadable visualizations and csv files for personal use. Residential consumption and price data comes from the Energy Information Administration website (EIA)[9] which provides estimates from 1990-2019 for energy data. Household income data comes from the U.S. Bureau of Economic Analysis's (BEA) data tools[10], which allow for filtering of various income variables across states and counties. Finally, all climate related data including normals and extremes come from the National Oceanic and Atmospheric Administration. Extremes can be found under the U.S. Climate Extremes Index (CEI) and normals are found under Climate at a Glance[11]. As mentioned previously, extremes are measured differently than traditional climate variables in that values correspond to multiple states within a given region. There are 9 climate regions defined by the NOAA in their measurements. Units for extremes are given in percentage of days in the year where they occur. For example, a value of 10% for extremes in 1 day precipitation would indicate that 10% of the days in that year experienced extremes in rains. This can also be looked at as the frequency of extremes during the year. A brief overview of the data is provided below using the descriptive statistics command in STATA (See Table 1).

Table 1
Descriptive Statistics of Panel Data

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
Residential Annual Sales (Megawatt Hours)	1440	2.59E+07	2.52E+07	1719933	1.57E+08
Residential Annual Price (cents/KwH)	1440	9.949139	3.14589	4.36	21.92
Personal Income Per Capita	1440	34440.83	11885.71	13356	77273
Annual Maximum Temperature	1440	63.86146	8.072312	47.4	83.6
Annual Minimum Temperature	1440	41.48771	7.769055	25.6	63.6
Annual Average Temperature	1440	52.67618	7.80915	36.5	73.4
Annual Precipitation	1440	38.07033	14.88225	6.24	79.48
Extremes in Max. Temperature Above Average	1440	21.59479	31.08316	0	100
Extremes in Max. Temperature Below Average	1440	4.005486	12.00328	0	78.7
Extremes in Min. Temperature Above Average	1440	27.46431	35.63783	0	100
Extremes in Min. Temperature Below Average	1440	0.8378472	4.41292	0	49.1
Extremes in 1 Day Rain	1440	15.30292	10.92853	0	62.6

6. Methodology

The economic approach in this paper first begins with considering the fixed-effects model as a starting point to analyze panel data. While this approach was able to account for omitted variables that vary over states or years, it leads to an endogeneity problem as the macroeconomic variables for the next year are partially affected by the electric consumption for the current year. This violates the strict exogeneity condition required by the fixed-effects model. If demand for electricity prices are high in a given year, then the provider will increase prices in response over the course of the next year, causing a feedback effect. For personal income per capita, this is also a problem as greater consumption can lead to growth in jobs and income for those working in energy and other related sectors. In return, more jobs and higher income then further push up consumption, repeating the cycle. To correct for these issues, several other models choose instrumental variables. However due to the lack of potential IVs with available data in the time span of this model, this is not possible.

Because of this, the Arellano Bond estimator for dynamic panel data is used for the model. All following regressions utilize the robust standard error. The Arellano Bond Estimator takes the first difference estimator of the model to eliminate the individual effect that is time invariant as shown in Eq. 5[7]. The removal of the individual affect also removes the α_{i} time invariant effect that cannot be observed. Its distinction is in the use of lags of weakly exogenous variables and the outcome variables as instruments. While the dependent variable is not initially lagged in the panel data set, it is done so here because of the implied endogeneity. These lags are represented in Eq. 6[7], using the first and second lags of the outcome variable as regressors. These lags are then used as instrumental variables if there is a problem with endogeneity occurring between the regressors and dependent variables. In the paper's model, residential electric consumption, personal income per capita, and residential annual price are all lagged and used as instrumental variables. While this does reduce the number of observations available, this is not an issue as each variable contains 1440 observations.

$$\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1} = \Delta\beta_1 X_{i,t} + \Delta\beta_2 X_{i,t} + \ldots \Delta\beta_{10} X_{i,t} + \Delta\mu_{i,t} \quad (5)$$

$$\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1} = \Delta\beta_1 X_{i,t} + \rho\Delta Y_{i,t-1} + \rho\Delta Y_{i,t-2} + \Delta\mu_{i,t} \quad (6)$$

The regressions began by excluding certain variables and considering the number lags of the weakly exogenous variables and the dependent variable. Two regressions were selected that gave the most robust results in relation to the significance and coefficient signs for each variable. The first regression (see Table 2) includes all variables mentioned in the model specification having lagged consumption, price, and income twice for use as instruments. However, there was a problem with the variable extremes in maximum temperature above average as it had a negative coefficient. This would mean that days that are hotter than normal would have a negative effect on consumption when prior theory states that the opposite should occur. Because of this, I then performed multiple regressions excluding this variable and found that the most robust regression involves using 3 lags of consumption, price and income (see Table 3). The conclusion is that by removing this variable, the overall model becomes more significant as certain climate extremes that were not significant before are significant now.

Table 2
Regression results using 2 lags and all variables

Number of Instruments = 179 Number of Observations = 1344 Number of Groups = 48

Residential Annual Sales (Megawatt Hours)	Coefficient	Robust Standard Error	Z	P >| z	[95% Confidence Interval]	
Residential Annual Sales (Megawatt Hours) L.1	0.9415085	0.0127492	73.85	0	0.9165206	0.9664964
Residential Annual Price (cents/KwH)	-239075.5	48654.72	-4.91	0	-334437.1	-143714
Personal Income Per Capita	43.16002	9.376104	4.6	0	24.78319	61.53685
Annual Maximum Temperature	-253549.3	629866	-0.4	0.687	-1488064	980965.3
Annual Minimum Temperature	25299.86	629563.5	0.04	0.968	-1208622	1259222
Annual Average Temperature	498301.3	1227573	0.41	0.685	-1907698	2904300
Annual Precipitation	-49535.53	10120.25	-4.89	0	-69370.84	-29700.21
Extremes in Max. Temperature Above Average	-15056.08	3892.028	-3.87	0	-22684.31	-7427.842
Extremes in Max. Temperature Below Average	-3028.924	5675.097	-0.53	0.594	-14151.91	8094.061
Extremes in Min. Temperature Above Average	230.5492	2971.219	0.08	0.938	-5592.934	6054.032
Extremes in Min. Temperature Below Average	53048.69	16931.08	3.13	0.002	19864.38	86233
Extremes in 1 Day Rain	23745.47	4980.7	4.77	0	13983.48	33507.46

_cons	-6539228	4669608	-1.4	0.161	-15700000	2613035

Table 3
Regression results using 3 lags and excluding one extreme

Number of Instruments = 258 Number of Observations = 1344 Number of Groups = 48

Residential Annual Sales (Megawatt Hours)	Coefficient	Robust Standard Error	Z	P >| z	[95% Confidence Interval]	
Residential Annual Sales (Megawatt Hours)						
L.1	0.9239569	0.0157103	58.81	0	0.8931652	0.9547486
Residential Annual Price (cents/KwH)	-222890.9	49319.02	-4.52	0	-319554.4	-126227.4
Personal Income Per Capita	47.66106	10.0108	4.76	0	28.04025	67.28187
Annual Maximum Temperature	-451637.7	625176.5	-0.72	0.47	-1676961	773685.8
Annual Minimum Temperature	202477.7	634105.7	0.32	0.749	-1040347	1445302
Annual Average Temperature	422764.6	1241851	0.34	0.734	-2011219	2856749
Annual Precipitation	-43605.57	9618.628	-4.53	0	-62457.73	-24753.4
Extremes in Max. Temperature Below Average	-12565.54	6400.952	-1.96	0.05	-25111.18	-19.90821
Extremes in Min. Temperature Above Average	-8297.876	2363.335	-3.51	0	-12929.93	-3665.824
Extremes in Min. Temperature Below Average	63197.9	18778.7	3.37	0.001	26392.32	100003.5
Extremes in 1 Day Rain	24622.22	5105.947	4.82	0	14614.74	34629.69
_cons	2574585	4755634	0.54	0.588	-6746286	1.19E+07

7. Discussion of Results

In understanding the implications of these empirical findings I first analyze the variables that are statistically significant, and their implied effects on consumption through their coefficients the first regression including all variables, personal income per capita is shown to be statistically significant, having a positive effect on residential consumption of 43.16 megawatt hours for every additional dollar. On the other hand, annual price for the residential sector is shown to negatively impact household consumption, by a reduction of 239,075 megawatt hours per dollar increase in the price. This would confirm the previous assumptions that price would have a larger impact on consumption that income would. Annual measures of average, maximum, and minimum temperature were not statistically significant. However, annual precipitation was found to be significant as an increase in rainfall by one inch reduces consumption by 49,535 megawatt hours. This can be explained by greater rainfall being associated with cooler regions which reduces the incidences of high temperatures and drought.

For the climate extreme variables, only three out of five were significant. Extremes in minimum temperature below average had a positive impact on consumption, as for each percent increase in annual extreme days, the minimum temperature led to an increase of 53,048 megawatt hours. Extremes in one-day rain also increase consumption by 23,745 megawatt hours for each percent increase in annual extreme days. This effect can be explained by households staying inside and increasing their consumption of heating and other electronics in response to heavy rainfall. Because household expectations are that these extremes are not sustained in the long run, they will not adapt accordingly. However, while extremes in maximum temperature was significant, the sign of its coefficient was confusing as the variable was shown to have a negative effect on consumption. The expectation would be that days hotter than normal would increase consumption of air conditioning and other cooling sources. A possible explanation for this could be that extreme heat days can lead to blackouts and brownouts for providers unable to handle the increased load. This would either cut power to households through transmission failure, or artificially through dampening transmission to the residential sector. Given the unusual nature of this variable, the model specification of the next regression omits it.

In the subsequent regression, statistical significance improved for climate extreme variables. All other variables including price, income, annual temperature averages, and annual precipitation remained relatively the same with very minor changes. Extremes in minimum temperature below average and in one day precipitation became more significant. Both extremes in minimum temperature above average (-8,927) and maximum temperature below average (-12,565) were significant, as these deviations from the mean approach 70-79 degrees where no heating or cooling is needed by households. By removing extremes in maximum temperature above average, other climate extremes that were previously not significant now are.

While the results of these regressions isolate household responses to a choice in how much electricity to consume, this is not the case in the long-run scenario. Households can adapt by purchasing equipment that helps to control the interior temperature. This includes insulation, more efficient heating units, and the installation of central air conditioning in households who previously relied on window units. Many states also offer tax incentives or grants to help household renovate their homes to be more energy efficient. This would help them reduce electricity consumption not just in heating and cooling demand, but in other areas as well. Improvements in heating and cooling efficiency for units may lower consumption over time, but the purchases of these depend on the individual household's income and current equipment. This is not represented in the data due to the lack of household level panel data that accounts for these capital purchases. Another potential issue involves household expectations, as while climate extremes are measured in how many days of the year they occur, there is not indication of their length or seasonality. If extremes in heat or cold occur several days in a row in similar seasons every year, then a household will expect this to occur and adapt their expectations of future climate. This includes capital purchases as a form of adaptation. If it is sporadic instead, then this will not occur, causing households to consume more electricity as they more sensitive to extremes they do not expect. Unless more specific data can be collected, it will be difficult for future literature to address these adaptations by households. Climate variables alone do not explain a household's response.

A final issue to be considered is how these results can be applied to policy decisions for the energy sector in the United States. In the case for improving existing electric generation and transmission infrastructure, it is important to consider how weather extremes can greatly increase consumption beyond the current limits to provide for. Failure of existing infrastructure in due to extreme cold (e.g.) Texas 2021 or extreme heat (e.g. California 2020) necessitate improvements in generation capability and in resistance to degradation from these conditions. Specific to the empirical results, temperatures colder than usual and 1-day extremes in precipitation are both significant and harmful for infrastructure. Therefore, policy should be geared towards building pipes that deliver electricity sources and towers that transmit electricity with more cold-resistant materials. Measures should also be in place to prevent flooding such as building facilities at higher elevations and in areas with historically lower instances of extreme rainfall. Climate change further exacerbates this issue, as these extremes will become more intense over time. Assuming populations and sectors will continue to grow, the consequences of blackouts will become more severe for businesses and households. Increases in funding towards energy storage development may also help, but this has be ongoing for several decades due to the prohibitive expenditures required that many state governments are not willing to undergo. Given these recent events that show the vulnerabilities of the power grid throughout the U.S., there is a greater need now more than ever to begin the renovation of this existing infrastructure.

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