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Impacts of Climate Change on Residential Electricity Consumption

Evidence from Billing Data

Anin Aroonruengsawat and Maximilian Auffhammer

11.1 Introduction

Forecasts of electricity demand are of central importance to policymakers and utilities for purposes of adequately planning future investments in new generating capacity. Total electricity consumption in California has more than quadrupled since 1960, and the share of residential consumption has grown from 26 percent to 34 percent (Energy Information Administration [EIA] 2008). Today, California's residential sector alone consumes as much electricity as Argentina, Finland, or roughly half of Mexico. The majority of electricity in California is delivered by three investor-owned utilities and over a hundred municipal utilities.

On a per capita basis, California's residential consumption has stayed almost constant since the early 1970s, while most other states have experienced rapid growth in per capita consumption. The slowdown in growth of California's per capita consumption coincides with the imposition of aggressive energy efficiency and conservation programs during the early 1970s. The average annual growth rate in per capita consumption during 1960 to

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1973 was approximately 7 percent and slowed to a remarkable 0.29 percent during 1974 to 1995. Growth rates during the last decade of available data have increased to a higher rate of 0.63 percent, and this difference in growth rates is statistically significant.

California's energy system faces several challenges in attempting to meet future demand (California Energy Commission [CEC] 2005). In addition to rapid population growth, economic growth and an uncertain regulatory environment, the threat of significant global climate change has recently emerged as a factor influencing the long-term planning of electricity supply. The electric power sector will be affected by climate change through higher cooling demand, lower heating demand, and potentially stringent regulations designed to curb emissions from the sector.

This chapter simulates how the residential sector's electricity consumption will be affected by different scenarios of climate change. We make three specific contributions to the literature on simulating the impacts of climate change on residential electricity consumption. First, through an unprecedented opportunity to access the complete billing data of California's three major investor-owned utilities, we are able to provide empirical estimates of the temperature responsiveness of electricity consumption based on micro-data. Second, we allow for a geographically specific response of electricity consumption to changes in weather. Finally, we explore socioeconomic and physical characteristics of the population, which help explain some of the variation in temperature response.

The chapter is organized as follows: section 11.2 reviews the literature assessing the impacts of climate change on electricity consumption. Section 11.3 describes the sources of the data used in this study. Section 11.4 contains the econometric model and estimation results. We simulate the impacts of climate change on residential electricity consumption in section 11.5. Section 11.6 explores the heterogeneity in temperature response, and section 11.7 concludes.

11.2 Literature Review

The historical focus of the literature forecasting electricity demand has been on the role of changing technology, prices, income, and population growth (e.g., Fisher and Kaysen 1962). Early studies in demand estimation have acknowledged the importance of weather in electricity demand and explicitly controlled for it to prevent biased coefficient estimates as well as wanting to gain estimation efficiency (e.g., Houthakker and Taylor 1970). Simulations based on econometrically estimated demand functions had, therefore, focused on different price, income, and population scenarios, while assuming a stationary climate system. The onset of anthropogenic climate change has added a new and important dimension of uncertainty over future demand, which has spawned a small academic literature on climate change impacts estimation, which can be divided into two approaches.

In the engineering literature, large-scale bottom-up simulation models are utilized to simulate future electricity demand under varying climate scenarios. The advantage of the simulation model approach is that it allows one to simulate the effects of climate change given a wide variety of technological and policy responses. The drawback to these models is that they contain a large number of response coefficients and make a number of specific and often untestable assumptions about the evolution of the capital stock and its usage. The earliest impacts papers adopt this simulation approach and suggest that global warming will significantly increase energy consumption. Cline (1992) provides the earliest study on the impacts of climate change in his seminal book *The Economics of Climate Change*. The section dealing with the impact on space cooling and heating relies on an earlier report by the U.S. Environmental Protection Agency (1989). That study of the potential impact of climate change on the United States uses a utility planning model developed by Linder, Gibbs, and Inglis (1987) to simulate the impact on electric utilities in the United States and finds that increases in annual temperatures ranging from 1.0°C to 1.4°C (1.8°F to 2.5°F) in 2100 would result in demand of 9 percent to 19 percent above estimated new capacity requirements (peak load and base load) in the absence of climate change. The estimated impacts rise to 14 percent and 23 percent for the year 2055 and an estimated 3.7°C (6.7°F) temperature increase.

Baxter and Calandri (1992) provide another early study in this literature and focus on California's electricity use. In their study, they utilize a partial equilibrium model of the residential, commercial, agriculture, and water pumping sectors to examine total consumption as well as peak demand. They project electricity demand for these sectors to the year 2100 under two global warming scenarios: a rise in average annual temperature of 0.6°C (1.1°F—low scenario) and of 1.9°C (3.4°F—high scenario). They find that electricity use increases from the constant climate scenario by 0.6 percent to 2.6 percent, while peak demand increases from the baseline scenario by 1.8 percent to 3.7 percent. Rosenthal, Gruenspecht, and Moran (1995) focus on the impact of global warming on energy expenditures for space heating and cooling in residential and commercial buildings. They estimate that a 1°C (1.8°F) increase in temperature will reduce U.S. energy expenditures in 2100 by \$5.5 billion (1991 dollars).

The economics literature has favored the econometric approach to impacts estimation, which is the approach we adopt in the current study. While there is a large literature on econometric estimation of electricity demand, the literature on climate change impacts estimation is small and relies on panel estimation of heavily aggregated data or cross-sectional analysis of more microlevel data. The first set of papers attempts to explain variation in a cross section of energy expenditures based on survey data to estimate the impact of climate change on fuel consumption choices. Mansur, Mendelsohn, and Morrison (2008) and Mendelsohn (2003) endogenize fuel choice, which is usually assumed to be exogenous. They find that

warming will result in fuel switching toward electricity. The drawback of the cross-sectional approach is that one cannot econometrically control for unobservable differences across firms and households, which may be correlated with weather or climate. If that is the case, the coefficients on the weather variables and corresponding impacts estimates may be biased.

Instead of looking at a cross section of firms or households, Franco and Sanstad (2008) explain pure time series variation in hourly electricity load at the grid level over the course of a year. They use data reported by the California Independent System Operator (CalISO) for 2004 and regress it on a population-weighted average of daily temperature. The estimates show a nonlinear impact of average temperature on electricity load and a linear impact of maximum temperature on peak demand. They link the econometric model to climate model output from three different global circulation models (GCMs) forced using three quasi-official scenarios based on the Intergovernmental Panel for Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) to simulate the increase in annual electricity and peak load from 2005 to 2099. Relative to the 1961 to 1990 base period, the range of increases in electricity and peak load demands are 0.9 percent to 20.3 percent and 1.0 to 19.3 percent, respectively. Crowley and Joutz (2003) use a similar approach where they estimate the impact of temperature on electricity load using hourly data in the Pennsylvania, New Jersey, and Maryland interconnection. Some key differences, however, are that they control for time-fixed effects and define the temperature variable in terms of heating and cooling degree days. They find that a 2°C (3.6°F) increase in temperature results in an increase in energy consumption of 3.8 percent of actual consumption, which is similar to the impact estimated by Baxter and Calandri (1992).

Deschênes and Greenstone (2007) provide the first panel data-based approach to estimating the impacts of climate change on residential total energy consumption, which includes electricity, natural gas, and oil as the main nonrenewable sources of energy. They explain variation in U.S. state-level annual panel data of residential energy consumption using flexible functional forms of daily mean temperatures. The identification strategy behind their paper, which is one we will adopt here as well, relies on random fluctuations in weather to identify climate effects on electricity consumption. The model includes state fixed effects, census division by year fixed effects, and controls for precipitation, population, and income. The temperature data enter the model as the number of days in twenty predetermined temperature intervals. The authors find a U-shaped response function where electricity consumption is higher on very cold and hot days. The impact of climate change on annual electricity consumption by 2099 is in the range of 15 percent to 30 percent of the baseline estimation or 15 to 35 billion (2006 US\$). The panel data approach allows one to control for differences in unob-

servables across the units of observation, resulting in consistent estimates of the coefficients on temperature.

The current chapter is the first study using a panel of household level electricity billing data to examine the impact of climate change on residential electricity consumption. Through a unique agreement with California's three largest investor-owned utilities, we gained access to their complete billing data for the years 2003 to 2006. We identify the effect of temperature on electricity consumption using within-household variation in temperature, which is made possible through variation in the start dates and lengths of billing periods across households. Because our data set is a panel, we can control for household fixed effects, month fixed effects, and year fixed effects. The drawback of this data set is that the only other reliable information we have about each individual household is price and its five-digit zip code location.

11.3 Data

11.3.1 Residential Billing Data

The University of California Energy Institute (UCEI) jointly with California's investor-owned utilities established a confidential data center, which contains the complete billing history for all households serviced by Pacific Gas and Electric (PG&E), Southern California Edison, and San Diego Gas and Electric (SDG&E) for the years 2003 to 2006. These three utilities provide electricity to roughly 80 percent of California households.

The data set contains the complete information for each residential customer's bills over the four-year period. Specifically, we observe an ID for the physical location, a service account number, bill start date, bill end date, total electricity consumption (in kilowatt-hours [kWh]) and the total amount of the bill (in \$) for each billing cycle as well as the five-digit zip code of the premises.¹ Only customers who were individually metered are included in the data set. For the purpose of this chapter, we define a customer as a unique combination of premise and service account number. It is important to note that each billing cycle does not follow the calendar month, and the length of the billing cycle varies across households with the vast majority of households being billed on a twenty-five to thirty-five-day cycle. While we have data covering additional years for two of the utilities, we limit the study to the years 2003 to 2006 to obtain equal coverage. Hereafter, we will refer to this data set as "billing data." Figure 11.1 displays the zip codes we have data for, which is the majority of the state.

Due to the difference in climate conditions across the state, California is

1. The premise identification number does not change with the occupant of the residence. The service account number, however, changes with the occupant of the residence.

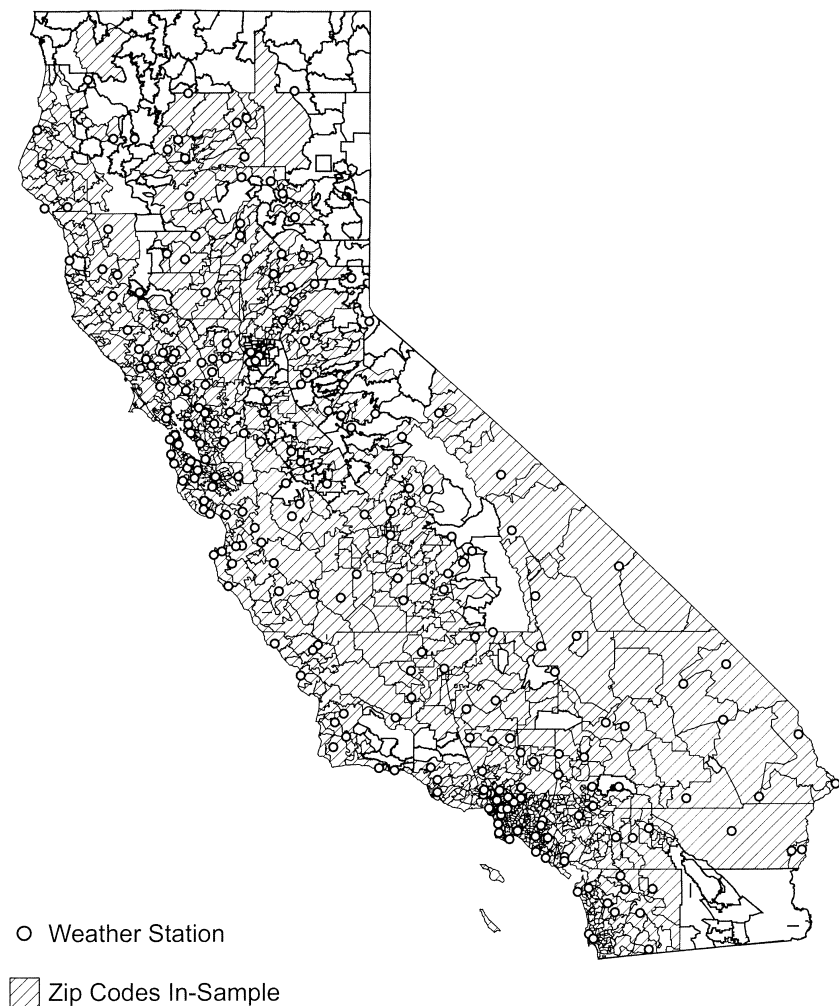


Fig. 11.1 Observed residential electricity consumption 2003–2006 and National Oceanic and Atmospheric Administration cooperative weather stations

Note: The map displays five-digit zip codes with available geographic boundaries.

divided into sixteen building climate zones, each of which require different minimum efficiency building standards specified in an energy code. The climate zones are depicted in figure 11.2.² We expect this difference in building standards to lead to a different impact of temperature change on electricity consumption across climate zones. We will, therefore, estimate the impact

2. The California climate zones shown are not the same as what one would commonly call an area like desert or alpine climate. The climate zones are based on energy use, temperature,

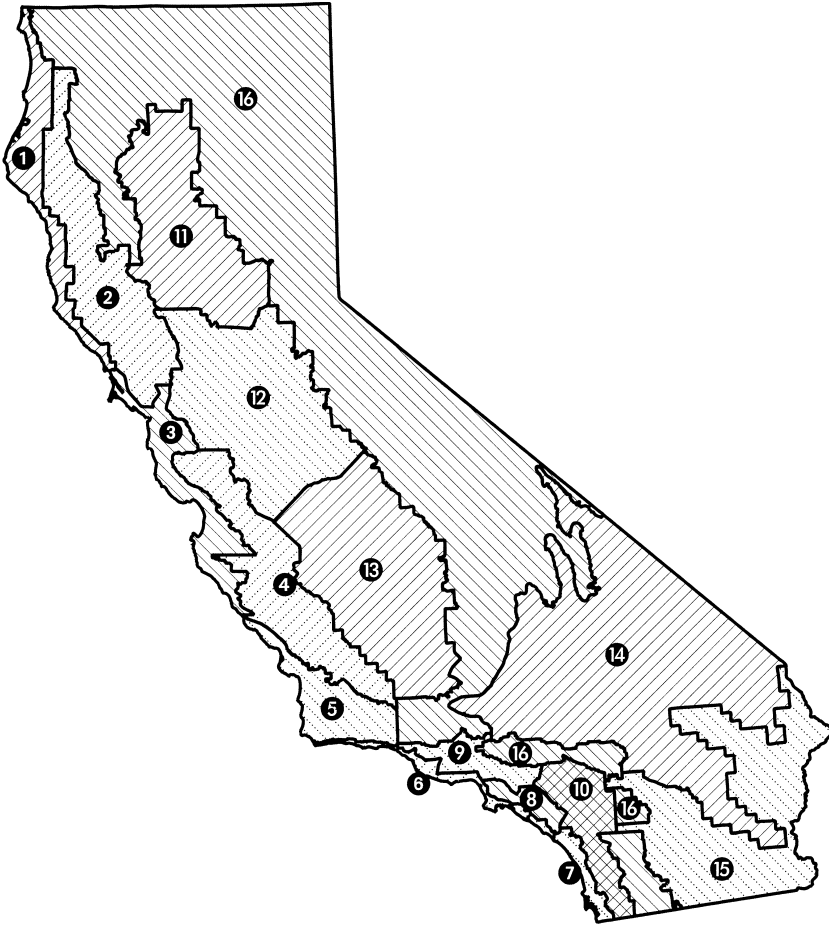


Fig. 11.2 California Energy Commission building climate zones

Source: California Energy Commission.

of mean daily temperature on electricity consumption separately for each climate zone. We later empirically explore the sources of this variation in section 11.6. We assign each household to a climate zone via their five-digit zip code through a mapping, which we obtained from the California Energy Commission.

weather, and other factors. They are essentially a California Energy Commission (CEC)-defined geographic area that has similar climatic characteristics. Each climate zone has a representative city. These are for each of the climate zones: (1) Arcata, (2) Santa Rosa, (3) Oakland, (4) Sunnyvale, (5) Santa Maria, (6) Los Angeles, (7) San Diego, (8) El Toro, (9) Pasadena, (10) Riverside, (11) Red Bluff, (12) Sacramento, (13) Fresno, (14) China Lake, (15) El Centro, and (16) Mount Shasta.

The billing data set contains 300 million observations, which exceeds our ability to conduct estimation using standard statistical software. We, therefore, resort to sampling from the population of residential households to conduct econometric estimation. We designed the following sampling strategy. First, we only sample from households with regular billing cycles, namely twenty-five to thirty-five days in each billing cycle which have at least thirty-five bills over the period of 2003 to 2006.³ We also removed bills with an average daily consumption less than 2 kWh or more than 80 kWh. The reason for this is our concern that these outliers are not residential homes but rather vacation homes and small-scale “home based manufacturing and agricultural facilities.” Combined with the fact that our data does not contain single-metered multifamily homes, our sampling strategy is likely to result in a slight under representation of multifamily and smaller single-family homes. These are more likely to be rental properties than larger single-family units. Our results should be interpreted keeping this in mind.⁴

From the population subject to the preceding restrictions, we take a random sample from each zip code, making sure that the relative sample sizes reflect the relative sizes of the population by zip code. We draw the largest possible representative sample from this population given our computational constraints. For each climate zone, we test whether the mean daily consumption across bills for our sample is different from the population mean and fail to reject the null of equality, suggesting that our sampling is indeed random, subject to the sample restrictions discussed above. We proceed with estimation of our models by climate zone, which makes concerns about sampling weights mute. Figure 11.3 displays the spatial distribution of 2006 consumption shares across zip codes.

Finally, California has a popular program for low-income families—California Alternate Rates for Energy (CARE)—where program-eligible customers receive a 20 percent discount on electric and natural gas bills. Eligibility requires that total household income is at or below 200 percent of federal poverty level. For the first set of models, we exclude these households from our sample. We then explore the robustness of our simulations by including these households in a separate simulation. The concern here is that omitting these smaller homes with lower HVAC saturation rates may lead to an overestimation of impacts.

No single zip code is responsible for more than 0.5 percent of total consumption. Table 11.1 displays the summary statistics of our consumption

3. With the regular billing cycle, there should be forty-eight bills for the households in our sample during the period 2003 to 2006.

4. After removing outlier bills, we compared the population average daily consumption of bills with billing cycles ranging from twenty-five to thirty-five days to the average daily consumption of bills for any length. The average daily consumption by climate zone in the subset of bills we sample from is roughly 1/10th of a standard deviation higher than the mean daily consumption of the complete population including bills of any length.

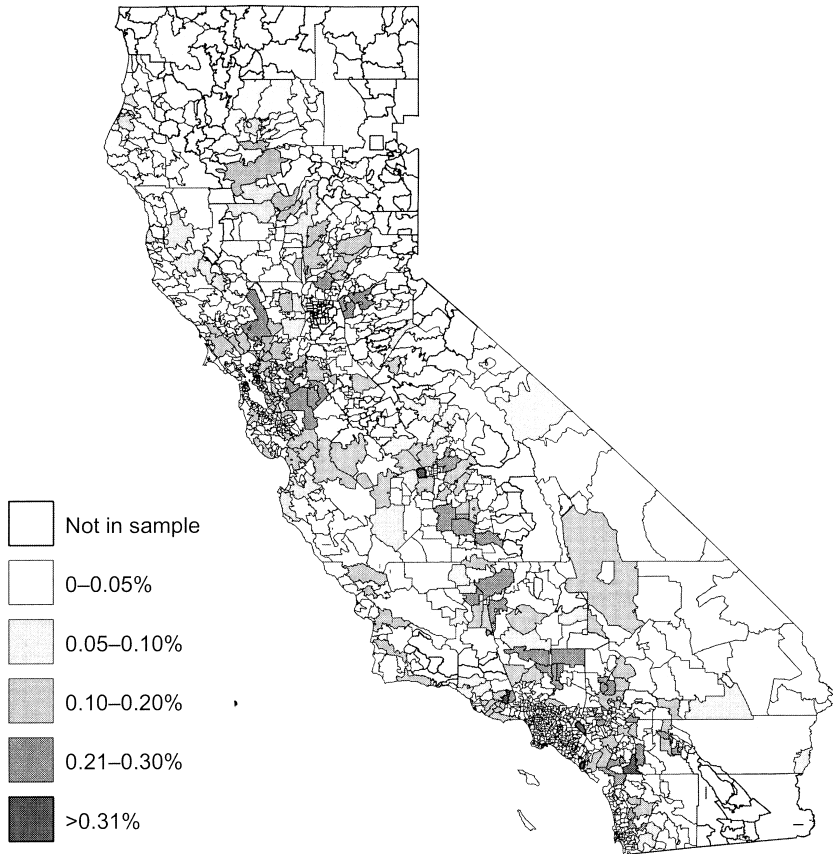


Fig. 11.3 Share of total residential electricity consumption for 2006 by five-digit zip code

sample by climate zone. There is great variability in average usage across climate zones, with the central coast's (zone 3) average consumption per bill at roughly 60 percent that of the interior southern zone 15. The average electricity price is almost identical across zones, at thirteen cents per kWh.

11.3.2 Weather Data

To generate daily weather observation to be matched with the household electricity consumption data, we use the Cooperative Station Dataset published by National Oceanic and Atmospheric Administration's (NOAA) National Climate Data Center (NCDC). The data set contains daily observations from more than 20,000 cooperative weather stations in the United States, the U.S. Caribbean Islands, the U.S. Pacific Islands, and Puerto Rico. Data coverage varies by station. Because our electricity data cover the state of California for the years 2003 to 2006, the data set contains 370 weather

Table 11.1 **Summary statistics**

Zone	No. of observations	No. of households	Usage per bill per billing cycle (Kwh)		Average price per billing cycle (\$/Kwh)		Percentiles daily mean temperature distribution in sample (degree Fahrenheit)				
			Mean	S.D.	Mean	S.D.	1	5	50	95	99
1	1,459,578	31,879	550	354	0.13	0.03	34.5	37.5	54.7	77.0	80.0
2	2,999,408	65,539	612	385	0.13	0.03	36.0	39.0	55.5	77.5	80.5
3	3,200,851	69,875	469	307	0.13	0.02	42.0	44.3	57.0	75.0	78.0
4	4,232,465	92,294	605	362	0.13	0.03	40.5	42.8	57.8	81.4	85.5
5	2,621,344	57,123	504	317	0.13	0.03	42.0	44.3	58.8	76.0	78.5
6	2,970,138	64,145	529	334	0.13	0.03	48.5	50.4	62.0	78.0	81.0
7	3,886,347	85,169	501	327	0.15	0.04	47.0	48.9	61.5	77.5	80.0
8	2,324,653	50,373	583	364	0.14	0.03	49.5	51.5	63.3	80.6	83.3
9	3,067,787	66,231	632	389	0.13	0.03	48.0	50.3	63.0	81.0	83.5
10	3,202,615	70,088	700	416	0.14	0.03	35.5	39.0	61.0	81.8	84.5
11	4,106,432	90,245	795	455	0.13	0.03	28.5	32.8	54.8	84.3	87.0
12	3,123,404	68,342	721	420	0.13	0.03	38.5	40.8	58.5	84.0	87.0
13	3,827,483	84,493	780	464	0.13	0.03	36.6	39.3	59.0	87.8	90.0
14	4,028,225	88,086	714	413	0.13	0.03	32.0	35.0	57.5	91.3	95.0
15	2,456,562	54,895	746	532	0.13	0.03	34.5	37.8	63.8	97.0	99.5
16	3,401,519	74,644	589	409	0.13	0.02	22.5	26.5	52.3	83.0	86.5

Notes: The table displays summary statistics for residential electricity consumption for the non-CARE sample used in the estimation.
S.D. = standard deviation.

stations reporting daily data. In the data set, we observe daily minimum and maximum temperature as well as total daily precipitation and snowfall. Because the closest meaningful geographic identifier of our households is the five-digit postal zip code, we select stations as follows. First, we exclude any stations not reporting data in all years. Further, we exclude stations reporting fewer than 300 observations in any single year and stations at elevations more than 7,000 feet above sea level, which leaves us with 269 “valid” weather stations.⁵ Figure 11.1 displays the distribution of these weather stations across the state. While there is good geographic coverage of weather stations for our sample, we do not have a unique weather station reporting data for each zip code. To assign a daily value for temperature and rainfall, we need to assign a weather station to each zip code. We calculate the Vincenty distance of a zip code’s centroid to all valid weather stations and assign the closest weather station to that zip code. As a consequence of this procedure, each weather station on average provides data for approximately ten zip codes.

Because we do not observe daily electricity consumption by household, but rather monthly bills for billing periods of differing length, we require a complete set of daily weather observations. The NCDC data have a number of missing values, which we fill in using the following algorithm. First, we calculate the Vincenty distance of each zip code’s geographic centroid to all qualifying weather stations. We then identify the ten closest weather stations to each centroid, provided that each is less than fifty miles from the monitor. Of these stations, we identify the “primary station” as the closest station reporting data for at least 200 days a year. We fill in missing values by first regressing, for observations in which the primary weather station was active, the relevant climate weather variable for the primary station onto the same variable for the remaining nine closest stations. We use the predicted values from that regression to replace missing values. Following this step, primary station observations are still missing whenever one of the remaining nine closest stations is also missing an observation. To estimate the remaining missing values, we repeat the preceding step with the eight closest stations, then the seven closest, and so on. To check the performance of our algorithm, we conduct the following experiment. First, we select the set of data points for which the primary weather station has an observation. We then randomly set 10 percent of the temperature data for this station to missing. After applying the algorithm described in the preceding to this sample, we compare the predicted temperature data to the observations we had set aside. Even for observations in which a single additional weather station was used to predict a missing temperature, the correlation coefficient between actual

5. The cutoff of 300 valid days is admittedly arbitrary. If we limit the set of weather stations to the ones providing a complete record, we would lose roughly half of all stations. We conducted robustness checks using different cutoff numbers, and the results are robust.

and predicted temperatures exceeds 0.95. Plotting the actual and predicted series against each other provides an almost perfect fit. We, therefore, feel confident that our algorithm provides us with a close representation of the true data generating process for missing weather observations. We end up with a complete set of time series for minimum temperature, maximum temperature, and precipitation for the 269 weather stations in our sample. For the remainder of our empirical analysis, we use these patched series as our observations of weather.⁶

There is an important caveat to using daily weather data when studying households' response to climate change. By using daily weather shocks, we implicitly estimate individuals' response to changed *daily* temperatures. While climate change will affect daily temperatures on average, it is a more long-run process and should be thought of as the long-run moving average of weather. The estimated impacts for this reason may, on the one hand, be too high if individuals have lower cost options in the long run and relocate to cooler climates. The estimated impacts based on daily weather, on the other hand, may be too low if individuals adapt in the sense that areas that do not currently cool using electricity start seeing a high degree of air conditioner penetration. The overall sign of the bias is not clear. Unfortunately, it is not clear whether the perfect counterfactual to study this problem exists. One would require randomly assigned climate (not weather) to study this issue. This randomization would affect technology adoption. Electricity demand, in turn, is determined at the daily level by fluctuations in weather around a long-run trend.

The second caveat is that it would be preferable to have a weather index, which counts all relevant dimensions of weather, such as minimum and maximum temperature, humidity, solar radiation, and wind speed and direction. Unfortunately, these indicators are not available for the vast majority of stations at the daily level. One could, however, estimate a response function using such an index for locations that have sufficient data. We leave this for future research.

11.3.3 Other Data

In addition to the quantity consumed and average bill amount, all we know about the households is the five-digit zip code in which they are located. We purchased sociodemographics at the zip-code level from a firm aggregating this information from census estimates (zip-codes.com). We only observe these data for a single year (2006). The variables we will make use of are total population and average household income. The final sample used for estimation comprises households in zip codes that make up 81 percent of California's population. Table 11.2 displays summary statistics for all zip

6. We also tried an inverse distance weighting algorithm for filling in missing data, and the results are almost identical.

Table 11.2 **Summary statistics for zip codes in and out of sample**

Variable	<i>n</i>	Mean (not in sample)	S.D.	<i>n</i>	Mean (in sample)	S.D.	Difference
Population	239	19.83	20.86	1,325	20.39	20.67	0.56
Household size	239	2.66	0.60	1,325	2.79	0.60	0.14***
Household income	239	39.52	19.39	1,325	48.32	21.53	8.80***
House value	239	200.08	177.33	1,325	234.90	177.51	34.83***
Median age	239	36.92	7.34	1,325	36.85	7.50	-0.07
Elevation	239	1,081.45	1,526.95	1,325	439.63	737.94	-642***
Land area	239	69.66	130.12	1,325	68.05	140.45	-1.61

Note: S.D. = standard deviation.
***Significant at the 1 percent level.

codes in California with registered residential population, broken down by whether we observe households in a given zip. We observe households for 1,325 zip codes and do not observe households for 239 zip codes. The 239 zip codes are not served by the three utilities, which provided us with access to their billing data. Table 11.2 shows that the zip codes in our sample are more populated, have larger households, are wealthier, and are at lower elevations. There seems to be no statistically significant difference in population, median age, or land area. Taking these differences into consideration is important when judging the external validity of our estimation and simulation results.

Finally, we will explore which observable characteristics of households are consistent with differences in the temperature repose function. We use the year 2000 long form census data for the state of California to calculate indicators of observable characteristics of the average household or structure in that zip code. We obtain measures of the share of households using gas or electricity as heating fuel, year the average structure was built, the percent of urban households, and the percent of rental properties.

11.4 Econometric Estimation

As discussed in the previous section, we observed each household's monthly electricity bill for the period 2003 to 2006. Equation (1) shows our main estimating equation, which is a simple log-linear specification commonly employed in aggregate electricity demand and climate change impacts estimation (e.g., Deschênes and Greenstone 2007).

$$(1) \quad \log(q_{it}) = \sum_{p=1}^k \beta_p D_{pit} + \gamma Z_{it} + \alpha_i + \phi_m + \gamma_y + \varepsilon_{it}$$

$\log(q_{it})$ is the natural logarithm of household i 's electricity consumed in kWhs during billing period t . For estimation purposes, our unit of observation is a unique combination of premise and service account number, which is associated with an individual and structure. We thereby avoid the issue of having individuals moving to different structures with more or less efficient capital or residents with different preferences over electricity consumption moving in and out of a given structure. California's housing stock varies greatly across climate zones in its energy efficiency and installed energy consuming capital. We estimate equation (1) separately for each of the sixteen climate zones discussed in the data section, which are also displayed in figure 11.2. The motivation for doing so is that we would expect the relationship between consumption and temperature to vary across these zones as there is a stronger tendency to heat in the more northern and higher altitude zones and a stronger tendency to cool, but little heating taking place, in the hotter interior zones of California.

The main variables of interest in this chapter are those measuring temperature. The last five columns of table 11.1 display the median, 1st, 5th,

90th, and 95th percentile of the mean daily temperature distribution by climate zone. The table shows the tremendous differences in this distribution across climate zones. The southeastern areas of the state, for example, are significantly hotter on average yet also have greater variances.

Following recent trends in the literature, we include our temperature variables in a way that imposes a minimal number of functional form restrictions in order to capture potentially important nonlinearities of the outcome of interest in weather (e.g., Schlenker and Roberts 2006). We achieve this by sorting each day's mean temperature experienced by household i into one of k temperature bins.⁷ In order to define a set of temperature bins, there are two options found in the literature. The first is to sort each day into a bin defined by specific equidistant (e.g., 5°F) cutoffs. The second approach is to split each of the sixteen zones' temperature distributions into a set of percentiles and use those as the bins used for sorting. The latter strategy allows for more precisely estimated coefficients because there is guaranteed coverage in each bin. The equidistant bins strategy runs the risk of having very few observations in some bins, and, therefore leading to unstable coefficient estimation, especially at the extremes.

There is no clear guidance in the literature on which approach provides better estimates, and we, therefore, conduct our simulations using both approaches. For the percentile strategy, we split the temperature distribution into deciles yet break down the upper and bottom decile further to include buckets for the 1st, 5th, 95th, and 99th percentile to account for extreme cold or heat days. We, therefore, have a set of fourteen buckets for each of the sixteen climate zones. The thresholds for each vary by climate zone. For the equidistant bins approach, we split the mean daily temperature for each household into a set of 5° bins. In order to avoid the problem of imprecise estimation at the tails due to insufficient data coverage, we require that each bin have at least 1 percent of the data values in it for the highest and lowest bin. The highest and lowest bins in each zone therefore contain a few values that exceed the 5° threshold.

For each household, bin definition and billing period we then counted the number of days the mean daily temperature falls into each bin and recorded this as D_{pit} . The main coefficients of interest to the later simulation exercise are the β_p s, which measure the impact of one more day with a mean temperature falling into bin p on the log of household electricity consumption. For small values, β_p s interpretation is approximately the percent change in household electricity consumption due to experiencing one additional day in that temperature bin.

Z_{it} is a vector of observable confounding variables which vary across billing periods and households. The first of two major confounders we observe at the

7. We use mean daily temperature as our temperature measure. This allows a flexible functional form in a single variable. An alternate strategy we will explore in future work is separating the temperature variables into minimum and maximum temperature, which are highly correlated with our mean temperature measure.

household level are the average electricity price for each household for a given billing period. California utilities price residential electricity on a block rate structure. The average price experienced by each household in a given period is, therefore, not exogenous because marginal price depends on consumption (q_{it}). Identifying the price elasticity of demand in this setting is problematic, and a variety of approaches have been proposed (e.g., Hanemann 1984; Reiss and White 2005). The maximum likelihood approaches are computationally intensive and given our sample size cannot be feasibly implemented here. More important, however, we do not observe other important characteristics of households (e.g., income) that would allow us to provide credible estimates of these elasticities. For later simulation, we will rely on the income specific price elasticities provided by Reiss and White (2005), who used a smaller sample of more detailed data based on the national level Residential Energy Consumption (REC) survey. We have run our models by including price directly, instrumenting for it using lagged prices, and omitting it from estimation. The estimation results are almost identical for all three approaches, which is reassuring. While one could tell a story that higher temperatures lead to higher consumption and, therefore, higher marginal prices for some households, this bias seems to be negligible given our estimation results. In the estimation and simulation results presented in this chapter, we omit the average price from our main regression.⁸ The second major time varying confounder is precipitation in the form of rainfall. We calculate the amount of total rainfall for each of the 269 weather stations, filling in missing values using the same algorithm discussed in the previous section. We control for rainfall using a second-order polynomial in all regressions.

The α_i are household fixed effects, which control for time invariant unobservables for each household. The ϕ_m are month-specific fixed effects, which control for unobservable shocks to electricity consumption common to all households. The γ_y are year fixed effects, which control for yearly shocks common to all households. To credibly identify the effects of temperature on the log of electricity consumption, we require that the residuals conditional on all right-hand side variables be orthogonal to the temperature variables, which can be expressed as $E(\epsilon_{it} D_{pit} | D_{pit}, Z_{it}, \alpha_i, \phi_m, \gamma_y) = 0$. Because we control for household fixed effects, identification comes from within-household variation in daily temperature after controlling for shocks common to all households, rainfall, and average prices.

We estimate equation (1) for each climate zone using a least squares fitting criterion and a clustered variance covariance matrix clustered at the zip code.⁹ Figure 11.4 plots the estimated temperature response coefficients

8. The full set of estimation results are available upon request from the authors.

9. Clustering along the time dimension would be desirable but due to the temporal nesting structure of the billing dates not possible to our knowledge. We also used the White sandwich variance covariance matrix, which yielded smaller standard errors than the ones obtained from clustering by zip.

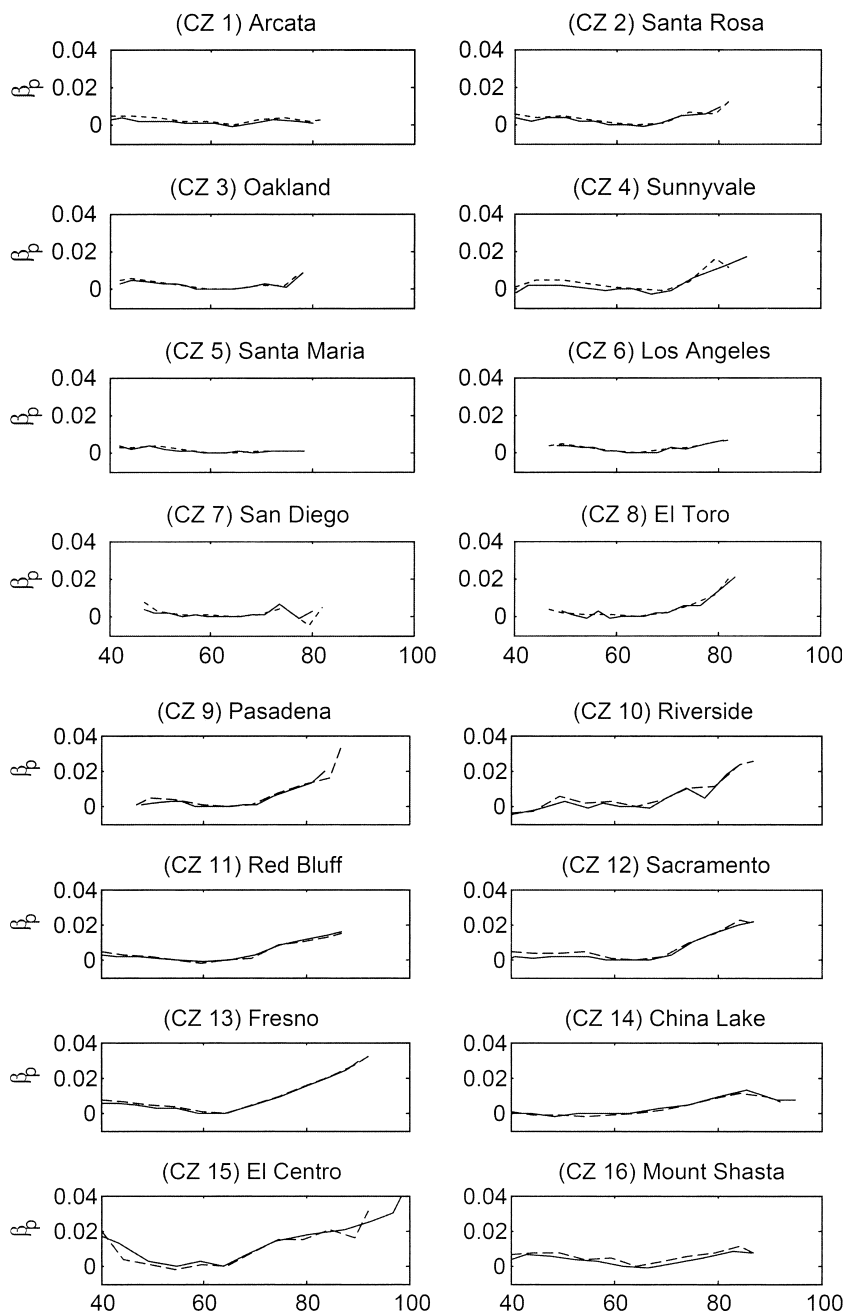


Fig. 11.4 Estimated climate response functions for California Energy Commission climate zones 1–16

Notes: The panels display the estimated temperature slope coefficients for each of the fourteen percentile bins (solid) and the equidistant bins (dashed) against the midpoint of each bin. The plots were normalized using the coefficient estimate for the 60 to 65 temperature bin. The title of each panel displays the name of a representative city for that climate zone.

for each of the climate zones against the midpoints of the bins for the percentile and equidistant bin approaches. The coefficient estimates are almost identical, which is reassuring. We do not display the confidence intervals around the estimated coefficients. The coefficients are so tightly estimated that for visual appearance, displaying the confidence intervals simply makes the lines appear thick. From this figure, several things stand out. First, there is tremendous heterogeneity in the shape of the temperature response of electricity consumption across climate zones. Many zones have almost flat temperature response functions, such as southern coastal zones (5, 6, and 7). Other zones display a very slight negative slope at lower temperatures, especially the northern areas of the state (1, 2, and 11), indicating a decreased consumption for space heating as temperatures increase. California's households mostly use natural gas for space heating, which explains why for most areas we do not see a steeper negative slope at lower temperatures. This is consistent for a lower share of homes using electricity for heat in California (22 percent) than the national average (30 percent). Further, many of these electric heaters are likely located in areas with very low heating demand, given the high cost of using electricity for space heating compared to using natural gas. While there is use of electricity for heating directly, a significant share of the increased consumption at lower temperatures is likely to stem from the operation of fans for natural gas heaters. On the other end of the spectrum, for most zones in the interior and southern part of the state, we note a significant increase in electricity consumption in the highest temperature bins (4, 8, 9, 10, 11, 12, 13, and 15). We further note that the relative magnitude of this approximate percent increase in household electricity consumption in the higher temperature bins varies greatly across zones as indicated by the differential in slopes at the higher temperatures across zones.

We now turn to simulating electricity consumption under different scenarios of climate change using these heterogeneous response functions as the underlying functional form relationship between household electricity consumption and temperature.

11.5 Simulations

In this section, we simulate the impacts of climate change on electricity consumption under two different Special Report on Emissions Scenarios (SRES). We calculate a simulated trajectory of aggregate electricity consumption from the residential sector until the year 2100, which is standard in the climate change literature.

To simulate the effect of a changing climate on residential electricity consumption, we require estimates of the climate sensitivity of residential electricity consumption as well as a counterfactual climate. In the simulation for this section, we use the estimated climate response parameters shown in

figure 11.4. Using these estimates as the basis of our simulation has several strong implications. First, using the estimated β_p parameters implies that the climate responsiveness of consumption within climate zones remains constant throughout the century. This is a strong assumption because we would expect that households in zones that currently do not require cooling equipment may potentially invest in such equipment if the climate becomes warmer. This would lead us to believe that the temperature responsiveness in higher temperature bins would increase over time. On the other hand, one could potentially foresee policy actions, such as more stringent appliance standards, which improve the energy efficiency of appliances such as air conditioners. This would decrease the electricity per cooling unit required and shift the temperature response curve downward in the higher buckets.

As is standard in this literature, the counterfactual climate is generated by a GCM. These numerical simulation models generate predictions of past and future climate under different scenarios of atmospheric greenhouse gas (GHG) concentrations. The quantitative projections of global climate change conducted under the auspices of the IPCC and applied in this study are driven by modeled simulations of two sets of projections of twenty-first century social and economic development around the world, the so-called A2 and B1 storylines in the 2000 Special Report on Emissions Scenarios (SRES; Intergovernmental Panel on Climate Change [IPCC] 2000). The SRES study was conducted as part of the IPCC's Third Assessment Report, released in 2001. The A2 and B1 storylines and their quantitative representations represent two quite different possible trajectories for the world economy, society, and energy system and imply divergent future anthropogenic emissions, with projected emissions in the A2 being substantially higher. The A2 scenario represents a "differentiated world," with respect to demographics, economic growth, resource use, energy systems, and cultural factors, resulting in continued growth in global CO₂ emissions, which reach nearly 30 gigatons of carbon (GtC) annually in the marker scenario by 2100. The B1 scenario can be characterized as a "global sustainability" scenario. Worldwide, environmental protection and quality and human development emerge as key priorities, and there is an increase in international cooperation to address them as well as convergence in other dimensions. A demographic transition results in global population peaking around midcentury and declining thereafter, reaching roughly 7 billion by 2100. Economic growth rates are higher than in A2 so that global economic output in 2100 is approximately one-third greater. In the B1 marker scenario, annual emissions reach about 12 GtC in 2040 and decline to about 4 GtC in 2100.

We simulate consumption for each scenario using the National Center for Atmospheric Research Parallel Climate Model 1 (NCAR). These models were provided to us in their downscaled version for California using the Bias Correction and Spatial Downscaling (BCSD) and the Constructed Analogues (CA) algorithms (Maurer and Hidalgo 2008). There is no clear

guidance in the literature as to which algorithm is preferable for impacts estimation. We, therefore, provide simulation results using both methods. To obtain estimates for a percent increase in electricity consumption for the representative household in zip code j and period $t + h$, we use the following relation:

$$(2) \quad \frac{q_{j,t+h}}{q_{j,t}} = \frac{\exp\left(\sum_{p=1}^k \hat{\beta}_{pj} D_{pj,t+h}\right)}{\exp\left(\sum_{p=1}^k \hat{\beta}_{pj} D_{pj,t}\right)}$$

We implicitly assume that the year fixed effect and remaining right-hand side variables are the same for period $t + h$ and period t , which is a standard assumption made in the majority of the impacts literature. Figure 11.5 shows the change in the number of days spent in each 5° bin of the temperature distribution from 1980 to 1999 to 2080 to 2099 using the NCAR Paral-

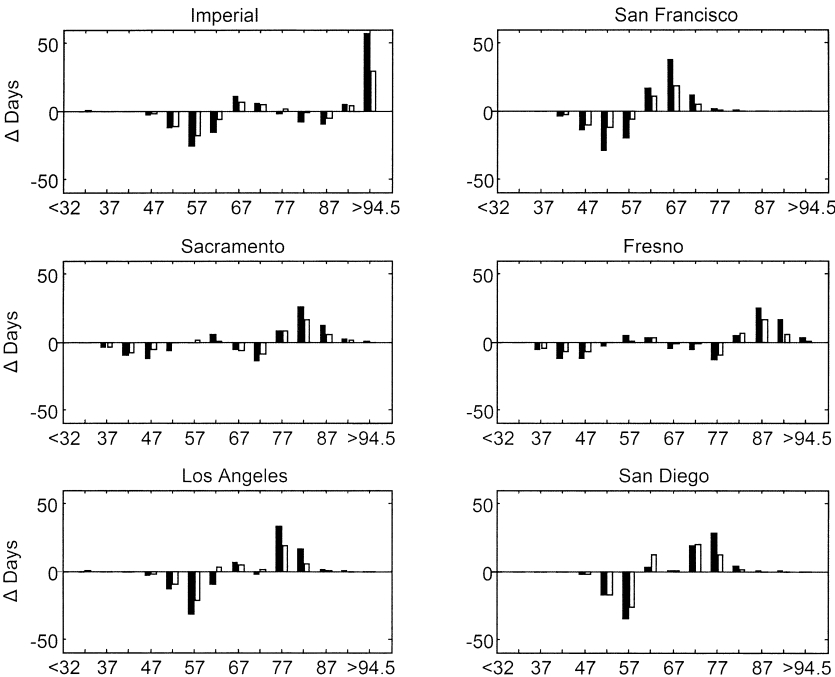


Fig. 11.5 Change in number of days in each 5-degree temperature bin for 2080–2099 relative to 1980–1999 for six selected California cities and Intergovernmental Panel for Climate Change Special Report on Emissions Scenarios A2 (black) and B1 (white) using the National Center for Atmospheric Research Parallel Climate Model with the constructed analogues downscaling method

lcl Climate Model (PCM) forced by scenarios A2 and B1 for six selected California locations. A clear upward shift of the temperature distribution is apparent for all six locations. For locations with upward sloping temperature response functions, this entails increases in electricity consumption due to more days spent in higher temperature bins. Inspecting these graphs for all major urban centers in California, in addition to the six displayed here, confirms the pattern emerging from figure 11.5. The areas with the steepest response functions at higher temperature bins happen to be the locations with highest increases in the number of high and extremely high temperature days. While this is not surprising, this correspondence leads to very large increases in electricity consumption in areas of the state experiencing the largest increases in temperature, which also happen to be the most temperature sensitive in consumption—essentially the southeastern parts of the state and the Central Valley.

The first simulation of interest generates counterfactuals for the percent increase in residential electricity consumption by a representative household in each zip code. We feed each of the two climate model scenarios through equation (2) using the 1980 to 1999 average number of days in each temperature bin as the baseline. Figure 11.6 displays the predicted percent increase in per household consumption for the periods 2020 to 2039, 2040 to 2059, 2060 to 2079 and 2080 to 2099 using the NCAR PCM model forced by the A2 scenario using the percentile bins. Figure 11.7 displays the simulation results for the SRES forcing scenario B1.

Changes in per household consumption are driven by two factors: the shape of the weather-consumption relationship and the change in projected climate relative to the 1980 to 1999 period. The maps show that for most of California, electricity consumption at the household level will increase. The increases are largest for the Central Valley and areas in southeastern California, which have a very steep temperature response of consumption and large projected increases in extreme heat days. Simulation results for this model and scenario suggest that some zip codes in the Central Valley by the end of the century may see increases in household consumption in excess of 100 percent. The map also shows that a significant number of zip codes are expected to see drops in household level electricity consumption—even at the end of the current century. It is important to keep in mind that the current projections assume no change in the temperature electricity response curve. Specifically, the current simulation rules out an increased penetration of air conditioners in areas with currently low penetration rates (e.g., Santa Barbara) or improvements in the efficiency of these devices. The projected drops essentially arise from slightly reduced heating demand. We conduct a simulation in the following, which addresses this concern. Figure 11.7 displays the simulated household increase in electricity consumption by zip code for the lower emissions scenario B1. The maps display an almost identical spatial pattern yet a smaller overall increase in consumption.

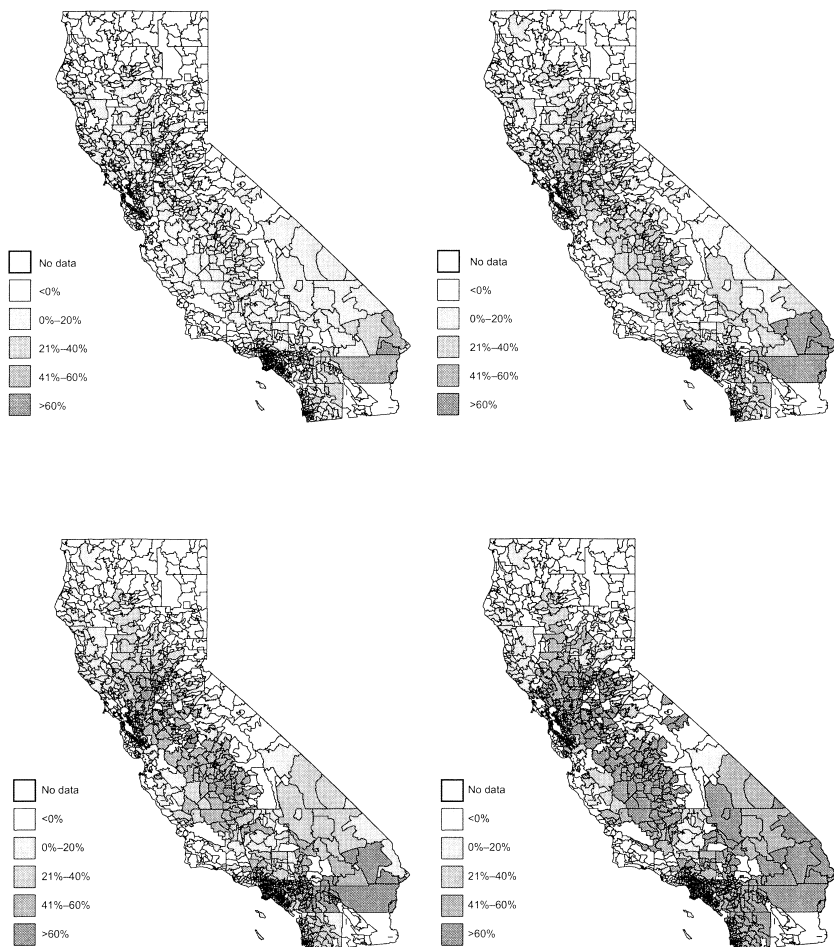


Fig. 11.6 Simulated increase in household electricity consumption by zip code for the periods 2020–2039 (a), 2040–2059 (b), 2060–2079 (c), and 2080–2099 (d) in percent over 1980–1999 simulated consumption. National Center for Atmospheric Research Parallel Climate Model forced by Intergovernmental Panel for Climate Change Special Report on Emissions Scenario A2.

While changes in per household consumption are interesting, from a capacity planning perspective, it is overall consumption that is of central interest from this simulation. We use the projected percent increase in household consumption by zip code and calculate the weighted overall average increase, using the number of households by zip code as weights, in order to arrive at an aggregate percent increase in consumption. The top panel of table 11.3 displays these simulation results for aggregate consumption. Predicted aggregate consumption across all zip codes in our

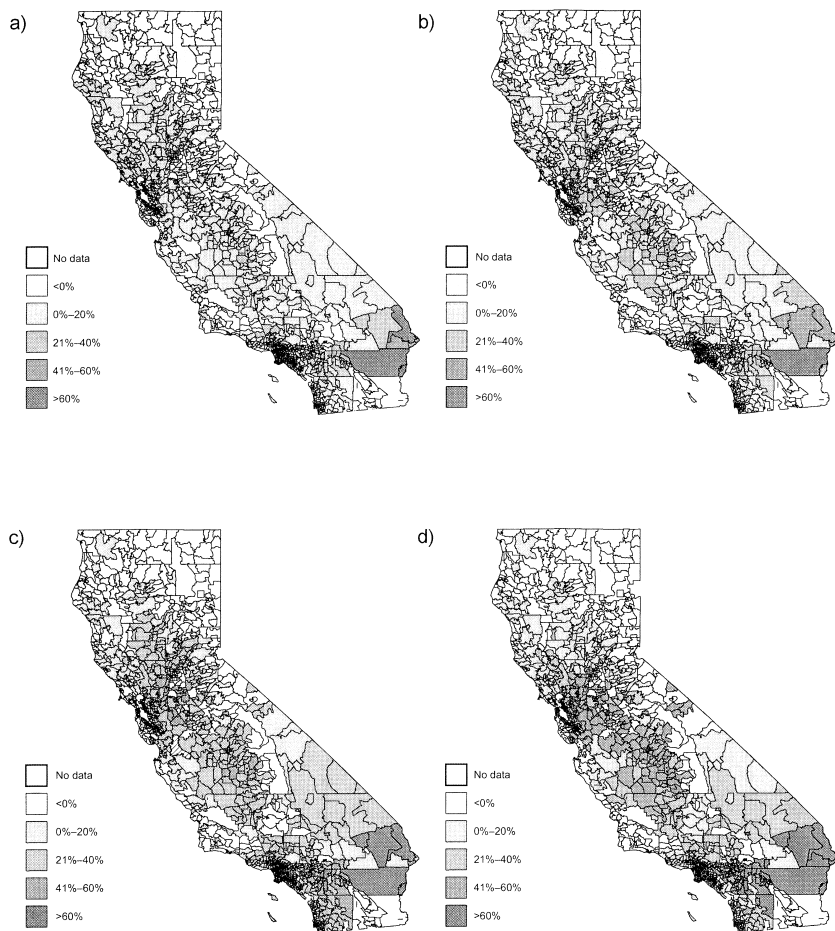


Fig. 11.7 Simulated increase in household electricity consumption by zip code for the periods 2020–2039 (a), 2040–2059 (b), 2060–2079 (c), and 2080–2099 (d) in percent over 1980–1999 simulated consumption. National Center for Atmospheric Research Parallel Climate Model forced by Intergovernmental Panel for Climate Change Special Report on Emissions Scenario B1.

data set ranges from an 18 percent increase in total consumption to 55 percent increase in total consumption by the end of the century. To put this into perspective, this represents an annual growth rate of aggregate electricity consumption between 0.17 percent and 0.44 percent, if all other factors are equal. These growth rates accelerate from period to period as the number of extreme heat days predicted from the GCMs increases in a slightly nonlinear fashion. For the first twenty-year period, the simulated annual growth rates range from 0.10 percent per year to 0.29 percent per

Table 11.3 Simulated percent increase in residential electricity consumption relative to 1980–2000 for the temperature only, price + temperature and population growth + temperature (%)

		Equidistant				Percentile			
		BCSD		CA		BCSD		CA	
Price increase		A2	B1	A2	B1	A2	B1	A2	B1
<i>Temperature only scenario</i>									
2000–2019	±0	5	2	5	3	6	3	5	3
2020–2039	±0	5	8	7	8	6	9	7	8
2040–2059	±0	15	9	17	10	17	11	17	10
2060–2079	±0	24	15	28	16	28	17	28	16
2080–2099	±0	48	18	50	20	55	21	50	20
<i>High price + temperature scenario</i>									
2000–2019	±0	5	2	5	3	6	3	5	3
2020–2039	+30	–6	–3	–5	–4	–5	–3	–4	–3
2040–2059	+30	3	–2	3	–2	6	–1	5	–1
2060–2079	+30	11	3	11	2	15	5	15	4
2080–2099	+30	33	6	29	4	39	9	35	7
<i>Population + temperature scenario</i>									
2000–2019	±0	17	13	16	14	18	14	16	15
2020–2039	±0	31	34	33	34	32	35	34	35
2040–2059	±0	48	41	50	41	52	42	53	42
2060–2079	±0	66	52	68	51	72	55	73	54
2080–2099	±0	113	65	113	65	124	70	123	70

Notes: Equidistant and Percentile pertain to bin type. BCSD = bias correction and spatial downscaling; CA = constructed analogues. A2 and B1 represent the Intergovernmental Panel for Climate Change scenarios.

year. Because these simulations hold population constant, the correct comparison of these growth rates for the current simulation is, therefore, one with current growth in per capita household electricity consumption for California. Figure 11.8 depicts historical per capita electricity consumption since 1960 (EIA 2008). The average annual growth rate in per capita consumption during 1960 to 1973 was approximately 7 percent and slowed down to a remarkable 0.29 percent during 1974 to 1995. Growth rates during the last decade of available data have increased to a higher rate of 0.63 percent, and this difference in growth rates is statistically significant. The estimates from our simulation are lower than this growth rate and for the 2000 to 2019 period suggest that 26 percent to 60 percent of this growth may be due to changing climate.

All of the results presented in the chapter so far have excluded CARE customers from the estimation sample. One potential concern is that these households live on fewer square feet, are more likely to be renting, have lower average use and lower HVAC saturation rates. This would suggest



Fig. 11.8 California residential per capita electricity consumption

Source: Author's calculations based on EIA (2008) SEDS data.

that the temperature response for these households is potentially lower than for the households in the full sample. The number of CARE households in California is large. The SCE reports over 1 million customers on CARE, which is roughly one-quarter of residential accounts. For PG&E and SDG&E, the share of accounts is roughly 20 percent. We, therefore, separately sample from only the CARE households by zip code, adopting the same sampling restrictions as in the non-CARE sample. We then estimate temperature response functions by climate zone, which are slightly less steep in the higher temperature bins. We then conduct the simulations for the CARE households separately. To obtain an estimate of the overall impacts, when we include CARE, we weight impacts for each zip code by the share of CARE to non-CARE households in that zip code. Table 11.4 reports these results for the Bias Correction Spatial (BCS) downscaling algorithm and equidistant bin simulations. As suspected, the CARE households are slightly less affected by higher temperatures, yet the overall weighted average is very close to the simulations presented in table 11.3.

11.5.1 Temperature and Price Simulations

The assumed flat prices from the previous section should be considered as a comparison benchmark. It is meaningful and informative to imagine climate change imposed on today's conditions. It is worth pointing out,

Table 11.4 Simulated percent increase in residential electricity consumption relative to 1980–2000 for California Alternate Rates for Energy (CARE) and non-CARE households (%)

	Price increase	Non-CARE		CARE		Weighted	
		A2	B1	A2	B1	A2	B2
2000–2019	±0	5	2	4	2	5	2
2020–2039	±0	5	8	4	6	5	7
2040–2059	±0	15	9	12	8	14	9
2060–2079	±0	24	15	20	12	23	14
2080–2099	±0	48	18	39	15	46	17

Notes: For this table, an equidistant bins approach was used, as well as the BCSD downscaling. A2 and B1 represent the Intergovernmental Panel for Climate Change scenarios.

however, that real residential electricity prices in California have been, on average, flat since the early-mid 1970s spike. In this section, we will relax the assumption of constant prices and provide simulation results for increasing electricity prices under a changing climate.

While we have no guidance on what will happen to retail electricity prices twenty years or further out into the future, we consider a discrete 30 percent increase in real prices starting in 2020 and remaining at that level for the remainder of the century. This scenario is based upon current estimates of the average statewide electricity rate impact by 2020 of AB 32 compliance combined with natural gas prices to generators within the electric power sector. These estimates are based on analysis commissioned by the California Public Utilities Commission. This scenario represents the minimum to which California is committed in the realm of electricity rates. This scenario could be interpreted as one assuming very optimistic technological developments post-2030, implying that radical CO₂ reduction does not entail any cost increases, or as a California and worldwide failure to pursue dramatic CO₂ reductions such that California’s AB 32 effort is not expanded.

To simulate the effects of price changes on electricity consumption, we require good estimates of the price elasticity of demand. In this chapter, we rely on the estimates of mean price elasticity provided by Reiss and White (2005). Specifically, they provide a set of average price elasticities for different income groups, which we adopt here. Because we do not observe household income, we assign a value of price elasticity to each zip code based on the average household income for that zip code. Households are separated into four buckets, delineated by \$18,000, \$37,000, and \$60,000 with estimated price elasticities of −0.49, −0.34, −0.37, and −0.29, respectively. It is important to note that these price elasticities are short-run price elasticities. These are valid if one assumes a sudden increase in prices, as we do in this chapter. To our knowledge, reliable long-term price elasticities based on microdata for California are not available, but in theory, they are larger than

the elasticities used in this chapter. The second panel in table 11.3 presents the simulation results under the scenarios of climate change given a sudden persistent increase in electricity prices in the year 2020. Given the sizable assumed price elasticity estimates, it is not surprising that the simulated increases in residential electricity consumption for the first period after the price increase are roughly 6 percent to 12 percent lower than the predicted increases given constant prices. For the NCAR model under both considered forcing scenarios the path of electricity consumption under this price scenarios returns to levels below its 1980 to 2000 mean for the 2020 to 2040 period, given this assumed price trajectory. By the end of the century, we still observe significant increases in electricity demand for the higher forcing scenario (A2). It is important to note that these effects are conditional on the estimated price elasticities being correct. Smaller elasticities would translate into price-based policies, such as taxes or cap and trade systems, being less effective at curbing demand compared to standards.

11.5.2 Temperature and Population

California has experienced an almost sevenfold increase in its population since 1929 (Bureau of Economic Analysis [BEA] 2008). California's population growth rate over that period (2.45 percent) was more than twice that of the national average (1.17 percent). Over the past fifty years, California's population has grown by 22 million people to almost 37 million in 2007 (BEA 2008). To predict what the trajectory of California's population will look like until the year 2100, many factors have to be taken into account. The four key components driving future population are net international migration, net domestic migration, mortality rates, and fertility rates. The State of California provides forecasts fifty-five years out of sample, which is problematic because we are interested in simulating end-of-century electricity consumption. The Public Policy Institute of California has generated a set of population projections until 2100 at the county level.

For illustration purposes, we use their "low" series, where population growth slows as birth rates decline, migration out of the state accelerates, and mortality rates show little change. This low series is equivalent to a 0.18 percent growth rate and results in a population 18 percent higher than today's. Projections are available at the county level and not at the zip code level. We, therefore, assume that each zip code in the same county experiences an identical growth rate.

The bottom panel of table 11.3 displays the simulated aggregate electricity consumption given the "low" population growth scenarios. This table holds prices constant at the current level. It is not surprising to see that population uncertainty has much larger consequences for simulated total electricity consumption compared to uncertainty over climate or uncertainty over prices. The simulations for the low forcing scenario B1 and the low population growth scenario show 65 percent to 70 percent increase in residential electricity consumption. If we consider the A2 forcing, the predicted low population

average increase in consumption is a 118 percent increase. The source of this disproportionate increase in overall consumption from a relatively modest increase in population the predicted increases in population in areas with steeper response functions (e.g., the Central Valley).

11.6 Adaptation

The major finding in the chapter so far is the heterogeneity in temperature response of residential electricity consumption across climate zones. While geographic location clearly plays an important role in determining this responsiveness, we wish to study whether there are household or structure characteristics, which help explain some of this difference in temperature response. We, therefore, construct a statewide sample by sampling 10 percent of the households from each of the sixteen climate zone-specific data sets used in the preceding. We restrict ourselves to non-Care customers in this exercise. We construct 10 percentile temperature bins, where the cutoffs are at every 10th percentile of the California-wide temperature distribution for the years 2003 to 2006. The smaller number of bins and percentile approach guarantee that there are enough observations in the extreme bins at meaningful cutoff points.

We then slice the preceding data set along several dimensions in order to see whether the temperature response varies with certain variables of interest from the census 2000 Summary File 3 (SF 3). Specifically, for each indicator, we divide this sample into two groups, a “low group” and a “high group,” based on the value of the variables of interest. The following are the variables of interest and percentiles used in estimation:

1. Percentage of household using electricity as heating fuel.
 - Low group: households in zip code with this variable ≤ 30 percent
 - High group: households in zip code with this variable ≥ 60 percent
2. Percentage of household using gas as heating fuel.
 - Low group: households in zip code with this variable ≤ 40 percent
 - High group: households in zip code with this variable ≥ 60 percent
3. Percentage of households in an urban area.
 - Low group: households in zip code with this variable ≤ 40 percent
 - High group: households in zip code with this variable ≥ 60 percent
4. Median year of structure built.
 - Low group (older building): zip codes with median year of structure built < 1959
 - High group (newer building): zip codes with median year of structure built > 1979

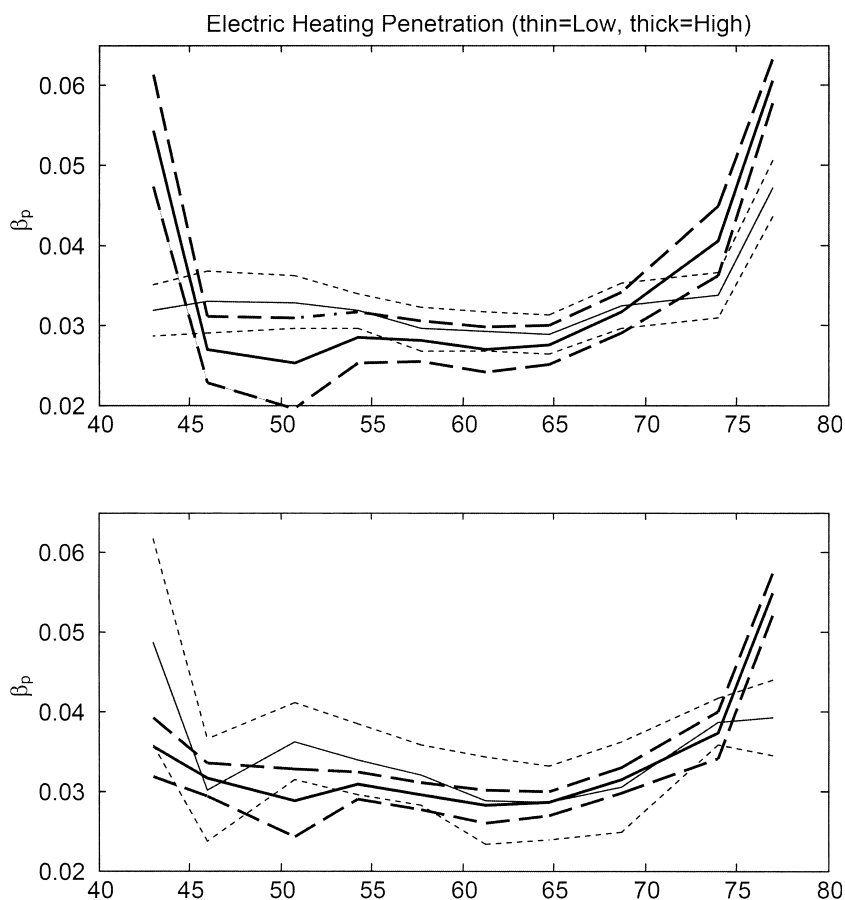


Fig. 11.9 Temperature response for households by major heating fuel

For each variable of interest, we estimate the same models as previously, while making sure that we are making a fair comparison across groups. For our regressions, we, therefore, limit the sample for both groups to those households with median household income between 40 to 60 percent of the distribution of census 2000 zip-code-level median household income.

For each variable of interest, we plot the estimated coefficients for each temperature bin against their midbin temperature. Each of the graphs has two sets of lines, one for “low group” (thin lines) and the other one for “high group” (thick lines). We also plot the 95 percent confidence intervals for each group. Figure 11.9 plots the response functions for households in zip codes with a high penetration of electricity as the major heating fuel against the response functions for households from zip codes with a low penetration of electricity of a heating fuel. The difference is drastic and

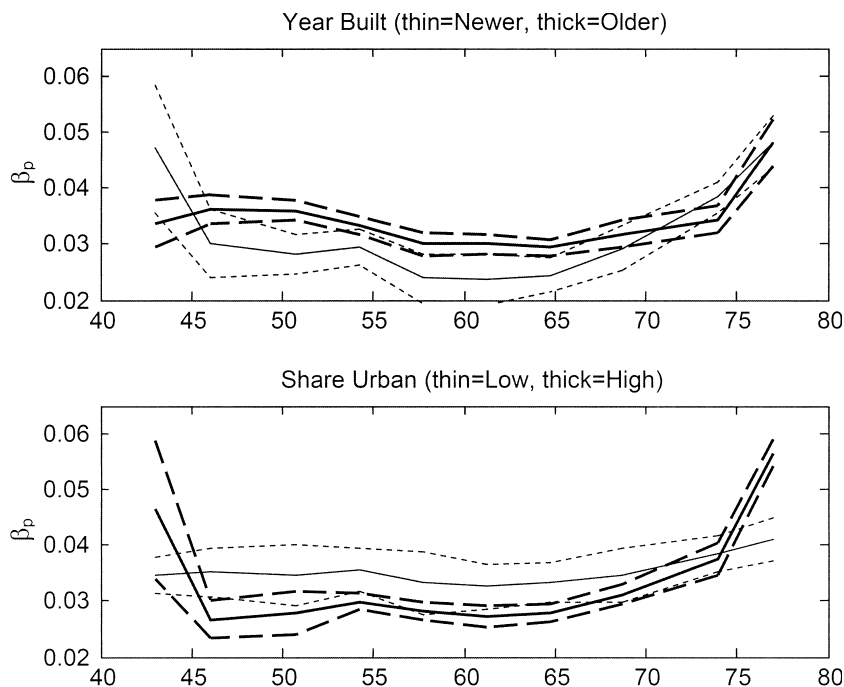


Fig. 11.10 Temperature response for households by year built and urban location

statistically significant. The zip codes using electricity as the major source of heat have significantly higher electricity consumption at low temperatures, while the low penetration zip codes have an almost flat response. The following panel displays the figure for natural gas. It is switched, which is not surprising, given that electricity and natural gas are the two major heating fuels in California. In the top panel, it is also noteworthy that households with higher electric heating have a drastically higher temperature response at high temperatures.

Figure 11.10 displays the temperature response functions for older houses versus newer houses in the top panel. At the low-temperature spectrum, newer houses seem to require more electricity to heat compared to older houses. At the high end of the temperature spectrum, older and newer houses appear to have an almost identical temperature response. The bottom panel of figure 11.10 displays the temperature response for houses located in mostly urban zip codes versus the temperature response of households located in mostly rural zip codes. The difference is quite drastic, with rural households having an almost flat temperature response function and urban households having the typical U-shaped response. This finding is due to the fact that much of the Central Valley and the greater Los Angeles area are considered urban.

11.7 Conclusions

This study has provided the first estimates of California's residential electricity consumption under climate change based on a large set of panel microdata. We use random and, therefore, exogenous weather shocks to identify the effect of weather on household electricity consumption. We link climate zone specific weather response functions to a state of the art down-scaled global circulation model to simulate growth in aggregate electricity consumption. We further explore the household characteristics potentially responsible for the heterogeneous temperature response of consumption.

There are two novel findings from this chapter. First, simulation results suggest much larger effects of climate change on electricity consumption than previous studies. This is largely due to the highly nonlinear response of consumption at higher temperatures. Our results are consistent with the findings by Deschênes and Greenstone (2007). They find a slightly smaller effect using national data. It is not surprising that impacts for California, a state with a smaller heating demand (electric or otherwise), would be bigger. Second, temperature response varies greatly across the climate zones in California—from flat to U-shaped to hockey stick-shaped. This suggests that aggregating data over the entire state may ignore important nonlinearities, which combined with heterogeneous climate changes across the state may lead to underestimates of future electricity consumption.

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