Impacts of Climate Change on Residential Electricity Consumption: Evidence from Billing Data*

Anin Aroonruengsawat
University of California, Berkeley

Maximilian Auffhammer
University of California, Berkeley

May 8, 2009

Abstract

This study simulates the impacts of higher temperatures resulting from anthropogenic climate change on residential electricity consumption for California. Flexible temperature response functions are estimated by climate zone, which allow for differential effects of days in different temperature bins on households' electricity consumption. The estimation uses a comprehensive household level dataset of billing data for California's three investor-owned utilities (Pacific Gas and Electric, San Diego Gas and Electric, and Southern California Edison). The results suggest that the temperature response varies greatly across climate zones. Simulation results using a downscaled version of the National Center for Atmospheric Research global circulation model suggest that holding population constant, total consumption for the households considered may increase by up to 55% by the end of the century. The study further simulates the impacts of higher electricity prices and different scenarios of population growth. Finally, simulations were conducted consistent with higher adoption of cooling equipment in areas which are not yet saturated, as well as gains in efficiency potentially due to aggressive energy efficiency policies.

Keywords: Climate change, adaptation, impacts estimation, electricity consumption.
JEL Codes: Q53, Q58

*We would like to thank Guido Franco and the Public Interest Energy Research (PIER) Program at the California Energy Commission for generous funding of this work. We thank the University of California Energy Institute (UCEI) and the investor-owned utilities of California for letting us gain access to the billing data at the UCEI data center. We also thank Severin Borenstein and Koichiro Ito for helping us understand the electricity data. We gratefully acknowledge constructive comments by Olivier Deschênes, one anonymous referee, seminar participants at the Energy and Resources Group and the UC Energy Institute. All findings and remaining errors in this study are those of the authors. For correspondence, contact Maximilian Auffhammer, Department of Agricultural and Resource Economics, UC Berkeley. 207 Giannini Hall, Berkeley, CA 94720-3310. Phone: (510) 643-5472; Email: auffhammer@berkeley.edu.

1. Introduction

Forecasts of electricity demand are of central importance to policy makers 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% to 34% (EIA SEDS 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 1960-1973 was approximately 7% and slowed to a remarkable 0.29% during 1974-1995. Growth rates during the last decade of available data have increased to a higher rate of 0.63%, and this difference in growth rates is statistically significant.

California's energy system faces several challenges in attempting to meet future demand (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 paper simulates how the residential sector's electricity consumption will be affected by different scenarios of climate change. We make four 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. Third, we provide simulations of future electricity consumption under constant and changing climate, electricity price, and population scenarios. Finally, we provide worst and best case simulation results, assuming uniform "best" and "worst" climate sensitivities for the entire state based on our estimation results. These simulations provide us with upper and lower bound estimates from different adaptation scenarios.

The paper is organized as follows: Section 2 reviews the literature assessing the impacts of climate change on electricity consumption. Section 3 describes the sources of the data used in this study. Section 4 contains the econometric model and estimation results. We simulate the impacts of climate change on residential electricity consumption in Section 5 and conclude in Section 6.

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 et al. (1987) to simulate the impact on electric utilities in the United States and finds that increases in annual temperatures ranging from 1.0°C-1.4°C (1.8°F-2.5°F) in 2010 would result in demand of 9% to 19% above estimated new capacity requirements (peak load and base load) in the absence of climate change. The estimated impacts rise to 14% and 23% 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 2010 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% to 2.6%, while peak demand increases from the baseline scenario by 1.8% to 3.7%. Rosenthal et al. (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 2010 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 micro-level 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 et al. (2008) and Mendelsohn (2003) endogenize fuel choice, which is usually assumed to be exogenous. They find that warming will result in fuel switching towards 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/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 Intergovernmental Panel for Climate Change (IPCC) scenarios (A1Fi, A2, and B1) to simulate the increase in annual electricity and peak load from 2005-2099. Relative to the 1961-1990 base period, the range of increases in electricity and peak load demands are 0.9%-20.3% and 1.0%-19.3%, 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% 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 electricity consumption. They explain variation in U.S. state-level annual panel data of residential electricity 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 20 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%-30% of the baseline estimation or 15 to 35 billion (2006 US$). The panel data approach allows one to control for differences in unobservables across the units of observation, resulting in consistent estimates of the coefficients on temperature.

The current paper is the first paper 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 2003-2006. 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. Since our dataset is a panel, we can control for household fixed effects, month fixed effects, and year fixed effects. The drawback of this dataset is that the only other reliable information we have about each individual household is price and the five-digit ZIP code location.

3. Data

3.1 Residential Billing Data

The University of California Energy Institute 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, Southern California Edison, and San Diego Gas and Electric for the years 2003-2006. These three utilities provide electricity to roughly 80% 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[1], 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. Only customers who were individually metered are included in the data set. For the purpose of this paper, 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 25-35 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 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 divided into 16

[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.

building climate zones, each of which require different minimum efficiency building standards specified in an energy code. 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 of mean daily temperature on electricity consumption separately for each climate zone. 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. The climate zones are depicted in Figure 2.

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 25-35 days in each billing cycle and which have at least 35 bills over the period of 2003-2006.[2] 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 multi-family 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.[3]

From the population subject to the restrictions above, 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

[2]With the regular billing cycle, there should be 48 bills for the households in our sample during the period 2003 to 2006.

[3]After removing outlier bills, we compared the population average daily consumption of bills with billing cycles ranging from 25-35 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 $\frac{1}{10}^{th}$ of a standard deviation higher than the mean daily consumption of the complete population including bills of any length.

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% discount on electric and natural gas bills. Eligibility requires that total household income is at or below 200% 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% of total consumption. Table 1 displays the summary statistics of our consumption 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% that of the interior southern zone 15. The average electricity price is almost identical across zones, at 13 cents per kWh.

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 dataset contains daily observations from more than 20,000 cooperative weather stations in the United States, U.S. Caribbean Islands, U.S. Pacific Islands, and Puerto Rico. Data coverage varies by station. Since our electricity data cover the state of California for the years 2003-2006, the dataset contains 370 weather stations reporting daily data. In the dataset we observe daily minimum and maximum temperature as well as total daily precipitation and snowfall. Since 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 7000 feet above sea level, which leaves us with 269 "valid" weather stations.[4] Figure 1 displays the distribution of these weather stations across the

[4] 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

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.

Since 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 50 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 above step with the 8 closest stations, then the 7 closest, etc. 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% of the temperature data for this station to missing. After applying the algorithm described above 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 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

numbers and the results are robust.

the 269 weather stations in our sample. For the remainder of our empirical analysis, we use these patched series as our observations of weather.[5]

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 socio demographics 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 which make up 81% of California's population. Table 2 displays summary statistics for all ZIP codes in California with registered residential population, broken down by whether we observe households in a given ZIP or not. 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 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.

4. Econometric Estimation

As discussed in the previous section, we observed each household's monthly electricity bill for the period 2003-2006. Equation (1) below 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).

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

$\log(q_{it})$ is the natural logarithm of household i's electricity consumed in kilowatt-hours during

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

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 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 paper are those measuring temperature. The last five columns of Table 1 display the median, first, fifth, ninetieth, and ninety-fifth percentile of the mean daily temperature distribution by climate zone. The table shows the tremendous differences in this distribution across climate zones. The south eastern 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.[6] 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 degree Fahrenheit) 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, since 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.

[6] 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.

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 first, fifth, ninety-fifth, and ninety-ninth percentile to account for extreme cold/heat days. We therefore have a set of 14 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 degree 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% 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 which exceed the 5 degree 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 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, since 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 importantly however, we do not observe other important characteristics of households (e.g., income) which 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 RECS 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 paper, we omit the average price from our main regression.[7] 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 $E[\varepsilon_{it} D_{pit} | D_{-pit}, Z_{it}, \alpha_i, \phi_m, \gamma_y] = 0$. Since 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.[8] Figure 4 plots the estimated temperature response coefficients 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

[7] The full set of estination results are available upon request from the authors.

[8] 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.

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%) than the national average (30%). 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.

5. Simulations

In this section we simulate the impacts of climate change on electricity consumption under two different SRES emissions scenarios, three different electricity price scenarios, and three different population growth scenarios. 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 understand the impact of uncertainty surrounding these three different factors on aggregate consumption, we introduce them sequentially.

5.1 Temperature Simulations

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 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, since we would expect that households in zones which 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 downwards in the higher buckets. We will deal with this issue explicitly in section 5.4.

As is standard in this literature, the counterfactual climate is generated by a General Circulation Model (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) (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 CO_2 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 mid-century 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:

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

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 5 shows the change in the number of days spent in each 5 degree bin of the temperature distribution from 1980-1999 to 2080-2099 using the NCAR 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 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 1980-1999 average number of days in each temperature bin as the baseline. Figure 6 displays the predicted percent increase in per household consumption for the periods 2020-2039, 2040-2059, 2060-2079 and 2080-2099 using the NCAR PCM model forced by the A2 scenario using the percentile bins. Figure 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 1980-1999 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 south eastern 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%. 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 below, which addresses this concern. Figure 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.

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 3 displays these simulation results for aggregate consumption. Predicted aggregate consumption across all ZIP codes in our dataset ranges from an 18% increase in total consumption to 55% 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% and 0.44%, 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 non-linear fashion. For the first 20-year period, the simulated annual growth rates range from 0.10% per year to 0.29% per year. Since 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 8 depicts historical per capita electricity consumption since 1960 (EIA 2008). The average annual growth rate in per capita consumption during 1960-1973 was approximately 7% and slowed down to a remarkable 0.29% during 1974-1995. Growth rates during the last decade of available data have increased to a higher rate of 0.63%, and this difference in growth rates is statistically significant. The estimates from our simulation are lower than this growth rate and for the 2000-2019 period suggest that 26%-60% of this growth may be due to changing climate.

5.2 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, 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 20 years or further out into the future, we construct two scenarios. The first scenario we consider is a discrete 30% 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 CO_2 reduction does not entail any cost increases, or as a California and worldwide failure to pursue dramatic CO_2 reductions such that California's AB 32 effort is not expanded. The second scenario we consider is one where electricity prices increase by 30% in 2020 and again by 30% in 2040 and remain at that level thereafter. We consider the additional increase in mid-century price in essence as an "increasing marginal cost" story. Under this scenario, AB 32 is successfully implemented and a path towards achieving the 2050 targets is put in place. These additional steps are assumed to be proportionally more expensive.

To simulate the effects of price changes on electricity consumption, we require good estimates of the price elasticity of demand. In this paper 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. Since 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, \$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 paper. To our knowledge, reliable long-term price elasticities based on micro data for California are not available, but in theory they are larger than the elasticities used in this paper. The second panel in Table 3 presents the simulation results under the two different scenarios of climate change given a sudden persistent increase in electricity prices in the year 2020. Given the range of 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%-12% lower than the predicted increases given constant prices. For the NCAR model under both considered forcing scenarios and both downscaling algorithms, the path of electricity consumption under these price scenarios returns to levels below its 1980-2000 mean for the 2020-2040 period, given this assumed price trajectory.

The third panel in Table 3 presents the simulation results for both forcing scenarios and downscaling methods given the high price scenario. Given the significant increase in prices after 2020 and again in 2040, the consumption trajectory stays flat for the entire simulation period using the NCAR model for the B1 scenario. The higher forcing scenario A2 shows a relatively flat trajectory, yet still predicts significant increases in consumption for the last decades of the century-even in the face of these higher prices. 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.

5.3 Temperature and Population

California has experienced an almost seven-fold increase in its population since 1929 (BEA 2008). California's population growth rate over that period (2.45%) was more than twice that of the national average (1.17%). Over the past 50 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 since 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.

The three sets of projections developed for California and its counties are designed to provide a subjective assessment of the uncertainty of the state's future population. The projections present three very different demographic futures. In the low series, population growth slows as birth rates decline, migration out of the state accelerates, and mortality rates show little improvement. In the high series, population growth accelerates as birth rates increase, migration increases, and mortality declines. The middle series, consistent with (but not identical to) the California Department of Finance projections assumes future growth in California will be similar to patterns observed over the state's recent history, patterns that include a moderation of previous growth rates but still large absolute changes in the state's population. In the middle series, international migration flows to California remain strong to mid-century and then subside, net domestic migration remains negative but of small magnitude, fertility levels (as measured by total fertility rates) decline slightly, and age-specific mortality rates continue to improve. The high projection is equivalent to an overall growth rate of 1.47% per year and results in a quadrupling of population to 148 million by the end of the century. The middle series results in a 0.88% annual growth rate and 2.3-fold increase in total population. The low series is equivalent to a 0.18% growth rate and results in a population 18% 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.

Table 4 displays the simulated aggregate electricity consumption given the three population growth scenarios. This table holds prices constant at the current level and therefore presents a "worst case scenario". 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%-70% increase in residential electricity consumption. The same figure for the medium growth scenario predicts a 179%-189% increase in consumption and the worst case scenario predicts a 350% increase in consumption. If we consider the A2 forcing, the predicted low population average increase in consumption is a 118% increase or a 478% increase for the high population growth scenario.

5.4 Adaptation Simulations

As mentioned at the beginning of this chapter, all previous simulation exercises we have conducted so far assumed that the temperature response functions are fixed for each climate zone until the end of the century. This implicitly assumes that people do not adapt to a changing climate, which is a crucial and potentially non-credible assumption. If the coastal areas of California will experience higher mean temperatures and more frequent extreme heat events, it is likely that newly constructed homes will have built in central air conditioning. Further, owners of existing homes may install air conditioning equipment ex-post. This type of adaptation would result in a stronger temperature response at higher temperatures, whereby the temperature elasticity in the highest bins would increase over time. On the other hand, forward-looking planners and policy makers may put in place more stringent building codes for new construction combined with more stringent appliance standards, which would decrease the energy intensity of existing capital and homes. California has a long history of these policies and is considered a worldwide leader in these energy efficiency policies. These more stringent policies are designed to offset future increases in consumption. Bottom up engineering models by design can capture the impact of building- and device-specific changes due to regulations on energy consumption.

Their drawback, however, is that they have to rely on a large number of assumptions regarding the composition of the housing stock and appliances, as well as making behavioral assumptions about the individuals using them.

While we cannot conduct a detailed simulation incorporating specific policy changes, we conduct the following thought experiment. Our baseline simulation has assumed that each climate zone maintains its specific response function throughout the remainder of the century. To bound how important the heterogeneity in the response function is to the aggregate simulation results, we design an "almost best case" scenario, where we assume that all zones have the response function of coastal San Diego (Zone 7). This zone's response function is relatively flat. The left panel of Table 5 shows the simulation results assuming this optimistic scenario.

Worst-case increases under forcing A2 results in a 3% increase in electricity consumption by the end of the century, which is essentially flat compared to the baseline simulation shown in Table 3. Next we come up with an "almost worst case" scenario, where we let all of California adopt the response function of Zone 12, the Central Valley. The right panel of Table 5 shows the results from this simulation. The overall increases in simulated electricity consumption are more than twice those of the baseline scenario across simulations considered in Table 3. The large impact of the assumed temperature responsiveness function on overall simulated residential electricity consumption underlines the importance of improving energy efficiency of buildings and appliances.

5.5 CARE Customers

All of the results presented in the paper 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 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. 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%. 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 6 reports these results for the BCSD 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 3.

6. Conclusions

This study has provided the first estimates of California's residential electricity consumption under climate change based on a large set of panel micro-data. 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 downscaled global circulation model to simulate growth in aggregate electricity consumption. We further incorporate potentially higher prices and population levels to provide estimates of the relative sensitivity of aggregate consumption to changes in these factors. Finally we show estimates of aggregate consumption under an optimistic and pessimistic scenario of temperature response.

There are several novel findings from this paper. First, simulation results suggest much larger effects of climate change on electricity consumption than previous studies. This is largely due to the highly non-linear response of consumption at higher temperatures. Our results are consistent with the findings by Greenstone and Deschênes (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. Third, population uncertainty leads to larger uncertainty over consumption than uncertainty over climate change. Finally, policies aimed at reducing the weather sensitivity of consumption can play a large role in reducing future electricity consumption. Specifically, region specific HVAC standards may play a significant role in offsetting some of the projecting increases in consumption.

References

[1] Baxter, L. W., and K. Calandri. 1992. ”Global warming and electricity demand: A study of California. Energy Policy 20(3): 233-244.

[2] Bureau of Economic Analysis. 2008. Regional Economic Accounts. Washington, D.C. www.bea.gov/regional/spi/default.cfm?series=summary.

[3] California Energy Commission. 2005. Integrated Energy Policy Report. Sacramento, California.

[4] Cline, W. R. 1992. The economics of global warming. Washington: Institute for International Economics.

[5] Crowley, C., and F. Joutz. 2003. Hourly electricity loads: Temperature elasticities and climate change. In 23rd U.S. Association of Energy Economics North American Conference.

[6] Deschênes, O., and M. Greenstone. 2007. Climate Change, Mortality and Adaptation: Evidence from annual fluctuations in weather in the U.S. MIT Department of Economics Working Paper No. 07-19.

[7] Energy Information Administration (EIA). 2008. State Energy Data System. Washington, D.C.

[8] Fisher, F. M., and C. Kaysen. 1962. A Study in Econometrics: The Demand for Electricity in the US. North Holland Publishing Company.

[9] Franco, G., and A. Sanstad. 2008. ”Climate change and electricity demand in California.” Climatic Change 87:139-151.

[10] Hanemann, W. 1984. ”Discrete/Continuous Models of Consumer Demand.” Econometrica 52: 541-561.

[11] Houthakker, H. S., and L. D. Taylor. 1970. Consumer Demand in the United States: Analyses and Projections. Cambridge, Mass: Harvard University Press.

[12] Intergovernmental Panel on Climate Change (IPCC). 2000. Emissions Scenarios. Cambridge, UK: Cambridge University Press.

[13] Linder, P., M. Gibbs, and M. Inglis. 1987. Potential impacts of climate change on electric utilities. Report 88-2. Albany, New York: New York State Energy Research and Development Authority.

[14] Mansur, E., R. Mendelsohn, and W. Morrison. 2008. ”Climate change adaptation: A study of fuel choice and consumption in the U.S. energy sector.” Journal of Environmental Economics and Management 55(2): 175-193.

[15] Maurer, E. P., and H. G. Hidalgo. 2008. ”Utility of daily vs. monthly large-scale climate data: An intercomparison of two statistical downscaling methods.” Hydrology and Earth System Sciences 12:551-563.

[16] Mendelsohn, R. 2003. The Impact of Climate Change on Energy Expenditures in California. Appendix XI in Wilson, Tom, and Larry Williams, Joel Smith, Robert Mendelsohn. Global Climate Change and California: Potential Implications for Ecosystems, Health, and the Economy. Consultant report 500-03-058CF to the Public Interest Energy Research Program, California Energy Commission.

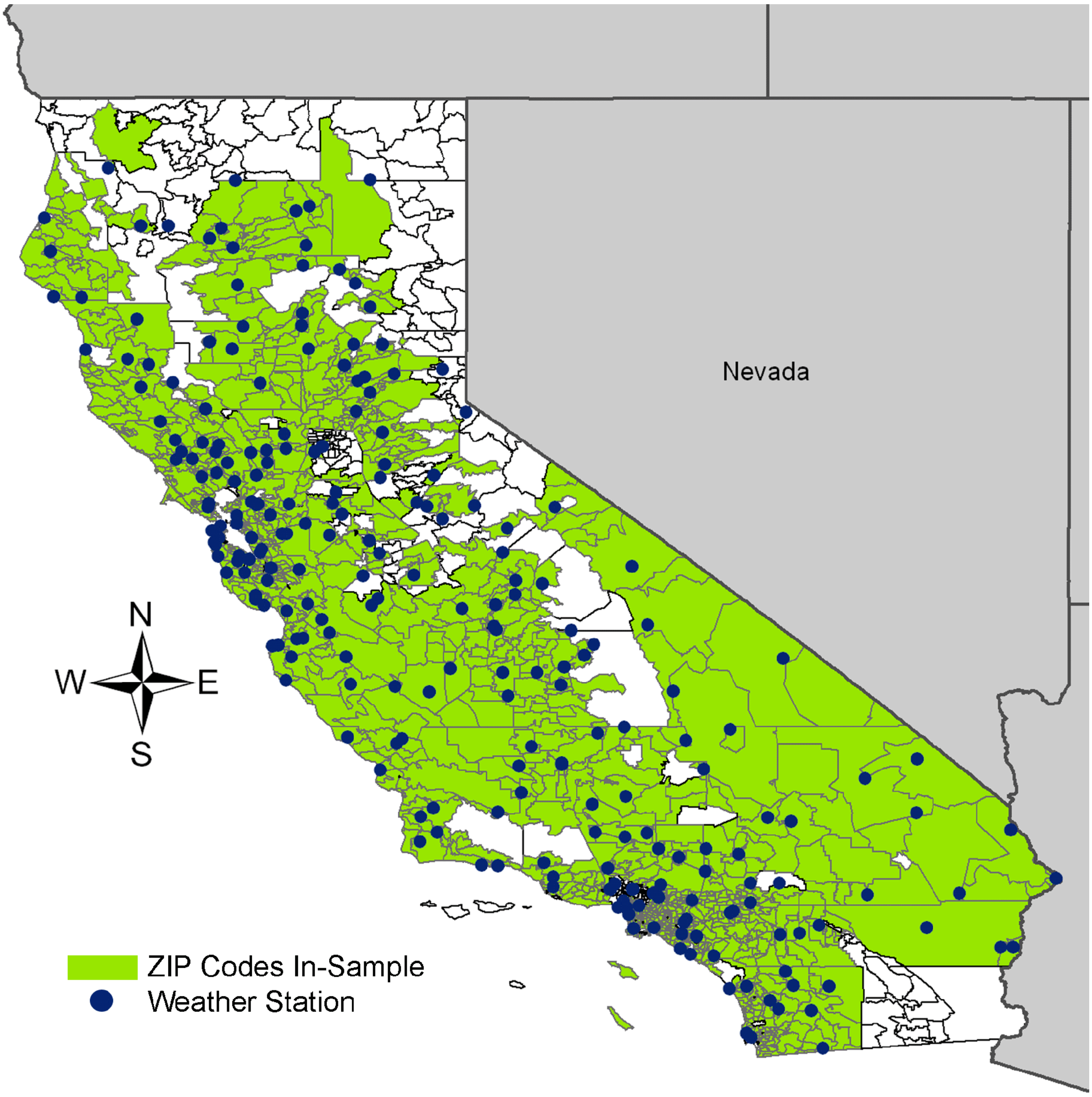
[17] Reiss, P. C., and M. W. White. 2005. "Household Electricity Demand Revisited." The Review of Economic Studies. 72:853-883

[18] Rosenthal, D., H. Gruenspecht, and E. Moran. 1995. "Effects of global warming on energy use for space heating and cooling in the United States." The Energy Journal 16:77-96.

[19] Schlenker, W., and M. Roberts. 2006. "Nonlinear Effects of Weather on Corn Yields." Review of Agricultural Economics 28(3): 391-398.

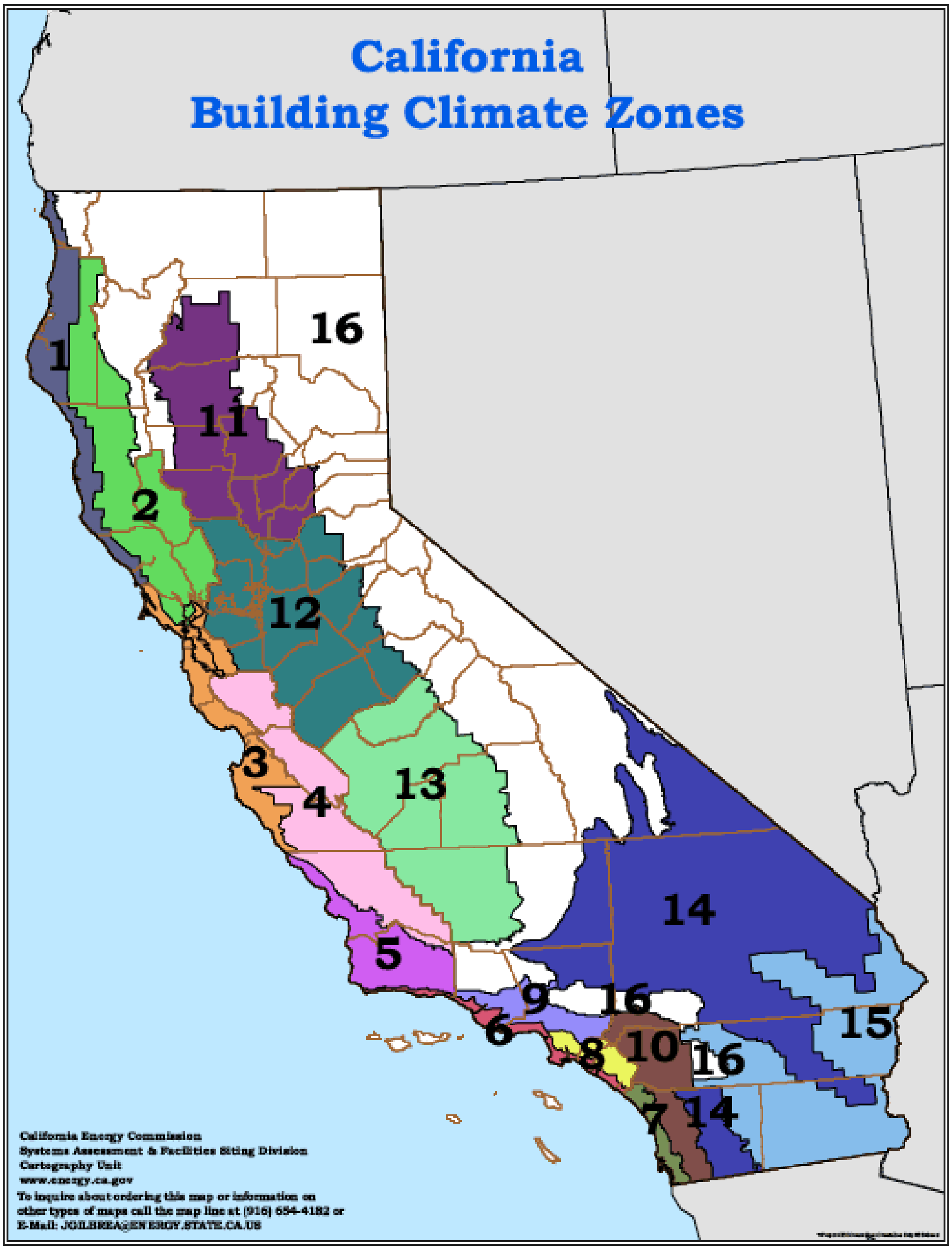
[20] U.S. Environmental Protection Agency. 1989. The potential effects of global climate change on the United States. Joel B. Smith and Dennis Tirpak, eds. Washington: Environmental Protection Agency.

Figure 1. Observed residential electricity consumption 2003–2006 and NOAA cooperative weather stations



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

Figure 2. California Energy Commission building climate zones



Source: California Energy Commission.

Figure 3. Share of total residential electricity consumption for 2006 by five-digit zip code

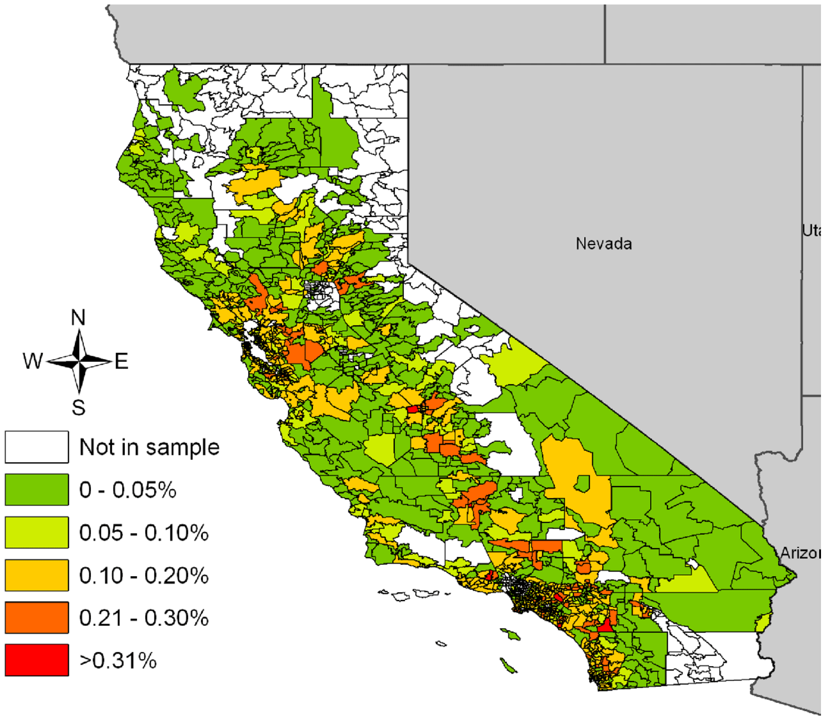
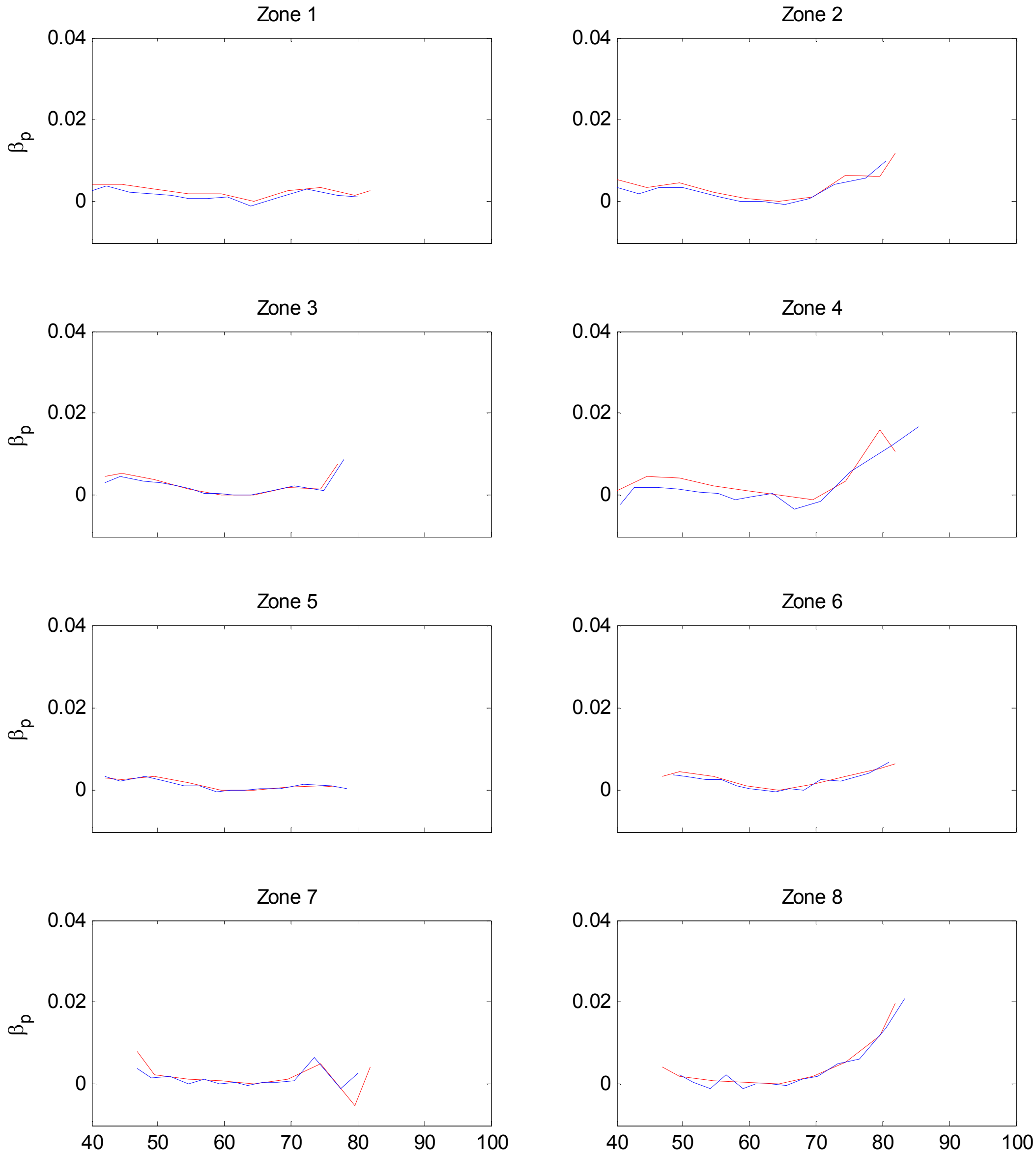
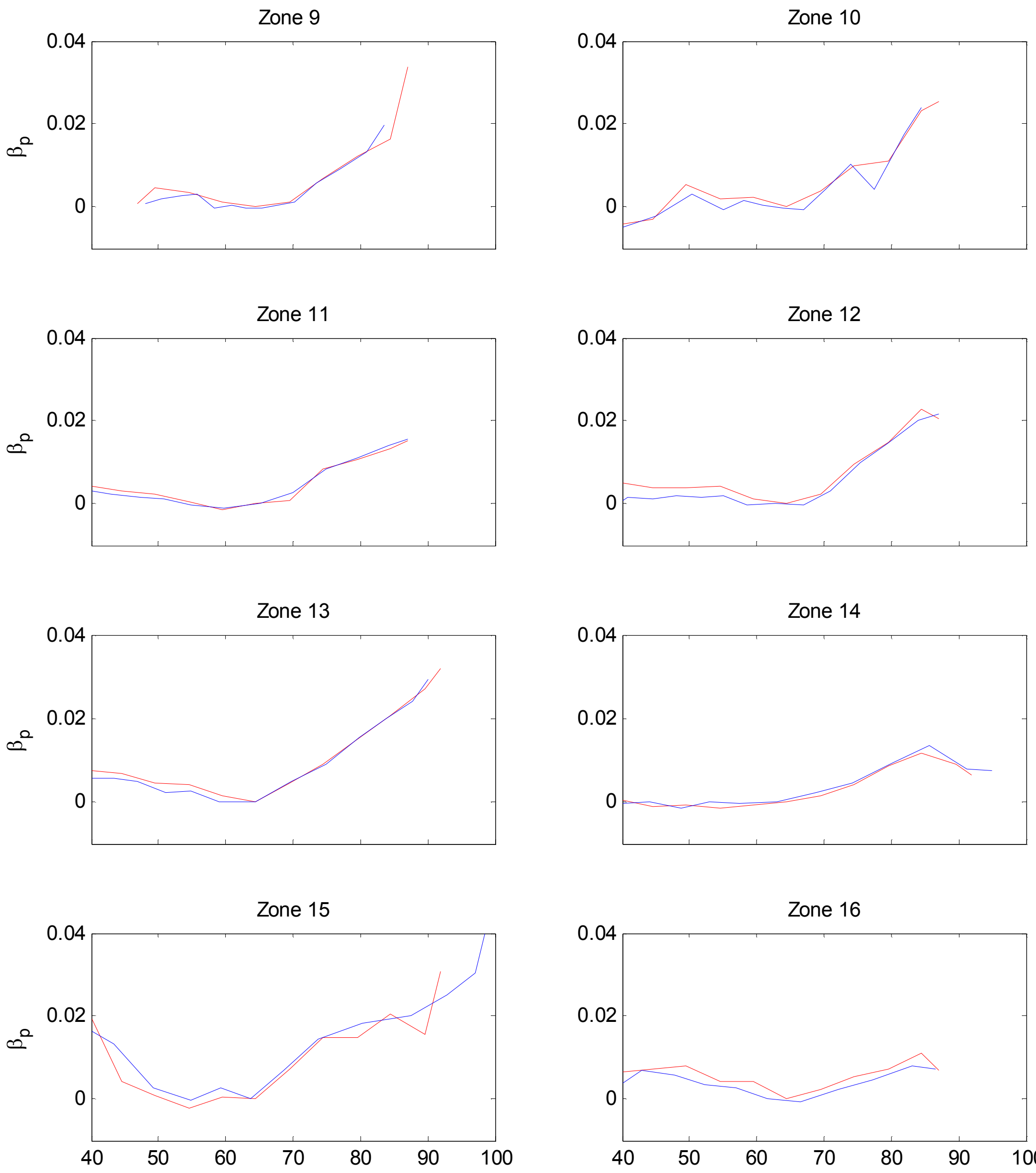


Figure 4. Estimated climate response functions for CEC climate zones 1–8.



Notes: The panels display the estimated temperature slope coefficients for each of the fourteen percentile bins (blue) and the equidistant bins (red) against the midpoint of each bin. The plots were normalized using the coefficient estimate for the 60–65 temperature bin.

Figure 4 continued. Estimated climate response functions for CEC climate zones 9–16.



Notes: The panels display the estimated temperature slope coefficients for each of the fourteen percentile bins (blue) and the equidistant bins (red) against the midpoint of each bin. The plots were normalized using the coefficient estimate for the 60–65 temperature bin.

Figure 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 IPCC SRES Scenario A2 (Black) and B1 (White) using the NCAR PCM with the constructed analogues downscaling method

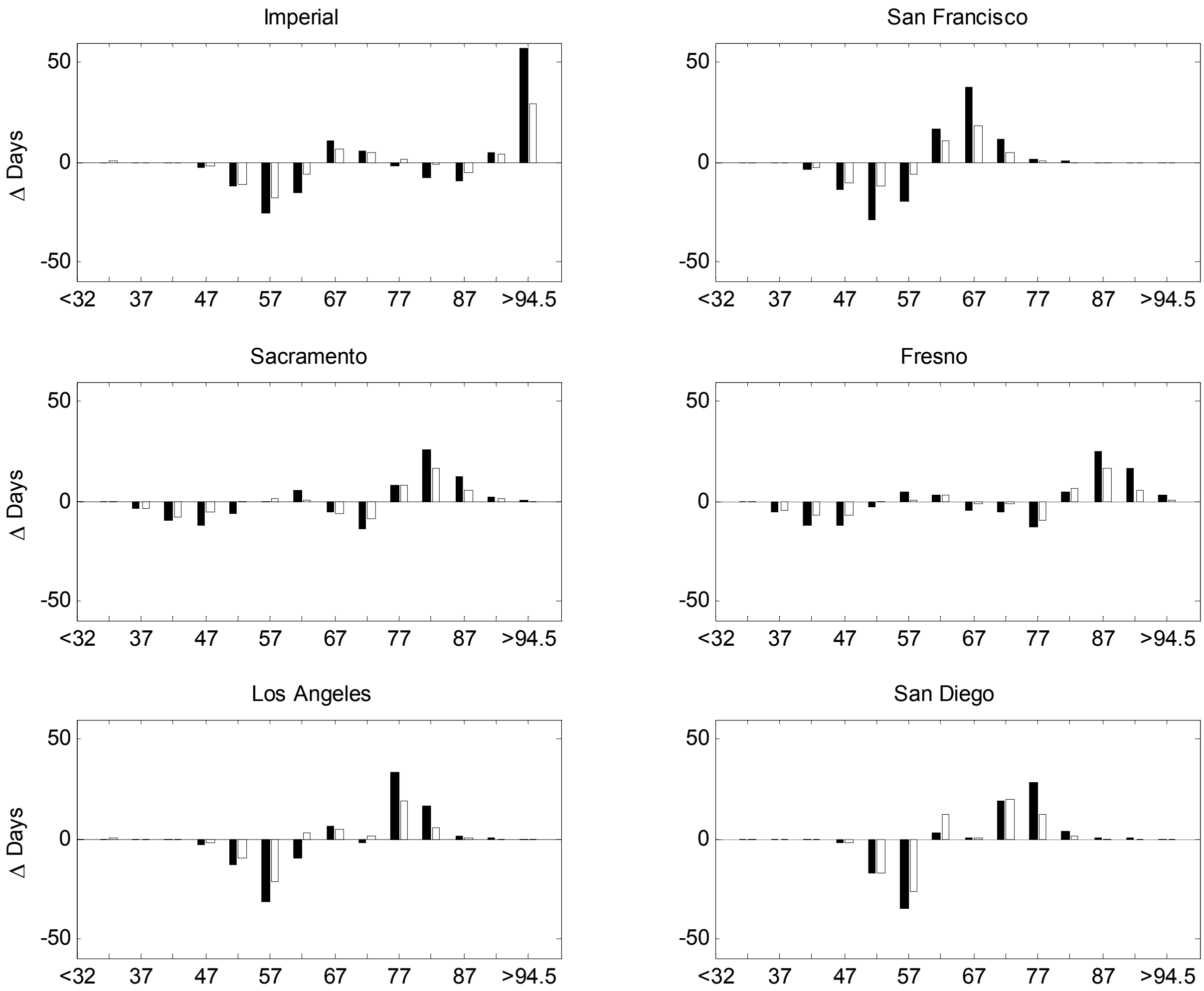


Figure 6. Simulated increase in household electricity consumption by zip code for the periods 2020–2039 (a), 2040–2059 (b), 2060–2079 (c), and 2080–2099 (d) in percent over 1980–1999 simulated consumption. Model NCAR PCM forced by IPCC SRES A2.

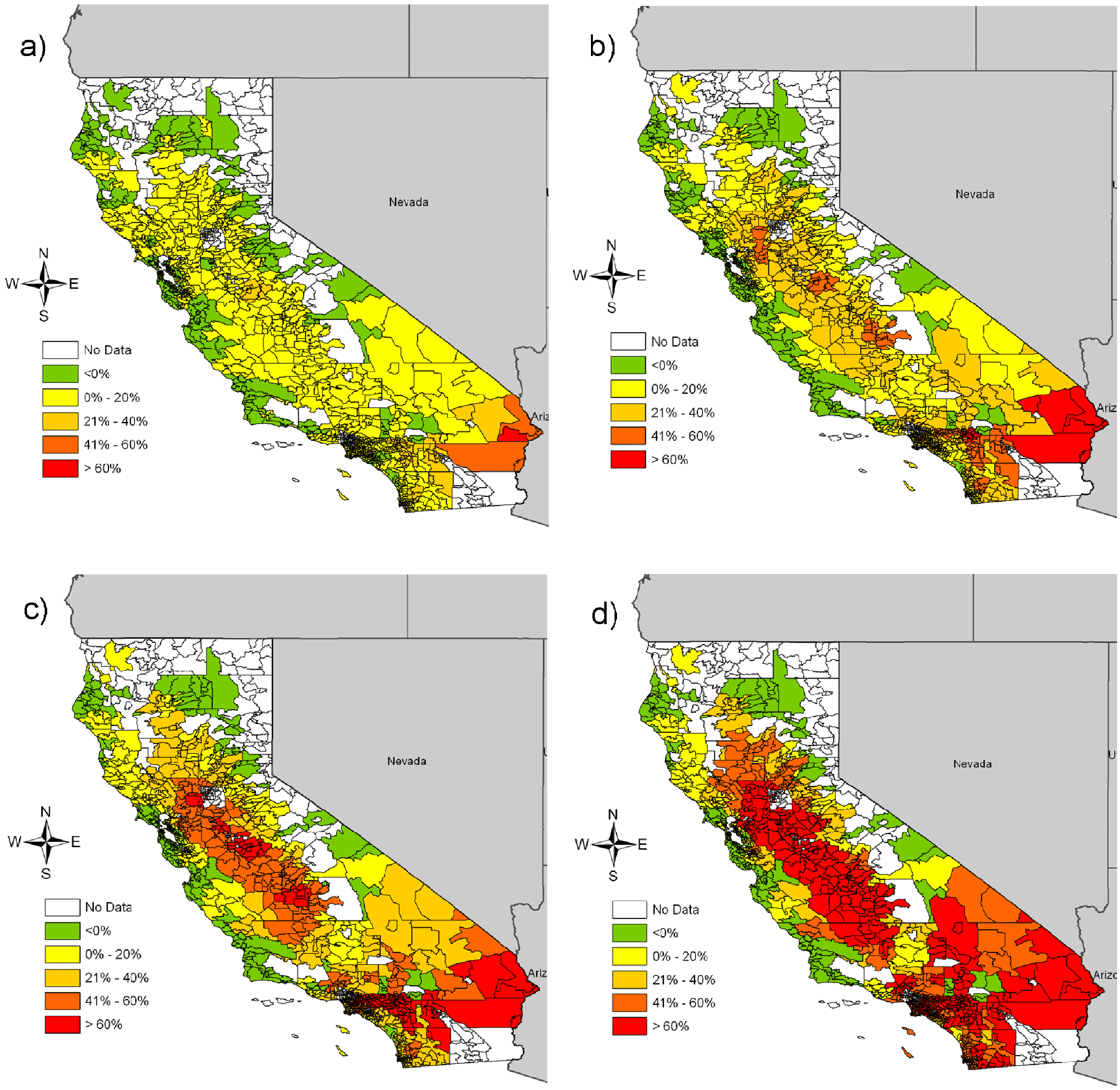


Figure 7. Simulated increase in household electricity consumption by zip code for the periods 2020–2039 (a), 2040–2059 (b), 2060–2079 (c), and 2080–2099 (d) in percent over 1980–1999 simulated consumption. Model NCAR PCM forced by IPCC SRES B1.

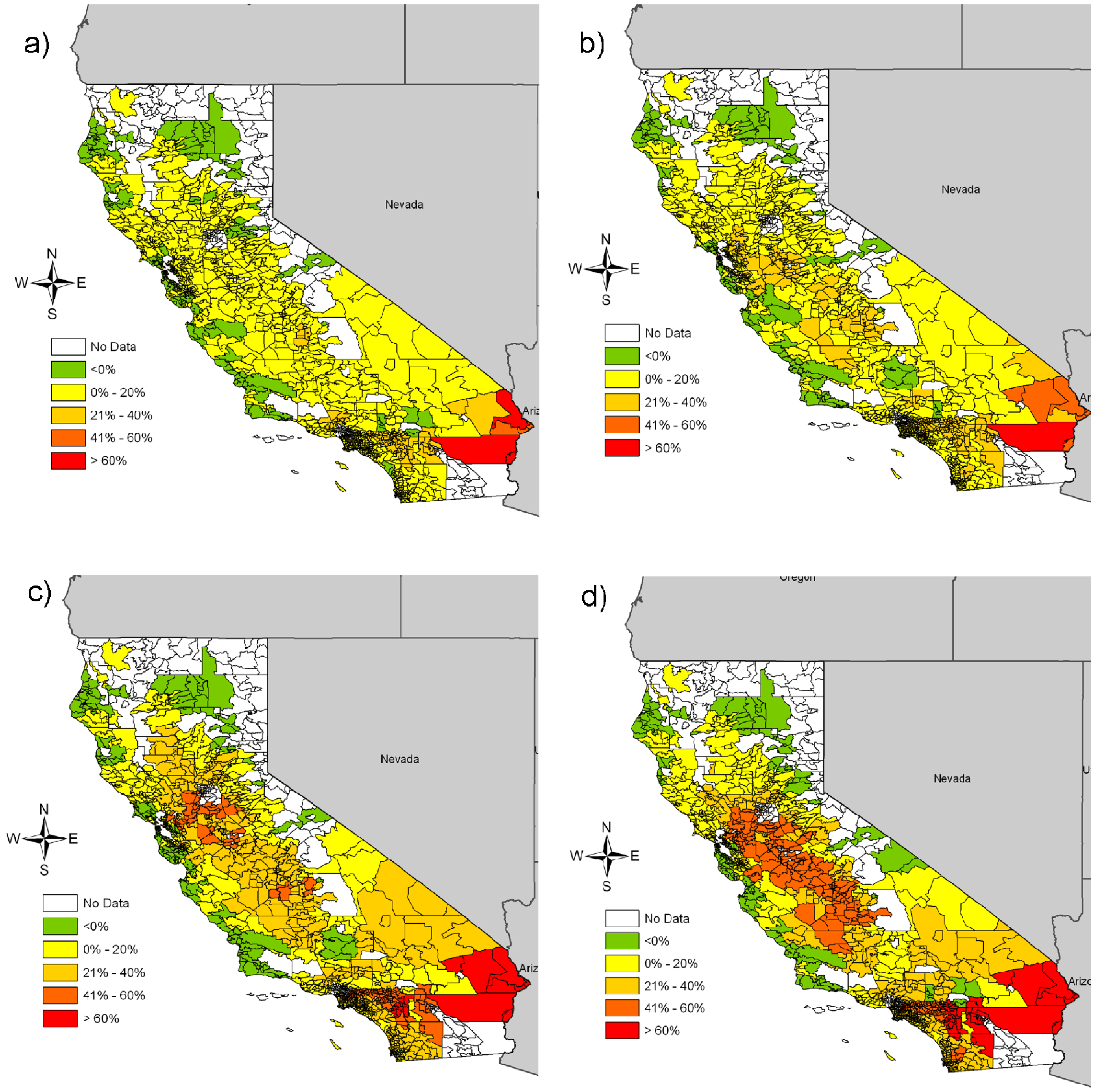
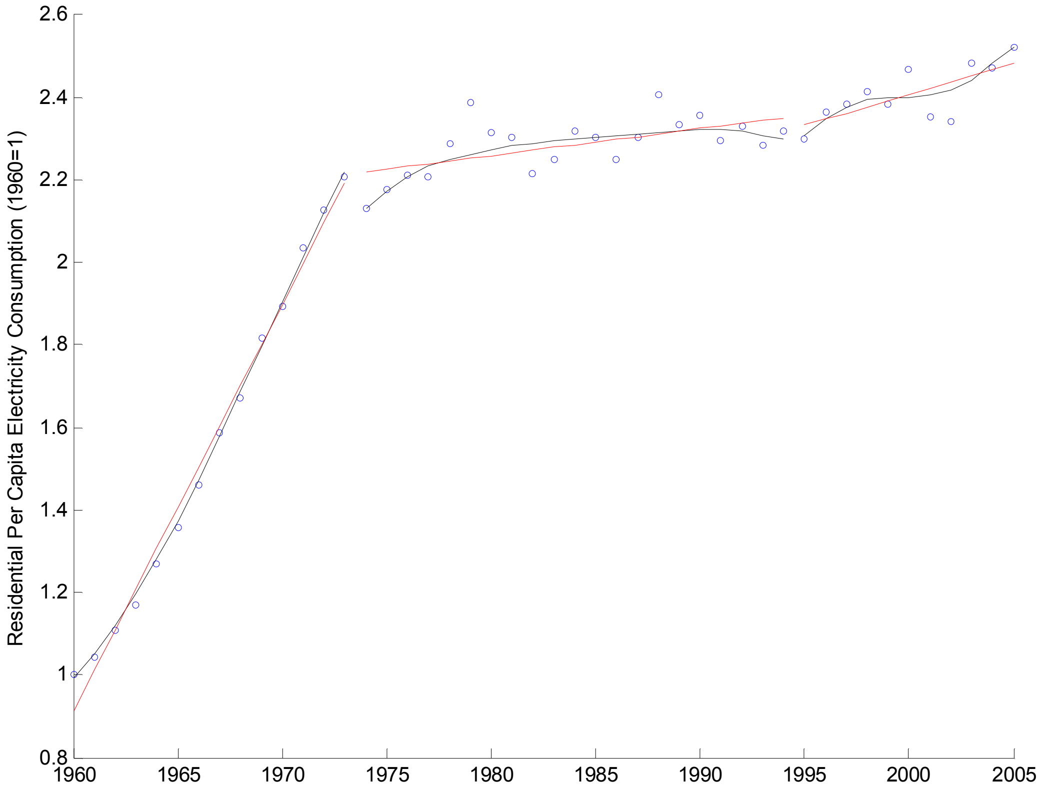


Figure 8. California residential per capita electricity consumption



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

Table 1. Summary statistics for non-CARE households

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

Table 2. Summary statistics for zip codes in and out of sample

Variable	n	Mean	Std. Dev.	n	Mean	Std. Dev.	Difference
		Not In Sample			In Sample		
Population	239	19.83	20.86	1325	20.39	20.67	0.56
Household Size	239	2.66	0.60	1325	2.79	0.60	0.14***
Household Income	239	39.52	19.39	1325	48.32	21.53	8.80***
House Value	239	200.08	177.33	1325	234.90	177.51	34.83***
Median Age	239	36.92	7.34	1325	36.85	7.50	-0.07
Elevation	239	1081.45	1526.95	1325	439.63	737.94	-642***
Land Area	239	69.66	130.12	1325	68.05	140.45	-1.61

Table 3. Simulated percent increase in residential electricity consumption relative to 1980–2000 for the constant, low price, and high price scenarios

Bin Type		Equidistant				Percentile			
Downscaling		BCSD		CA		BCSD		CA	
IPCC Scenario		A2	B1	A2	B1	A2	B1	A2	B1
	Price Increase								
2000-19	±0%	5%	2%	5%	3%	6%	3%	5%	3%
2020-39	±0%	5%	8%	7%	8%	6%	9%	7%	8%
2040-59	±0%	15%	9%	17%	10%	17%	11%	17%	10%
2060-79	±0%	24%	15%	28%	16%	28%	17%	28%	16%
2080-99	±0%	48%	18%	50%	20%	55%	21%	50%	20%
2000-19	±0%	5%	2%	5%	3%	6%	3%	5%	3%
2020-39	+30%	-6%	-3%	-5%	-4%	-5%	-3%	-4%	-3%
2040-59	+30%	3%	-2%	3%	-2%	6%	-1%	5%	-1%
2060-79	+30%	11%	3%	11%	2%	15%	5%	15%	4%
2080-99	+30%	33%	6%	29%	4%	39%	9%	35%	7%
2000-19	±0%	5%	2%	5%	3%	6%	3%	5%	3%
2020-39	+30%	-6%	-3%	-5%	-4%	-5%	-3%	-4%	-3%
2040-59	+60%	-9%	-13%	-8%	-13%	-6%	-12%	-7%	-12%
2060-79	+60%	-1%	-9%	-1%	-10%	2%	-7%	2%	-8%
2080-99	+60%	18%	-6%	15%	-7%	24%	-4%	20%	-5%

Table 4. Simulated percent increase in residential electricity consumption relative to 1980–2000 for the low, middle, and high population scenarios

Bin Type	Equidistant				Percentile			
Downscaling	BCSD		CA		BCSD		CA	
IPCC Scenario	A2	B1	A2	B1	A2	B1	A2	B1
Low Population Growth Scenario								
2000-19	17%	13%	16%	14%	18%	14%	16%	15%
2020-39	31%	34%	33%	34%	32%	35%	34%	35%
2040-59	48%	41%	50%	41%	52%	42%	53%	42%
2060-79	66%	52%	68%	51%	72%	55%	73%	54%
2080-99	113%	65%	113%	65%	124%	70%	123%	70%
Medium Population Growth Scenario								
2000-19	19%	15%	18%	16%	19%	16%	18%	16%
2020-39	48%	52%	51%	52%	50%	54%	52%	53%
2040-59	99%	88%	101%	89%	104%	91%	105%	91%
2060-79	154%	133%	157%	133%	164%	139%	166%	138%
2080-99	258%	179%	257%	179%	277%	189%	275%	188%
High Population Growth Scenario								
2000-19	23%	19%	22%	20%	23%	20%	22%	20%
2020-39	64%	68%	66%	68%	66%	70%	68%	69%
2040-59	135%	123%	137%	123%	141%	126%	142%	125%
2060-79	240%	212%	243%	211%	252%	219%	254%	218%
2080-99	464%	342%	462%	342%	495%	357%	490%	356%

Table 5. Simulated percent increase in residential electricity consumption relative to 1980–2000 assuming a common low (Zone 7) and high (Zone 12) temperature response function

	Zone 7		Zone 12	
Forcing	A2	B1	A2	B1
2000–19	1%	-1%	13%	7%
2020–39	1%	1%	5%	7%
2040–59	2%	1%	29%	13%
2060–79	2%	1%	57%	28%
2080–99	3%	0%	122%	40%

Table 6. Simulated percent increase in residential electricity consumption relative to 1980–2000 for CARE and non-CARE households.

		NON-CARE		CARE		WEIGHTED	
Bin Type		Equidistant		Equidistant		Equidistant	
Downscaling		BCSD		BCSD		BCSD	
IPCC Scenario		A2	B1	A2	B1	A2	B1
	Price Increase						
2000-19	±0%	5%	2%	4%	2%	5%	2%
2020-39	±0%	5%	8%	4%	6%	5%	7%
2040-59	±0%	15%	9%	12%	8%	14%	9%
2060-79	±0%	24%	15%	20%	12%	23%	14%
2080-99	±0%	48%	18%	39%	15%	46%	17%
2000-19	±0%	5%	2%	4%	2%	5%	2%
2020-39	30%	-6%	-3%	-6%	-4%	-6%	-4%
2040-59	30%	3%	-2%	1%	-3%	2%	-2%
2060-79	30%	11%	3%	8%	1%	10%	2%
2080-99	30%	33%	6%	25%	3%	31%	5%
2000-19	±0%	5%	2%	4%	2%	5%	2%
2020-39	30%	-6%	-3%	-6%	-4%	-6%	-4%
2040-59	60%	-9%	-13%	-11%	-14%	-9%	-13%
2060-79	60%	-1%	-9%	-5%	-10%	-2%	-9%
2080-99	60%	18%	-6%	11%	-9%	16%	-7%