Impact of Climate Change on Residential Electricity Consumption: Evidence from Weather Fluctuations across Building Climate Zones in California

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ABSTRACT

This paper estimates the relationship between temperature and residential electricity consumption by exploiting variation in weather conditions across 13 Building Climate Zones in California. Cross-sectional household data and daily weather data are obtained from the Energy Information Administration's 2005 Residential Electricity Consumption Survey and the National Oceanic and Atmospheric Administration's Global Summary of the Day dataset respectively. For each climate zone, daily mean temperatures are sorted into seven equidistant bins based on the state's temperature distribution in 2005. The estimated temperature bin coefficients along with two 21st-century climate forecasts are used to simulate changes in per-household consumption for a selected group of counties. The simulation results suggest that households located in regions that are expected to experience the largest transfer of days from lower to higher temperature bins may increase their consumption of electricity by more than 15% over the course of the century.

I. INTRODUCTION

In recent years, atmospheric scientists have confirmed that the pace of climate change, which is characterized by increasing global surface temperatures, melting of the polar icecaps and rising sea levels, has accelerated as a consequence of simultaneous increases in greenhouse gas (GHG) emissions. According to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2007), the 50-year linear warming trend between 1956 and 2005 (0.13°C per decade) was nearly twice that for the 100 years between 1906 and 2005. In addition, GHG emissions have increased by 70% between 1970 and 2004, with carbon dioxide (CO_2) emissions rising by about 80% (21 to 38 billion metric tons). To put this in perspective, CO_2 represented 77% of total anthropogenic GHG emissions in 2004. If the trend persists, the IPCC projects that worldwide losses due to climate change will reach $150 billion over this decade.

The Climate Framework for Uncertainty, Negotiation and Distribution (FUND), which was first developed by Nobel Prize-winning economist Richard S. Tol, is an integrated assessment model linking projections of populations, economic activity and emissions to a simple carbon cycle and climate model, and to a model predicting and monetizing welfare impacts. Monetized in 1995 dollars, modeled welfare impacts include agriculture, forestry, tropical storms, sea level rise, biodiversity loss, vector-borne and cardiovascular diseases, and energy consumption. FUND runs in time-steps of one year from 1950 to 2300, and distinguishes 16 major world regions. It was used by the U.S. government's Interagency Working Group on the Social Cost of Carbon in 2009, which estimated the cost of incremental damages from greenhouse gas emissions to be $21 per ton of CO_2. In the absence of any policy-induced energy efficiency improvement, the model predicts that the highest costs of adaptation will be increased electricity consumption. This makes it essential for utility companies and policymakers to have accurate models to estimate the relationship between climate change and growth in electricity consumption so as to effectively plan future investments in new infrastructure for generation and transmission and determine optimal levels of environmental regulation.

Between 1960 and 2005, total electricity consumption in California rose by 472%, with the share of the residential sector growing from 26% to 34% (EIA SEDS 2008). The state initiated aggressive energy efficiency programs beginning in the 1970s, as a result of which annual per-capita consumption growth slowed down from 7% in 1960-1973 to 0.29% from 1974-1995. In 2000-2001, California suffered an energy crisis characterized by electricity price instability and four major blackouts affecting millions of customers. This prompted the imposition of a five-tier block pricing schedule for electricity, which was aimed at discouraging high consumption and promoting energy conservation. However, given high population growth, uncertain environmental regulation and the occurrence of climate change, the state still faces numerous pressures in meeting future electricity demand. While commercial electricity usage is likely to be responsive to price, there is empirical evidence to suggest that residential customers do not perfectly optimize in response to price changes (Ito 2010). Thus, variation in residential consumption can only be explained using a wider range of factors, one of which is temperature.

Using household survey data gathered by the Energy Information Administration (EIA) and daily weather observations compiled by the National Climatic Data Center, this study aims to estimate the effect of temperature on residential electricity consumption by exploiting random variation in weather conditions across 13 Building Climate Zones in California in 2005. Here, Building Climate Zones refer to geographic regions that are subject to different minimum efficiency building standards under the energy code of the state. For each climate zone, the days in 2005 are sorted into seven equidistant temperature bins. The variation in electricity consumption is explained as a function of temperature, while controlling for a set of observable household characteristics. The temperature response coefficients are then used to simulate per-household electricity consumption growth under different scenarios of climate change.

Whether policymakers choose to target electricity consumption using an incentive-based means, such as increasing-block pricing, or a non-incentive-based means, such as energy efficiency programs or public education campaigns, it is important to consider the nature of end-use consumption. In addition to simulating the effect of temperature changes on household consumption, this study further estimates the short-run marginal effects of appliance ownership on consumption conditional on temperature. Here, "short-run" refers to the period during which each household's appliance stock is fixed.

The study proceeds as follows: Section II reviews the literature on this topic. Section III describes the data. Section IV presents the econometric model and estimation results. Section V discusses the basic framework and results of the simulation exercise and Section VI concludes the paper.

II. LITERATURE REVIEW

Within the economics discipline, there are two noteworthy studies conducted prior to the turn of the century that lay the groundwork for research in this field. In *The Economics of Climate Change* (1992), William Cline uses a utility planning model to simulate the impact of projected climate scenarios on electric utilities in the United States. Using data published by the U.S. Environmental Protection Agency in 1989, he finds that an annual temperature increase of 1°C-1.4°C (1.8°F-.5°F) in 2010 would raise demand 9% to 19% above peak load capacity requirements. In a similar study, Baxter and Calandri (1992) use a detailed electricity demand forecasting model to estimate total consumption and peak demand in the residential, commercial, agricultural and water-pumping sectors in California. Their results indicate that under a 1.9ºC (3.4ºF) increase in mean statewide temperature, electricity requirements would increase from 2.6% and 3.7% in 2010, relative to a stationary climate scenario.

Within the last decade, a wide range of econometric approaches that model electricity demand in the presence of climate change have been adopted. Using survey data and a discrete-continuous choice model, Mendelsohn (2003) and Mansur et al. (2005) measure the impact of climate change on demand and fuel consumption choices. By reducing heating needs and increasing cooling needs, they establish that warming will result in fuel switching from natural gas to electricity. Cross-sectional analyses like these most likely yield biased estimators since they do not control for unobservable confounding factors that vary across households and are correlated with climate. Using time-series variation in hourly electricity load, Franco and Sanstad (2008) regress electricity demand data reported by the California Independent System Operator in 2004 on average daily temperature and consumption. They find that peak demand varies linearly with maximum temperature, whereas electricity load varies nonlinearly with average temperature. Further, they model three IPCC scenarios (A1FI, A2 and B1) to simulate the annual increase in peak load and electricity demand from 2005-2099. Relative to the 30-year base period between 1961 and 1990, the former increases by 1.0%-19.3% and the latter increases by 0.9%-20.3% respectively. Crowley and Joutz (2003) conduct a similar analysis using hourly data in the Pennsylvania, New Jersey and Maryland Interconnection. After controlling for time fixed effects, their simulation results indicate that a 2°C (3.6°F) increase in temperature would result in energy consumption of 3.8%.

Deschênes and Greenstone (2007) conduct the first panel-data regression to explain variation in state-level residential electricity consumption using flexible functional forms of daily mean temperatures. This model relies on random variation in temperature, includes state-level fixed effects, census division-by-year fixed effects and controls for precipitation, population and income. By 2099, the impact of climate change on annual electricity consumption will be in the range of 15%-30% of the baseline estimation or $15 to $30 billion (measured in 2006 USD). Similarly, Aroonruengsawat and Auffhammer (2009) use a panel of household-level billing data from 2003 to 2006, which they obtain through the University of California Energy Institute's agreement with the state's three largest investor-owned utilities. Controlling for household fixed effects, month fixed effects and year fixed effects, they exploit within household variation in temperature. Moreover, they measure the effect of temperature on electricity consumption for each of the 16 climate zones. Their results suggest that total household electricity consumption could increase by up to 55% by the end of the century.

Relying on a similar identification strategy, this study draws on random fluctuations in daily temperature to estimate the effect on household electricity consumption, but controls for more descriptive household characteristics such as annual household income, number of residents, total house size and appliance ownership. In addition, the study tests whether the effect of appliance ownership on electricity consumption is sensitive to temperature. Finally, the simulation exercise uses the same combination of climate forecasting models and greenhouse gas emissions scenarios as those used in Deschênes and Greenstone (2007), but applies them to estimate future electricity consumption at the household level rather than at the aggregate level.

III. DATA

i. Household Survey Data

Every four years, the Energy Information Administration, which operates within the U.S. Department of Energy, conducts the Residential Energy Consumption Surveys (RECS) in order to obtain information on energy consumption, energy expenditures, household and housing-unit characteristics and appliance ownership. The survey gathers data from a nationally representative probability sample of households, with representative samples for several large states. This study uses the 2005 California subsample, which consists of 468 households. Since the results for the 2009 RECS were not available at the time of this study, temperature response functions could not be constructed separately for each climate zone in order to test the assumption that differences in building efficiency standards reflect differences in temperature sensitivity.

The quality of the consumption data and appliance information make the RECS a particularly valuable data source. However, it suffers from three major weaknesses. First, according to the U.S. Census, the average number of households in California was 12,392,852 between 2006 and 2010. Since the survey sample size is substantially smaller, the predicting power of the model could be low despite the random variation in the sample. Second, price and consumption are measured as annual averages. Since electricity charges are usually levied on a monthly basis, there is strong evidence to suggest that households do not respond to this measure of price. Third, even though the surveys are conducted in person, the EIA does not reveal the location of the households in order to protect their confidentiality. Nonetheless, it does disclose the climate zones that the households are located in upon personal request. Figure 1 presents a map of the climate zones in California. Due to the absence or insufficient number of sample households in zones 1, 2 and 15, these zones will not be considered in the analysis here.

ii. Weather Data

To obtain daily mean temperature and dew point temperature observations, I use the Global Summary of the Day Dataset published by the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC). The dataset contains daily observations from 115 weather stations in California. Data coverage varies by station and over time. The weather variables chosen from the dataset are daily average temperature and daily average dew point temperature.[1] Since the narrowest geographic identifier of the sample households is their climate zone, I obtain the climate zones that each of the weather stations are located in from the California Energy Commission. Then, I exclude weather stations that report fewer than 300 observations over the course of the year. This leaves 78 weather stations. Next, I calculate daily averages for the temperature observations across all weather stations in each climate zone. There are some plausible complications that could arise when doing this. First, the number of weather stations differs considerably across zones. This is partially corrected by the fact that climate zones differ in size, and the zones that cover larger areas have more weather stations. Second, depending on how far apart the weather stations are located within each zone, the temperature observations could exhibit large variations. However, comparing annual averages of temperature observations reported by each weather station shows that this is not the case. Third, the daily averages for the temperature observations in each zone should ideally be weighted by population. Unfortunately, the population data for each climate zone is not readily available. Nonetheless, from the population density map in Figure 2, it appears that the zones also vary in size based on their population. While the weather data from the NCDC dataset are

[1] Dew point temperature refers to the temperature at which the air becomes saturated given current levels of moisture. In order words, it is the temperature at which the water vapor in the air begins to condense.

used in the main sections of this study, the values for heating and cooling degree days[2], which are specified for each household in the RECS survey, are also used to study the marginal effects of appliance ownership on electricity consumption conditional on temperature.

IV. ECONOMETRIC ESTIMATION

Equation (1) displays the initial regression model. Similar to the aggregate electricity demand estimation used in Deschênes and Greenstone (2007), it uses a log-linear estimation:

$$\log(q_i) = \beta_m \sum_m T_{mi} + \gamma_n \sum_n H_{ni} + \delta Z_i + \varepsilon_i$$

$\log(q_i)$ is the natural logarithm of the annual electricity consumed by household i, measured in kilowatt-hours. The main variables of interest in this paper are those concerning temperature. To capture some significant nonlinearities of electricity consumption in weather, daily mean temperatures experienced by household i are sorted into one of m temperature bins. This has traditionally been achieved using one of two techniques. The first technique involves creating specific equidistant temperature cutoffs. The second involves splitting the distribution into a set of percentiles, which does allow for more precisely-estimated coefficients. While the former technique runs the risk of splitting the days unevenly across the bins, it also standardizes the temperature thresholds across all zones allowing for easier interpretation of the results. This study exclusively uses the equidistant bin approach. The temperature distribution consists of seven bins, which are split at 10°F intervals. Daily mean humidity observations are obtained

[2] Heating degree days are the number of degrees the daily mean temperature is below the base temperature (65°F). Cooling degree days are the number of degrees the daily mean temperature is above the base temperature. The EIA adds a random error to both heating and cooling degree days to mask the location of the weather station from which the data was obtained.

using the temperature and dew point temperature observations.[3] Using a similar equidistant bin approach, they are sorted into10 bins, split at 10 percent intervals. Running F-tests on the temperature and humidity variables confirms that they are both jointly significant.

Table A1 displays the number of households, annual mean electricity consumption, standard deviation of electricity consumption and number of days that fall into each temperature bin for each of the 13 climate zones. Similarly, Table A2 displays the number of days that falls into each humidity bin by zone. To adjust for the lack of days with temperatures below 40°F or above 90°F, both these bins are combined with their adjacent bins in the final estimation. Also, the bins in the middle of the distribution cannot be split because they must match the distribution format of the temperature forecasts (see Section V). Table A3 provides a description of all the independent variables in this model and Table A4 illustrates the correlation coefficients between the temperature and humidity variables.

For each household, the number of days when daily mean temperature falls into each bin is defined as T_{mi}. The main coefficients of interest are the β_m's, which measure the percentage change in electricity consumption caused by one additional day with mean temperature falling into bin m. In the estimation model, n represents each humidity bin and H_{ni} denotes the number of days when daily mean humidity falls into each bin. Z_i is a vector of observable confounding factors that vary across households.

Given the nature of the survey dataset, the annual average electricity price for a household can best be computed as the household's annual electricity expenditures divided by its annual consumption. This measure of price could potentially cause a division bias. Moreover, since marginal price depends on consumption under the increasing-block pricing structure, there

[3] Humidity is measured as follows: $\frac{Actual\ Vapor\ Pressure}{Saturation\ Vapor\ Pressure} = \frac{6.11*10.0^{\frac{7.5*Dew\ Point\ Temperature}{237.7+Dew\ Point\ Temperature}}}{6.11*10.0^{\frac{7.5*Temperature}{237.7+Temperature}}}$

is a strong reason to believe that price is endogenous. Unfortunately, the RECS dataset does not contain an exogenous variable that is correlated with price, which could have been used as an instrument to formally test for endogeneity. Estimating the price elasticity of demand under these circumstances is difficult, but some techniques have been proposed. Reiss and White (2005) use a computationally-intensive maximum likelihood approach to estimate household electricity demand, concluding that the price elasticity of demand for electricity is -0.39. Aroonruengsawat and Auffhammer (2009) attempt to address this problem by including price directly, instrumenting for it using lagged prices and omitting it from the estimation. In all three cases, they obtain identical results and decide to omit price from their model. For the reasons mentioned above, price is omitted from the regressions in this study as well.

Other confounding variables included in the model are the natural logarithm of household income, the number of household residents and the natural logarithm of total square footage. The appliances that enter the model have at least a 10% sample saturation rate, and annually consume at least 240 KwH of electricity on average (see Table A5). The correlation coefficients for each appliance are displayed in Table A6. ε_i accounts for all unobservable household characteristics.

The temperature bin coefficients from four robust OLS regressions are plotted in Figure 3 to examine the shapes of the temperature response functions under different assumptions. In particular, it is essential to observe the effects of combining the less than 40°F and 40°F to 50°F bins when the humidity bins are retained in the model versus when they are dropped. Since the days in both the temperature and humidity bins sum to 365, the above 90°F temperature bin and the 0% to 20% humidity bin are normalized to avoid multicollinearity. The temperature bin coefficients are interpreted as the effect of removing one day from the highest temperature bin and adding it in succession to each lower temperature bin. In Figures 3(a), (b) and (c), the higher absolute value of the coefficients on the bins in the middle of the temperature distribution (50°F to 60°F and 60°F to 70°F) imply that an additional day in those bins would decrease electricity consumption by a higher percentage than at the extreme bins (below 40°F and above 80°F). With the exception of Figure 3(d), the illustrations are generally consistent with the U-shaped temperature response function found in previous studies. However, the marginal difference between the 70°F to 80°F and the above 80° F bin coefficients in Figure 3(c) is substantially lower than the marginal difference between the 60°F to 70°F and the 70°F to 80°F bin coefficients. Moreover, the slope of the line connecting the 70°F to 80°F and the above 80° F bin coefficients in Figures 3(a) and (b) is negative. These problems could have been corrected to a certain extent had survey results from one or more additional year(s) been available. An independently pooled cross-section would create a larger sample and possibly allow for the response of household electricity consumption to be estimated separated for each climate zone. Aggregating data over the entire state often ignores important nonlinearities, which combined with random weather changes across the state, could lead to underestimates of future electricity consumption (Aroonruengsawat and Auffhammer, 2009). Also, as mentioned earlier, creating equidistant bins for temperature splits the days unevenly across the temperature bins, resulting in a concentration of days in the milder temperature bins and fewer days in the extreme temperatures bins (see Table A1). The weather data from the additional survey periods would compensate for the resulting loss in precision by contributing to the variation in the number of days in the higher temperature bins within each climate zone.

The effect of controlling for humidity explicitly is seen by contrasting the difference between Figures 3(a) and (b) to the difference between Figures 3(c) and (d). In addition to altering the magnitudes and signs of the temperature bin coefficients, controlling for humidity seems to make the temperature bin coefficients highly unstable. This is most likely to be a consequence of the significant negative correlation between the days in the temperature and humidity bins, as indicated in Table A4. To overcome this problem, I let the temperature variables capture the effect of humidity in the final estimation. Table A7 presents the results of a set of robust OLS regressions where the constant term is suppressed. The appliances added in the second output column are those that are relatively more sensitive to temperature. The appliances in the remaining output columns are added based on increasing annual average electricity consumption thresholds. The adjusted R-squared values[4], which range from 39.1% to 59.2% across the output columns, indicate that controlling for appliance ownership helps explain more of the variation in residential electricity consumption. The shape of the temperature response function, constructed using the coefficients from column (5), is identical to that in Figure 3(b).

In order to test the hypothesis that the marginal effect of owning a central air-conditioner or an electric space heater on total electricity consumption varies with temperature, the dummy variables representing ownership of these appliances are interacted with the number of heating and cooling degree days for each household in the sample. The log of household electricity consumption is regressed on these interaction terms, while controlling for the observable household characteristics in Z_i and zone fixed effects. Since heating and cooling degree days are continuous variables, the marginal effects are computed for two distinct values of heating and cooling degree days. The first value is the mean and the second value is 1,000 degrees above the mean, which is chosen arbitrarily for comparison. Since the interactions between the appliance dummy variables and household income, number of residents and house size do not yield

[4] The adjusted R-squared values are based on the robust OLS regression where the highest temperature bin is normalized. The F-statistics and adjusted R-squared values are not reported in Table A8 because the sum of squares of the dependent variable, accounted for by the intercept, are not included in the total sum of squares when the constant term is suppressed. Therefore, the goodness-of-fit estimates reported by such regressions are usually invalid.

statistically significant estimators, they do not enter this model. As presented in Table A8, the estimated marginal effect of electric space heater ownership on annual household electricity consumption increases by 9.63% as the number of heating degree days rises from 1,687 to 2,687.

V. SIMULATIONS

As is customary in the climate change literature, the impact of temperature on per-household residential electricity consumption is simulated for every ten-year period until the end of the century. This process involves using the temperature response coefficients generated in Section IV as well as a set of climate forecasts. There are some important assumptions regarding the simulation exercise that must be discussed. First, using the β_m estimated parameters implies that households' consumption behavior in response to temperature will remain constant throughout the century. In making this assumption, I am ruling out the possibility that households will engage in a wider range of adaptation strategies to mitigate their energy costs. For instance, as the climate becomes warmer, households that currently do not require air conditioners may invest in them in the future. Also, with policies that require higher appliance efficiency standards for air conditioners, the electricity required for each cooling unit may decline causing the temperature response curve to be lower at the higher bins.

The climate forecasts are generated using General Circulation Models (GCMs). These simulation models generate forecasts for past and future climate under different scenarios of greenhouse gas concentrations in the atmosphere. The two GCMs used in this study are the Hadley Centre's third Coupled Ocean-Atmosphere General Circulation Model and the National Center for Atmospheric Research's (NCAR) Community Climate System Model (CCSM) 3. Both models were used in the Fourth Assessment Report by the IPCC (IPCC 2007). Climate predictions generated by these models are available for several emissions scenarios. The two scenarios applied in this study are the A1FI and the A2, which are driven by two sets of projections for twenty-first century social and economic development that are described in the *Special Report on Emissions Scenarios* (SRES) (IPCC 2000). The SRES study was conducted as part of the IPCC's Third Assessment Report. As illustrated in Figure 4, the A1FI and A2 scenarios are evidently the more pessimistic scenarios, predicting the highest increases in CO_2 and N_2O emissions. The AIF1 scenario is characterized by income convergence and rapid economic growth driven by fossil fuel-intensive technology. Under these conditions, the scenario predicts that global population will reach 9 billion in 2050 and will gradually decline thereafter. The A2 scenario is characterized by a world of independently operating, self-reliant nations and regionally-oriented economic development. Furthermore, it predicts that global population will rise continuously. Under both scenarios, annual CO_2 emissions will reach 30 billion metric tons of carbon by 2100. Since these are considered to be the so-called "business as usual" scenarios, they are the proper scenarios to consider when judging policies targeted towards greenhouse gas abatement.

Deschênes and Greenstone (2007) use the same combination of GCMs and emissions scenarios to project changes in the number of days spent in each 10°F temperature bin by county-year for the 2010-2099 period relative to the 1968-2002 period. Therefore, this study uses their forecasts, which have been made publicly available by the American Economic Association. The temperature projections under the Hadley 3 A1FI scenarios are adjusted for model error by comparing the model's predictions for the 1990–2002 period with the actual realizations from the weather station data. For example, in the case of temperature, the Hadley 3 model errors are calculated separately for each of the 365 days in a year for each county as the average difference between county by day of year-specific average temperature from the weather station data and the Hadley 3 A1FI predictions during the 1990–2002 period. This county by day of year-specific error is then added to the Hadley 3 A1FI predictions to obtain an error-corrected climate change prediction.

In order to obtain estimates of a percent change in residential electricity consumption for a representative household in county j and period $t+h$, the following relation is commonly used in the climate impacts literature:

$$\frac{q_{j,t+h}}{q_{j,t}} = \frac{\exp(\sum_{m}^{k} \hat{\beta}_{mj} T_{mj,t+h})}{\exp(\sum_{m}^{k} \hat{\beta}_{mj} T_{mj,t})}$$

Given the assumption that the remaining independent variables will remain frozen at their 2005 levels both in period t and period $t+h$, these terms cancel out when the exponential functions are distributed. The $\hat{\beta}_m$ parameters are obtained from the robust OLS regression where the constant term is suppressed that the predicted changes in the number of days in each temperature bin are weighted by non-zero parameters. The coefficients are obtained specifically from the output column farthest to the right in Table A8. Figure 5 shows the change in the number of days spent in each 10°F bin of the temperature distribution from 1968-2002 to 2090-2099 using the Hadley 3 and CCSM models forced by scenarios A1FI and A2 for six California counties. There is a noticeable transfer of days from the lower temperature bins to the higher temperature bins for all counties. Figure 6 shows the corresponding changes when the below 40°F bin is combined with 40°F to 50°F bin and the 80°F to 90°F bin is combined with the above 90°F bin as specified in the estimation in Table A7. While the two extreme bins are combined with their adjacent bins to compensate for the scarcity of days in those bins, there are important consequences of reformatting the temperature variables that must be addressed.

The Hadley A1FI model predicts that Fresno and Imperial counties, which are located in the Central Valley and the south-eastern desert respectively, will experience large increases in the number of days in the above 90°F bin and slight decreases in the number of days in the 80°F to 90°F bin. In contrast, counties on the coast, such as Los Angeles and San Diego, are likely to experience larger increases in the 80°F to 90°F and substantially smaller increases in the above 90°F bins. However, when these bins are combined, the net change in the number of days in the above 80°F bin is higher for Los Angeles and San Diego than it is for Fresno and Imperial. Under these circumstances, the increase in household electricity consumption for days when temperature is predicted to be above 80°F will naturally be larger for coastal counties than for counties located in the Central Valley or the desert. Therefore, forecasting changes in household electricity consumption for counties in the latter category will yield inaccurate results. Therefore, the simulation exercise is only performed for counties where the difference in the predicted number of days in the 80°F to 90°F bin and the above 90° bin is at least 10. Since a larger number of counties experience a significant increase in the number of days in the above 90°F bin under the Hadley A1FI model, the region for which household electricity consumption is simulated will be more expansive under the CCSM A2 model. Given this reasoning, the counties for which consumption growth forecasts do not exist are likely to experience higher percent increases in consumption than counties for which growth forecasts do exist.

Figures 7 and 8 display a spatial distribution of the predicted changes in per-household electricity consumption in periods 2050-2059, 2070-2079 and 2090-2099 relative to consumption over the 1968-2002 base period. Changes in consumption are driven by two specific factors: the shape of the state-wide temperature-response function and the change in projected climate. As the maps indicate, electricity consumption will rise for almost all counties.

The simulation results for the Hadley A1FI model suggest that, among the selected regions, the south-eastern coast will experience the largest increase in consumption by the end of the century. While the spatial patterns for the 2090-2099 period looks similar under the “high-emissions” A1FI and “medium-high emissions” A2 scenarios, the growth patterns are strikingly different. This difference corresponds to the fact that the Hadley 3 model predicts that the number of days in each temperature bin will change substantially after the 2060-2069 period. On the other hand, the CCSM model predicts more profound changes in the earlier decades followed by a seemingly constant growth pattern in the latter half of the century. Lastly, the projections displayed here rule out the possibility of increased ownership of cooling appliances or efficiency improvements in counties where the penetration rates are currently low. The projected reductions in electricity consumption predicted for some counties could be a result of a drop in the demand for electricity, and possibly natural gas, for heating purposes.

VI. CONCLUSION

This study uses random fluctuations on exogenous shocks in weather to estimate the effect of temperature on residential electricity consumption. The estimated temperature response function, along with two sets of temperature forecasts generated by forcing two IPCC emissions scenarios on two distinct General Circulation Models, are used to simulate per-household electricity consumption for a selected group of counties in California.

The simulation results affirm that households located in regions that are expected to experience the largest transfer of days from lower to higher temperature bins are likely to increase their demand for electricity by more than 15% over the course of the century. It is important to note that the results presented here are likely to be understated given that the data does not allow for the estimation of geographically-differentiated responses of consumption to changing temperatures, which would capture sharper nonlinearities in the relationship. Nonetheless, the study sheds light on the consequences of delaying or refraining from implementing policies that target electricity consumption and specifically end-use consumption from appliances that are energy-intensive and more sensitive to temperature.

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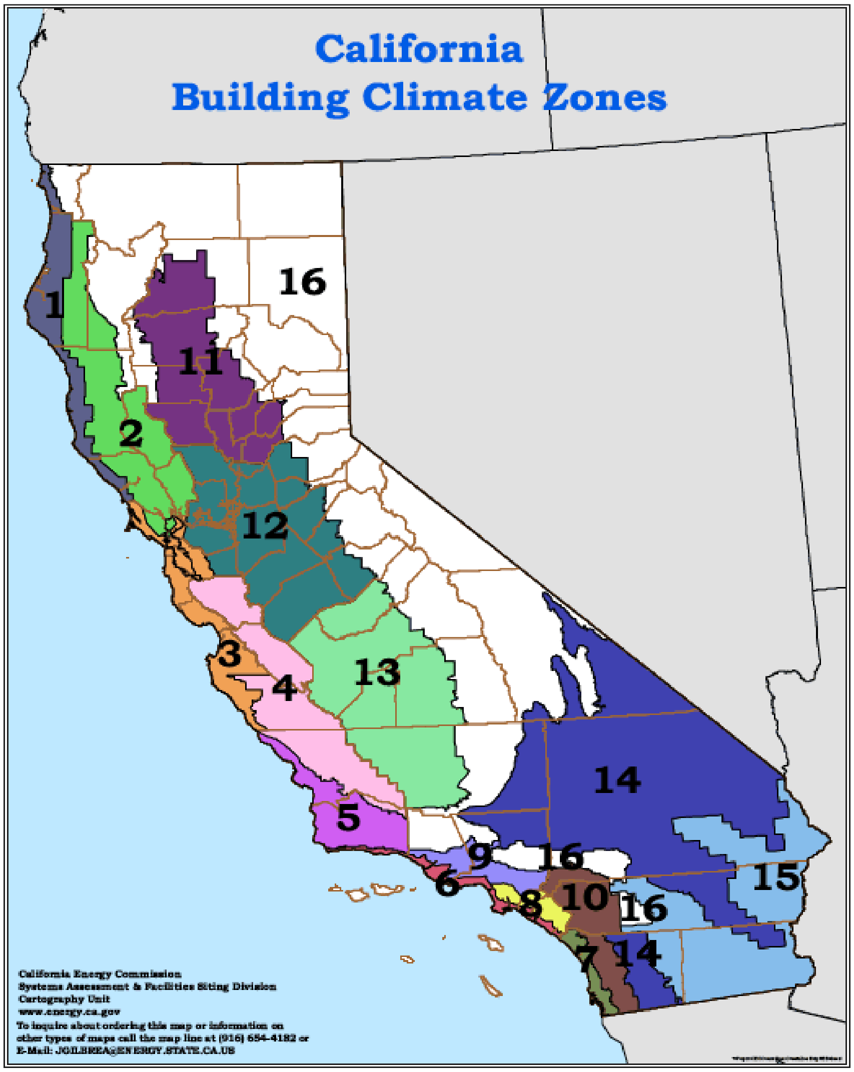
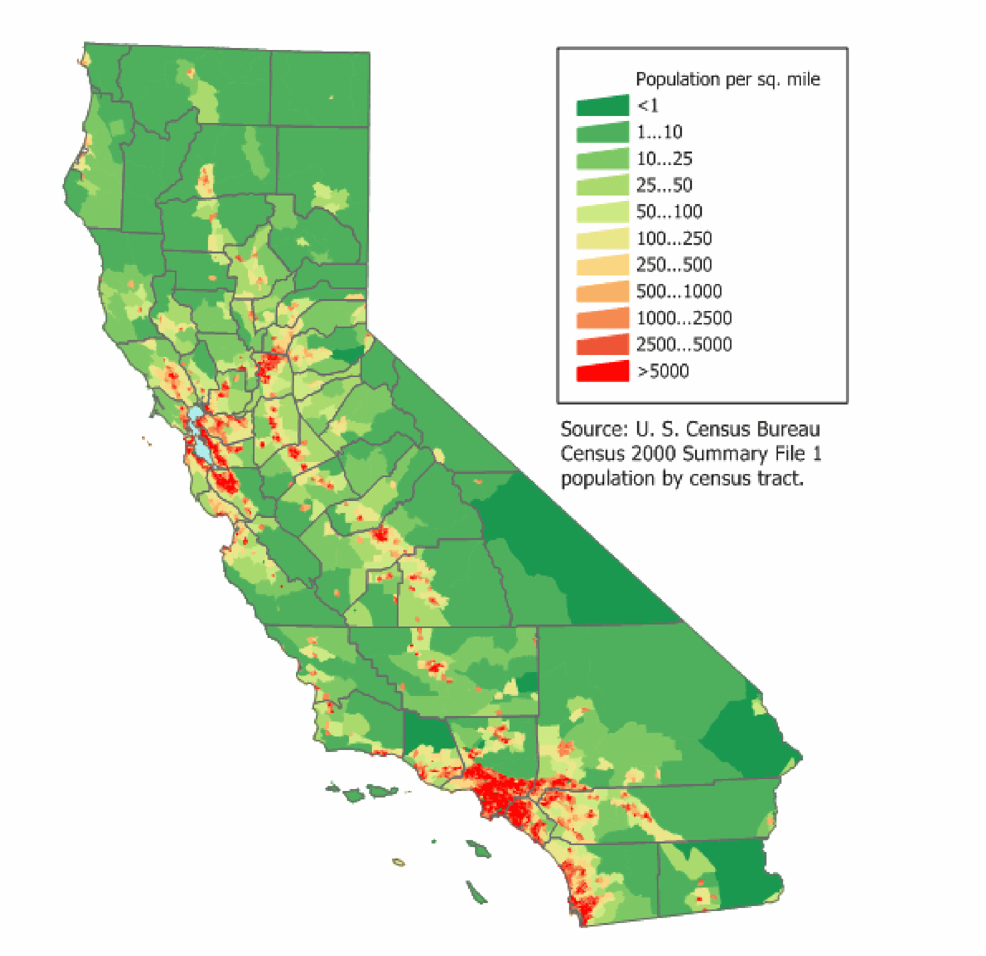
APPENDIX

Figure 1: California Energy Commission Building Climate Zones



Source: California Energy Commission

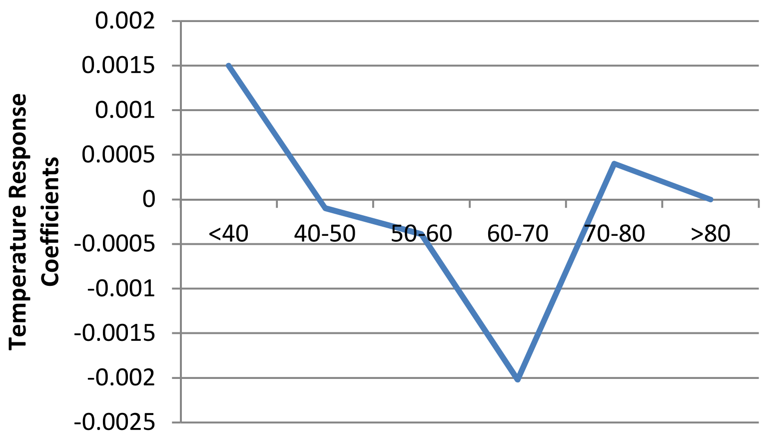
Figure 2: Population Density in California



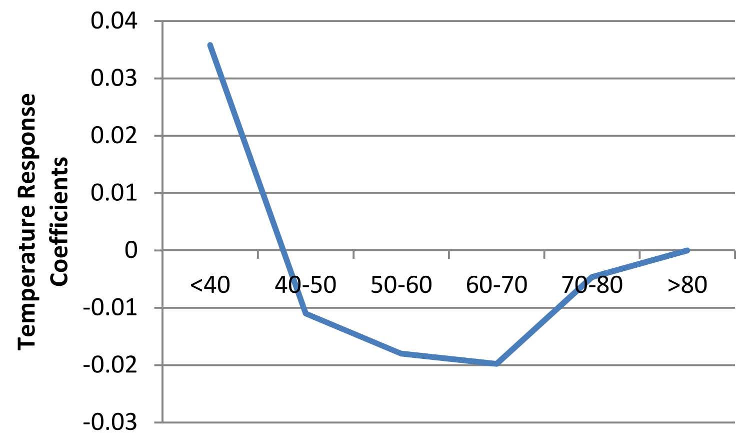
Source: U.S. Census Bureau, Census 2000 Summary File 1

Figure 3: Temperature response functions from robust OLS regressions with (a) the below 40°F and 40°F to 50°F temperature bins defined separately, (b) the below 40°F and 40°F to 50°F temperature bins combined, (c) the humidity bins present and the below 40°F and 40°F to 50°F temperature bins defined separately, and (d) the humidity bins present and the below 40°F and 40°F to 50°F temperature bins combined. The above 80°F temperature bin and 0% to 20% humidity bin are normalized.

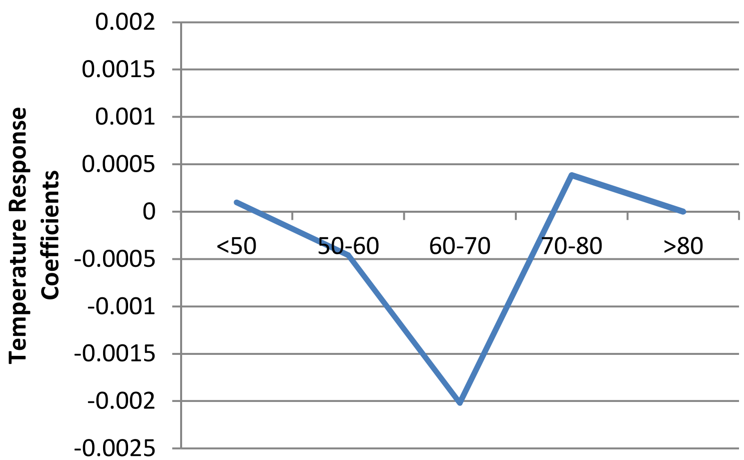
(a)



(c)



(b)



(d)

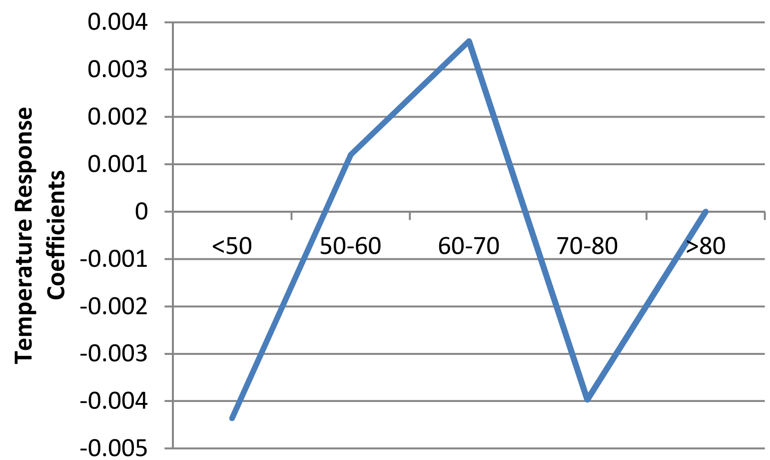
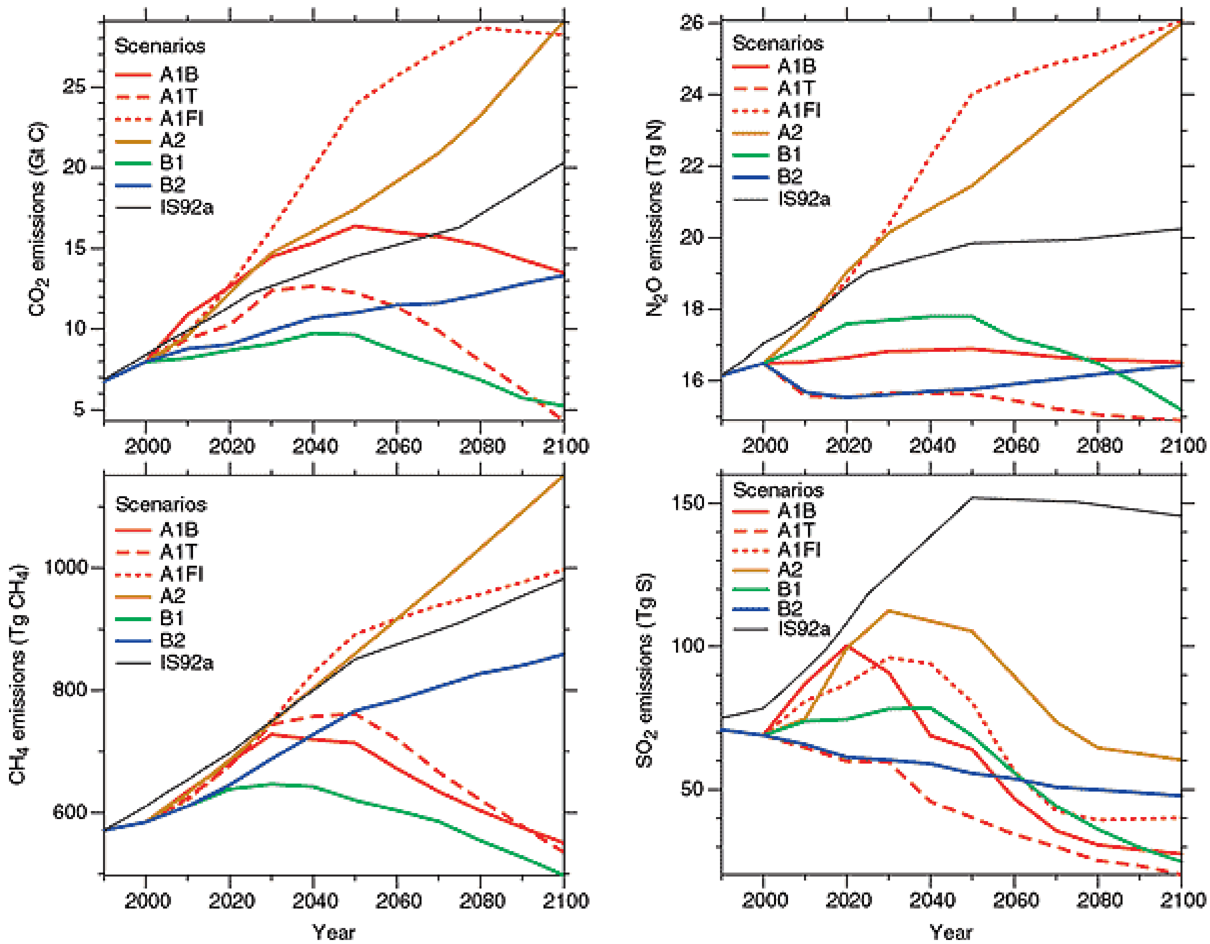


Figure 4: Emissions Projections under six SRES Scenarios



Source: *Special Report on Emissions Scenarios* (IPCC 2000)

Figure 5: Average number of days in each 10°F temperature bin for 1968-2002 (Blue) and change in number of days in each bin for 2090-2099 relative to 1968-2002 for six California counties using the Hadley 3 A1FI (Red) and the CCSM A2 (Green).

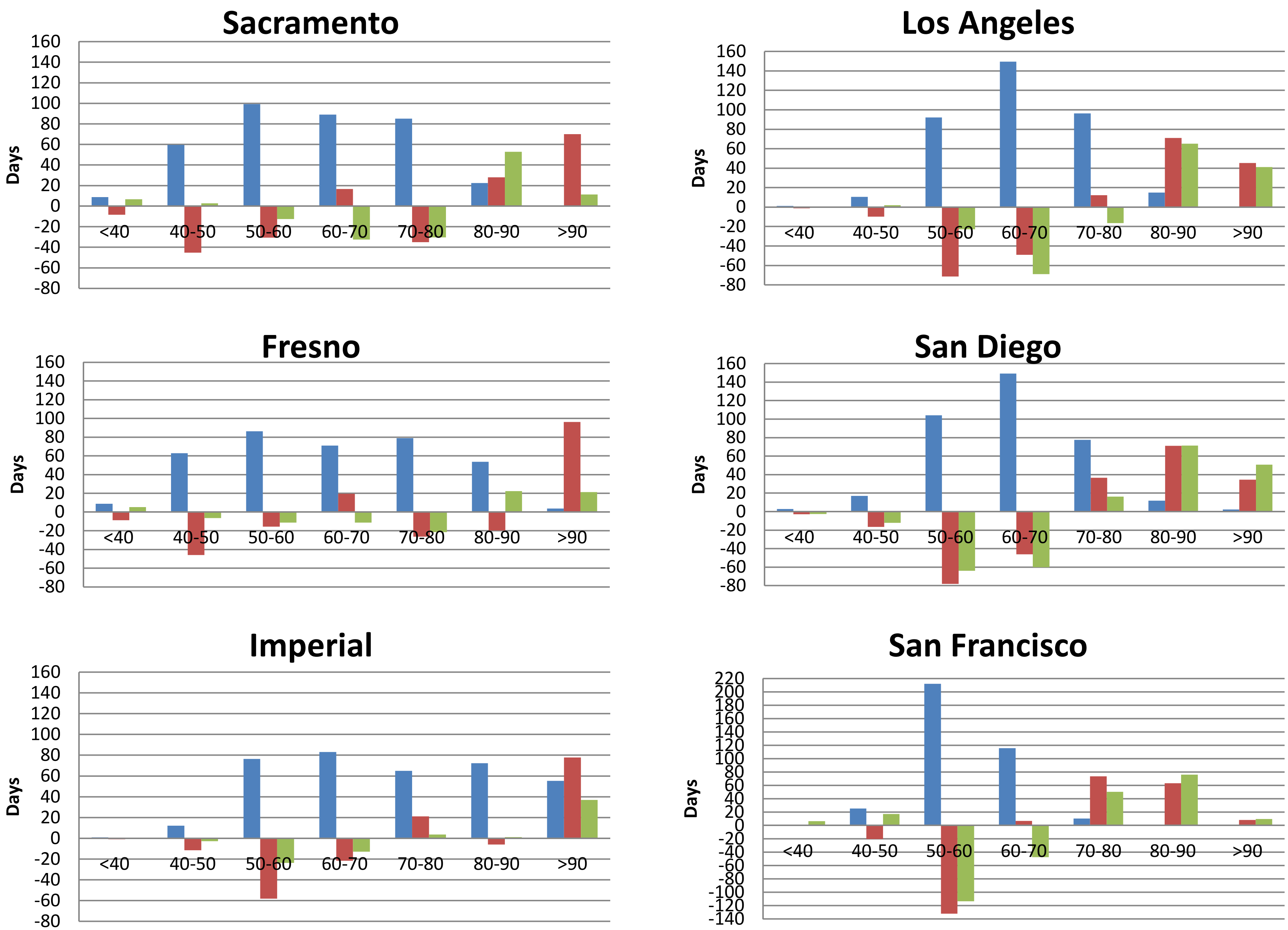


Figure 6: Average number of days in each 10°F temperature bin for 1968-2002 (Blue) and change in number of days in each bin for 2090-2099 relative to 1968-2002 for six California counties using the Hadley 3 A1FI (Red) and the CCSM A2 (Green). The days in the below 40° bin are combined with the days in the 40° to 50° bin and the days in the 80° to 90° bin are combined with the days in the above 90° bin.

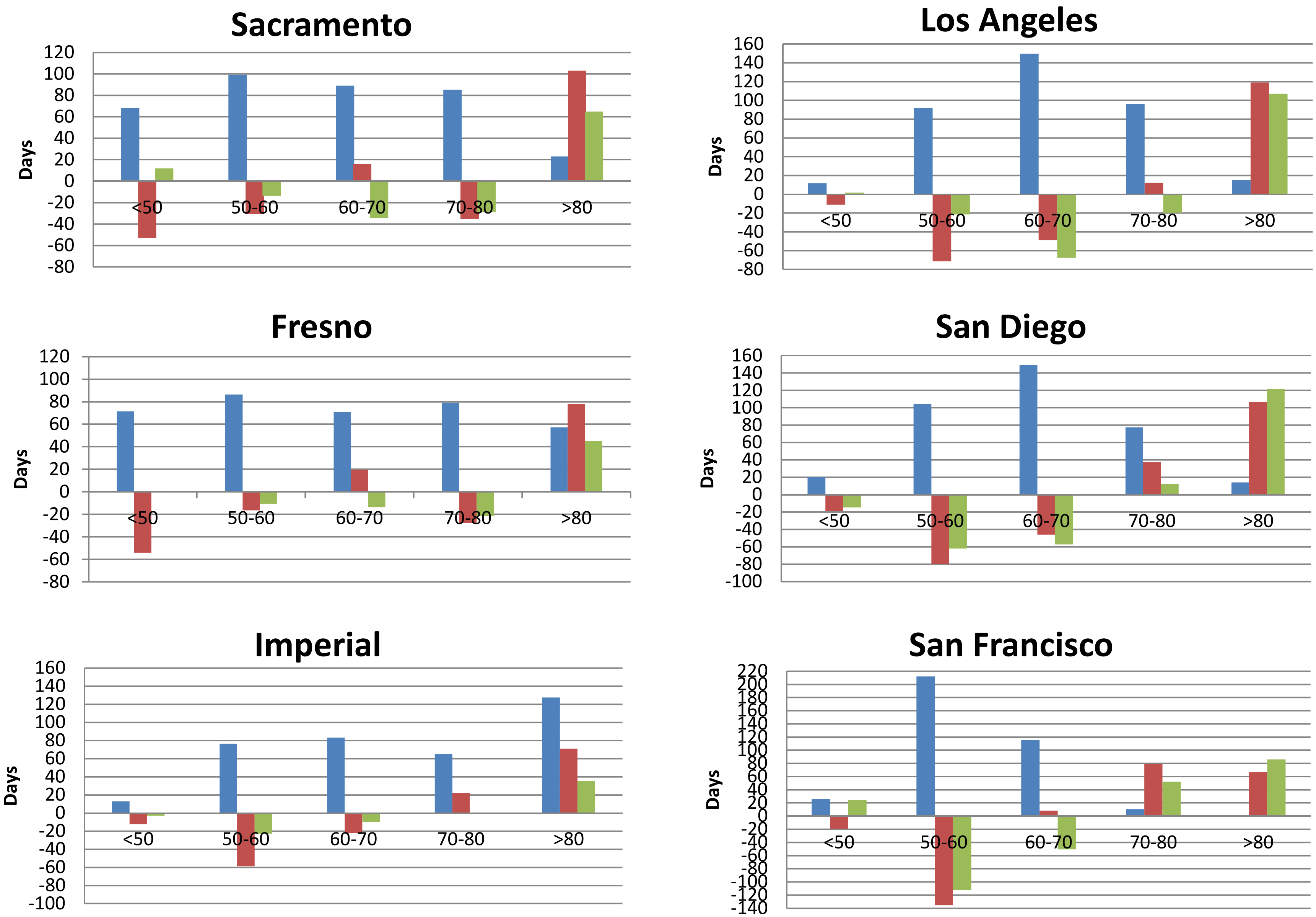
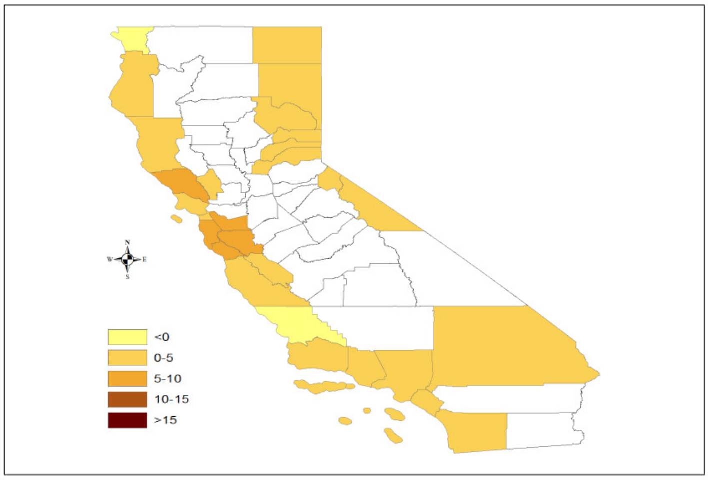
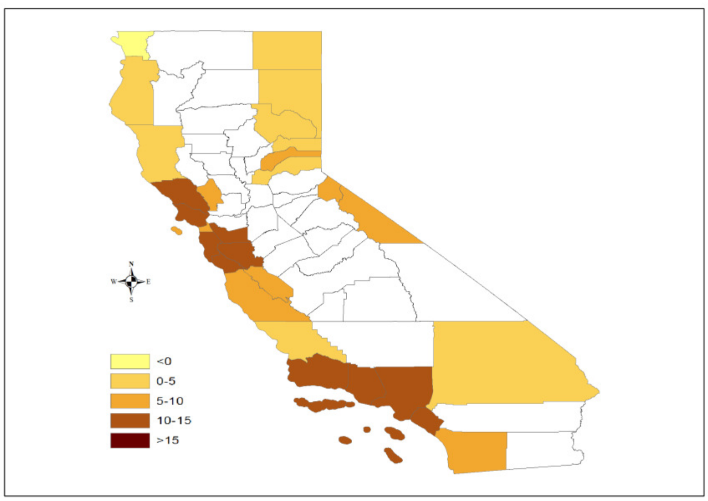


Figure 7: Simulated percent increase in per-household electricity consumption by county for the periods (a) 2050-2059, (c) 2070-2079, and (d) 2090-2099 relative to simulated consumption over 1968-2002. Model Hadley 3 forced by IPCC SRES A1FI.

(a)



(b)



(c)

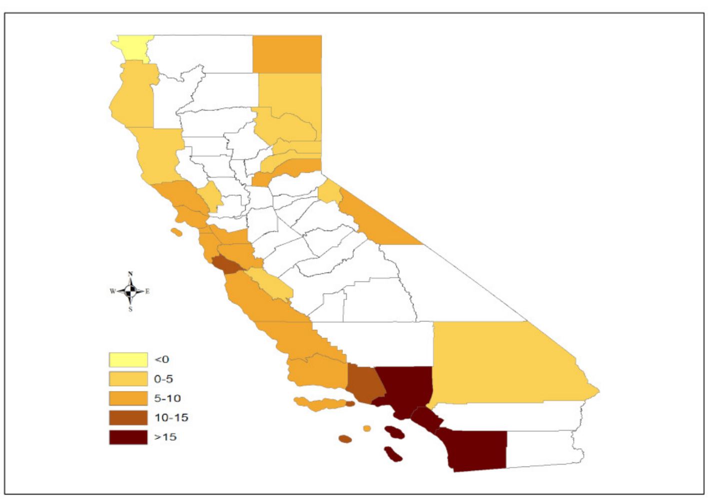
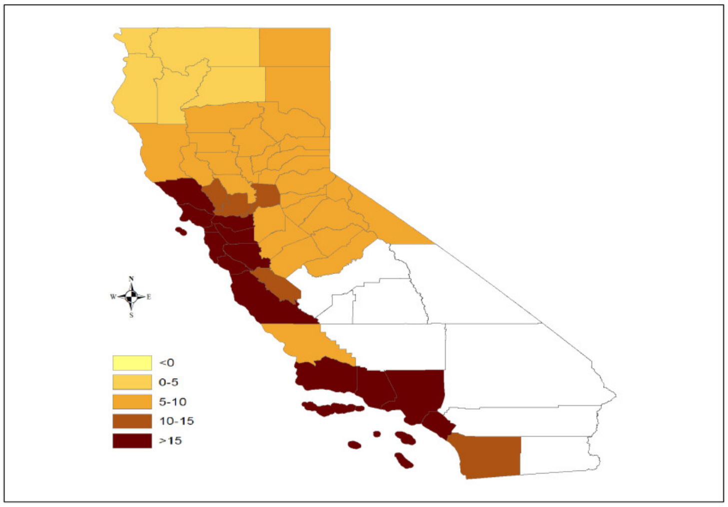
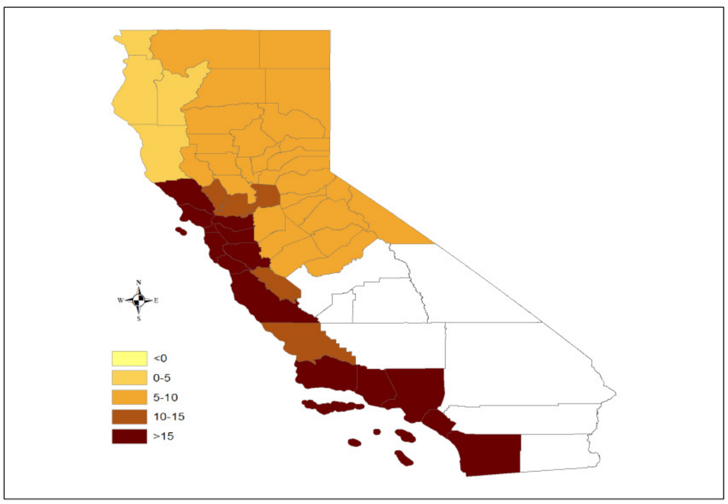


Figure 8: Simulated percent increase in per-household electricity consumption by county for the periods (a) 2050-2059, (c) 2070-2079, and (d) 2090-2099 relative to simulated consumption over 1968-2002. Model CCSM 3 forced by IPCC SRES A2.

(a)



(b)



(c)

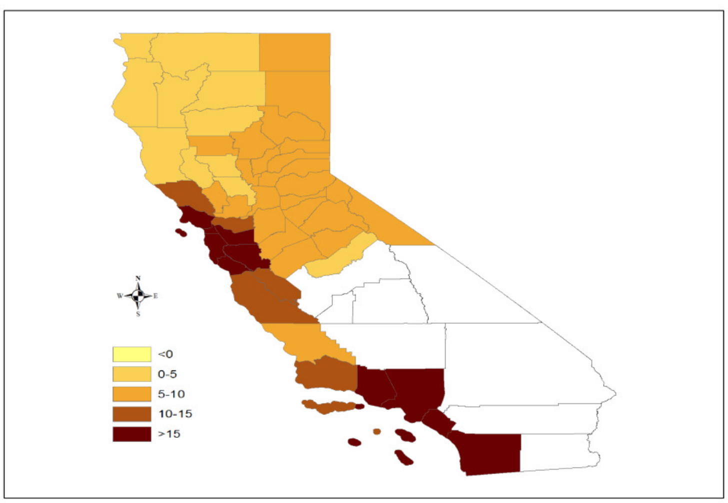


Table A1: Electricity Consumption and Temperature Statistics by Zone

		Annual Usage (KwH)		Daily Mean Temperature Distribution in 2005 (°F)						
Zone	No. of HH	Mean	Standard Deviation	<40	40-50	50-60	60-70	70-80	80-90	>90
3	64	5451.766	3470.707	0	31	160	170	4	0	0
4	17	6195	3229.878	0	34	153	163	15	0	0
5	17	5266.882	1881.35	0	17	262	86	0	0	0
6	31	7172.291	5566.194	0	2	132	215	16	0	0
7	34	6419.029	4291.748	0	5	141	187	32	0	0
8	51	5304	2947.423	0	2	76	205	77	5	0
9	67	5643.746	3982.458	0	9	117	144	82	13	0
10	50	7774.58	3931.049	0	9	98	112	92	52	2
11	21	12059.05	7194.698	9	58	144	72	61	47	4
12	67	9762.283	5342.956	1	58	132	103	65	6	0
13	22	7535.909	3288.259	1	48	117	81	65	50	3
14	11	5114.455	3598.935	3	52	104	65	56	68	17
16	15	7866.8	4257.137	24	129	110	74	28	0	0

Table A2: Humidity Statistics by Zone

	Daily Mean Humidity Distribution in 2005 (%)									
Zone	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
3	0	0	0	8	36	84	139	73	23	2
4	0	0	2	14	44	109	120	58	18	0
5	0	0	5	15	24	27	92	152	49	1
6	0	10	12	16	23	36	102	139	35	2
7	0	4	17	18	19	36	147	102	20	2
8	2	14	16	22	45	80	130	47	7	2
9	4	28	37	42	43	89	71	32	16	3
10	3	33	53	77	61	78	33	15	9	3
11	2	46	63	56	44	40	37	38	28	11
12	0	0	10	50	72	75	53	50	39	16
13	0	0	61	83	52	45	36	53	27	8
14	18	97	84	60	34	27	24	14	7	0
16	0	0	16	80	111	60	48	32	16	2

Table A3: Description of Variables

Variable	Description
lnkwh	log of annual average consumption in kilowatt-hours
price	annual average price, in 1995 dollars per kilowatt-hour
lnhhincome	log of household income
nhsldmem	number of residents
lntotsqft	log of total square footage
daysbelow40	number of days when daily mean temperature falls below 40°F
days40to50	number of days when daily mean temperature falls between 40°F and 50°F
days50to60	number of days when daily mean temperature falls between 50°F and 60°F
days60to70	number of days when daily mean temperature falls between 60°F and 70°F
days70to80	number of days when daily mean temperature falls between 70°F and 80°F
days80to90	number of days when daily mean temperature falls between 80°F and 90°F
daysabove90	number of days when daily mean temperature falls above 90°F
dh0to10	number of days when daily mean humidity falls between 0% and 10%
dh10to20	number of days when daily mean humidity falls between 10% and 20%
dh20to30	number of days when daily mean humidity falls between 20% and 30%
dh30to40	number of days when daily mean humidity falls between 30% and 40%
dh40to50	number of days when daily mean humidity falls between 40% and 50%
dh50to60	number of days when daily mean humidity falls between 50% and 60%
dh60to70	number of days when daily mean humidity falls between 60% and 70%
dh70to80	number of days when daily mean humidity falls between 70% and 80%
dh80to90	number of days when daily mean humidity falls between 80% and 90%
dh90to100	number of days when daily mean humidity falls between 90% and 100%
spaceheating	1 if household owns an electric space heating system
centralac	1 if household owns a central air-conditioner
roomac	1 if household owns a room air-conditioner
waterheating	1 if household owns an electric water heating system
secondfridge	1 if household owns a second refrigerator
separatefreezer	1 if household owns a separate freezer
washer	1 if household owns a washer
elecdryer	1 if household owns an electric dryer
dishwasher	1 if household owns a dishwasher
hottub	1 if household owns a hot tub
elecoven	1 if household owns an electric oven
elecstove	1 if household owns an electric stove
microwave	1 if household owns a microwave
tvcolor	number of television sets owned by household
personalcomputer	1 if household owns a personal computer

Table A4: T_m and H_n Correlation Coefficients

No.	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.	daysbelow40	1										
2.	days40to50	0.7691	1									
3.	days50to60	-0.1238	0.0905	1								
4.	days60to70	-0.4423	-0.6672	-0.1191	1							
5.	days70to80	-0.083	-0.1588	-0.7396	-0.2628	1						
6.	days80to90	0.0602	0.043	-0.3992	-0.5859	0.5538	1					
7.	daysabove90	0.1304	0.1839	-0.1976	-0.451	0.1586	0.7068	1				
8.	dh0to10	-0.0191	-0.1106	-0.3517	-0.2314	0.406	0.5546	0.8202	1			
9.	dh10to20	0.0553	-0.1582	-0.4307	-0.2761	0.4941	0.7118	0.7748	0.9032	1		
10.	dh20to30	0.1261	-0.0176	-0.4748	-0.5201	0.6338	0.93	0.6894	0.6503	0.8013	1	
11.	dh30to40	0.3911	0.4109	-0.4449	-0.7584	0.6649	0.7693	0.3828	0.2843	0.389	0.7446	1
12.	dh40to50	0.5595	0.7074	-0.3308	-0.6028	0.4269	0.2	-0.0262	-0.0497	-0.0701	0.1153	0.685
13.	dh50to60	-0.2108	-0.0786	-0.2541	0.1734	0.2776	-0.1741	-0.3778	-0.0444	-0.1222	-0.2326	-0.0595
14.	dh60to70	-0.3116	-0.4174	0.2604	0.8349	-0.5937	-0.7317	-0.4443	-0.3621	-0.4742	-0.7108	-0.9141
15.	dh70to80	-0.2007	-0.2256	0.6739	0.4214	-0.7531	-0.5722	-0.3148	-0.4803	-0.5052	-0.5648	-0.6586
16.	dh80to90	-0.0164	0.3448	0.6823	-0.2727	-0.4379	-0.3297	-0.2241	-0.4886	-0.4878	-0.3898	-0.1448
17.	dh90to100	0.077	0.5103	-0.0484	-0.5031	0.2888	0.0742	-0.0521	-0.2418	-0.1889	0.0065	0.3796

	12.	13.	14.	15.	16.	17.
12.	1					
13.	0.3572	1				
14.	-0.593	0.0961	1			
15.	-0.652	-0.5513	0.5508	1		
16.	-0.0332	-0.3773	-0.0979	0.5906	1	
17.	0.5213	-0.0074	-0.4895	-0.1942	0.05868	1

Table A5: Appliance Ownership and Consumption

Appliance	Number	Percent	Consumption[a]
Electric Space Heating	108	23.13	1,131
Central Air Conditioning	198	42.40	1,270
Room Air Conditioning	74	15.85	619
Electric Water Heating	52	11.13	2,389
Second Refrigerator	96	20.56	1,231
Separate Freezer	81	17.34	582
Washer	352	75.37	223
Electric Dryer	158	33.83	795
Dishwasher	253	54.18	241
Hot Tub	27	5.78	1,288
Electric Oven	190	40.69	N/A
Electric Stove	167	35.76	258
Microwave	400	85.65	388
Televisions	462	98.93	482
Computers	347	74.30	N/A[b]

[a] Annual consumption estimates are based on 1997 household data from Reiss and White (2005). While these figures are not used in this study, they are used to identify the appliances that consume relatively high amounts of electricity.

Table A6: *Z* Correlation Coefficients

No.	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.	lnhhincome	1										
2.	nhsldmem	0.1703	1									
3.	lntotsqft	0.4851	0.1838	1								
4.	waterheating	-0.0279	-0.1328	-0.1786	1							
5.	centralac	0.1607	0.0871	0.2494	-0.0971	1						
6.	roomac	-0.0456	-0.0806	-0.1969	0.126	-0.3723	1					
7.	spaceheating	-0.1021	-0.0223	-0.1266	0.4678	0.0433	0.0958	1				
8.	washer	0.403	0.1858	0.5962	-0.2085	0.1786	-0.2147	-0.217	1			
9.	elecdryer	0.1689	0.0743	0.2108	0.0634	0.1192	-0.0872	0.0371	0.3982	1		
10.	hottub	0.142	0.0057	0.1669	-0.0002	0.1402	-0.0572	-0.0706	0.1416	0.0168	1	
11.	elecstove	0.1044	-0.0594	-0.024	0.375	0.0018	0.1045	0.3113	-0.1232	0.2219	0.0257	1
12.	elecoven	0.2034	-0.046	0.0761	0.3443	0.0392	0.0823	0.2901	-0.0426	0.2093	0.0937	0.8827
13.	microwave	0.2426	-0.0225	0.1206	0.0866	0.0174	-0.0231	-0.0363	0.1347	0.1506	0.0752	0.0759
14.	dishwasher	0.4031	-0.0579	0.3893	0.107	0.276	-0.0834	0.0356	0.2923	0.2217	0.1358	0.211
15.	secondfridge	0.2472	0.1591	0.3193	-0.1295	0.1426	-0.0756	-0.0402	0.2416	0.0842	0.1691	-0.0147
16.	separatefreezer	0.0839	0.0774	0.2729	-0.1082	0.1448	-0.1059	-0.0903	0.2356	0.1266	0.0561	0.0948
17.	tvcolor	0.2441	0.3706	0.3535	-0.0988	0.1207	-0.0599	-0.0388	0.3257	0.1252	0.1406	-0.0429
18.	computer	0.4239	0.1077	0.3638	-0.0099	0.1277	-0.0669	-0.0378	0.2667	0.1512	0.1247	0.04

	12.	13.	14.	15.	16.	17.	18.
12.	1						
13.	0.0903	1					
14.	0.263	0.1508	1				
15.	0.0533	0.1024	0.1275	1			
16.	0.1387	0.0907	0.1943	0.1728	1		
17.	0.0185	0.0922	0.1543	0.3094	0.1473	1	
18.	0.1179	0.2206	0.3148	0.1536	0.0752	0.2146	1

Table A7: Estimated Coefficients (Robust OLS with suppressed constant term)

	Effect on log of annual household electricity consumption:				
Explanatory Variable	(1)	(2)	(3)	(4)	(5)
lnhhincome	0.134***	0.120***	0.0790*	0.0790*	0.0237
	(0.0348)	(0.0343)	(0.0307)	(0.0310)	(0.0302)
nhsldmem	0.0930***	0.0940***	0.0930***	0.0934***	0.0813***
	(0.0148)	(0.0151)	(0.0140)	(0.0132)	(0.0120)
lntotsqft	0.332***	0.331***	0.308***	0.269***	0.206***
	(0.0405)	(0.0393)	(0.0385)	(0.0375)	(0.0388)
daysbelow50	0.0149***	0.0143***	0.0146***	0.0152***	0.0171***
	(0.00133)	(0.00128)	(0.00118)	(0.00114)	(0.00122)
days50to60	0.0126***	0.0130***	0.0143***	0.0148***	0.0165***
	(0.00108)	(0.00106)	(0.00103)	(0.00103)	(0.00102)
days60to70	0.0111***	0.0112***	0.0126***	0.0133***	0.0149***
	(0.00104)	(0.00105)	(0.00102)	(0.000996)	(0.00104)
days70to80	0.0146***	0.0134***	0.0151***	0.0158***	0.0173***
	(0.00132)	(0.00128)	(0.00123)	(0.00121)	(0.00116)
daysabove80	0.0125***	0.0129***	0.0145***	0.0151***	0.0170***
	(0.00158)	(0.00159)	(0.00148)	(0.00143)	(0.00140)
spaceheating		0.201***	0.0291	0.0211	0.0311
		(0.0547)	(0.0551)	(0.0533)	(0.0472)
centralac		0.219***	0.222***	0.199***	0.180***
		(0.0579)	(0.0559)	(0.0536)	(0.0498)
roomac		0.121	0.117	0.106	0.0998
		(0.0635)	(0.0598)	(0.0597)	(0.0571)
waterheating			0.458***	0.424***	0.374***
			(0.0773)	(0.0766)	(0.0712)
secondfridge			0.268***	0.239***	0.182***
			(0.0561)	(0.0550)	(0.0541)

elecdryer			0.191***	0.158***	0.117**
			(0.0447)	(0.0432)	(0.0414)
separatefreezer				0.285***	0.254***
				(0.0503)	(0.0487)
elecoven				0.109*	0.102*
				(0.0433)	(0.0407)
dishwasher					0.0965*
					(0.0441)
microwave					0.194***
					(0.0555)
tvcolor					0.0823***
					(0.0147)
personalcomputer					0.111*
					(0.0476)
N	467	467	467	467	467

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table A8: Estimated Marginal Effects

	Effect on log of annual household electricity consumption conditional on:			
Explanatory Variable	1687 HDD	2687 HDD	1044 CDD	2044 CDD
spaceheating	.1928***	.2891**		
	.0543	.1016		
centralac			.1604**	.0226
			.0559	.115
roomac			.1117	-.1015
			.0699	.1413

Standard Errors in Parentheses
* p<0.05, ** p<0.01, *** p<0.001