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CLIMATE ADAPTIVE RESPONSE ESTIMATION: SHORT AND LONG RUN IMPACTS OF CLIMATE CHANGE ON RESIDENTIAL ELECTRICITY AND NATURAL GAS CONSUMPTION USING BIG DATA

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ABSTRACT

This paper proposes a simple two-step estimation method (Climate Adaptive Response Estimation - CARE) to estimate sectoral climate damage functions, which account for long- run adaptation. The paper applies this method in the context of residential electricity and natural gas demand for the world's sixth largest economy - California. The advantage of the proposed method is that it only requires detailed information on intensive margin behavior, yet does not require explicit knowledge of the extensive margin response (e.g., technology adoption). Using almost two billion energy bills, we estimate spatially highly disaggregated intensive margin temperature response functions using daily variation in weather. In a second step, we explain variation in the slopes of the dose response functions across space as a function of summer climate. Using 18 state-of-the-art climate models, we simulate future demand by letting households vary consumption along the intensive and extensive margins. We show that failing to account for extensive margin adjustment in electricity demand leads to a significant underestimate of the future impacts on electricity consumption. We further show that reductions in natural gas demand more than offset any climate-driven increases in electricity consumption in this context.

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1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) projects that the average global surface temperature will rise by between 1 and 3.7°C (1.8 - 6.7°F) by the end of the century. This shift in the mean of the global surface temperature distribution will be accompanied by significant increases in the frequency and intensity of extreme heat events (IPCC AR5, 2013). Humans respond to hot outdoor ambient temperatures by cooling the indoor environment at home and/or at work. If the frequency and intensity of hot days increases due to climate change, one would expect this to cause increased cooling and decreased heating demand. One of the three Integrated Assessment Models used in the calculation of the federal Social Cost of Carbon concludes that increased space cooling is *the* major driver of Global Climate Damages (Rose et al, 2014). This finding relies on an assumed temperature responsiveness of a simple space cooling function in the FUND Integrated Assessment model, which has little to no empirical basis (Anthoff and Tol, 2014).

Air conditioning is the main option for adaptation to hotter temperatures and it has been shown to be an effective strategy to mitigate the negative health impacts of hot days. In the United States, the mortality effect of a very hot day decreased by roughly 80% between 1900-1959 and 1960-2004 due to the increased penetration of air conditioners (Barreca et al., 2016). This observed trajectory of air conditioner installation has been driven by growth in incomes and falling prices of both AC units and the electricity required to operate them (Biddle, 2008). A changing climate represents a new driver of air conditioner adoption. If San Francisco with its pleasant coastal climate gets Fresno's hot climate by end of century, even cool San Franciscans will install window units in existing apartments and new construction will be built with central air conditioning. The cost of this adaptation mechanism comes in the form of both installation and operating costs, while the benefits accrue in the form of better health and increased comfort.

There is a dearth of causal estimates of empirically calibrated damage functions to quantify the short- *and* long-run relationship of higher temperatures and electricity consumption from space cooling (Auffhammer and Mansur, 2014). This paper attempts to partially fill this gap. It also makes a significant step forward in the estimation of credible *long-run* climate impacts, which has been the main challenge in the literature estimating climate change impacts across sectors (e.g., agriculture, health, labor productivity, crime) and spatial scales (Dell et al., 2014, Carleton and Hsiang, 2016). It does so by using a combination of short-run weather variation in a panel context and long-run climate variation in a cross-sectional context. The proposed method is applicable beyond climate impact dose response functions. It could be applied in any setting where the short-run and long-run response of agents differs (e.g., responses to exogenous changes in air and water pollution, pricing, and income).

In both the short and long run, the main adaptation response to the higher incidence of extreme heat days will be the more frequent operation of existing air conditioning equipment, which we will refer to as the *intensive margin adjustment* for the remainder of the paper. The long-run response will be the climate change driven installation of air conditioners in areas that currently see little penetration of this equipment. We will refer to this dimension of adaptation as the *extensive margin adjustment*. While there are a number of papers attempting to quantify the intensive margin adjustment for a number of sectors (e.g., agriculture, mortality, crime), it is extremely difficult to carry out a full empirical characterization of the additional extensive margin response at fine enough levels of aggregation to be useful to planners. In the case of electricity, this is due to the lack of data on installed air conditioners over time and space in the United States.[1]

The main innovation of this paper is that we lay out a simple method to estimate both the intensive and extensive margin impacts of climate change on consumption when one *does not have data on installed capital* (e.g., air conditioners). In a first step, using household-level billing data, we estimate the causal temperature response function of household electricity consumption at a fine level of spatial aggregation - the five-digit ZIP code level. These response functions allow us to examine how the intensive margin adjustment ("increased usage of existing equipment") varies across 1,165 ZIP codes in California in our sample.

A warmer climate has benefits as well. California's residential consumers consume the majority of their natural gas during the winter time to heat their homes. Milder winters will require

[1]Davis and Gertler (2015) is the only example for a large country (Mexico) which utilizes data both on appliance holdings and electricity consumption for a large share of the population.

less heating and hence decrease natural gas consumption. We use our household level billing data for natural gas to estimate a weather response of natural gas consumption for each ZIP code. Estimation at this fine level of aggregation is made possible by the fact that we observe almost 2 billion electricity and natural gas bills, which represent 79 percent of California's households over a decade.

In a second step, we use regression to explain cross-sectional variation in these "first-step" estimated slopes of each ZIP code's temperature response function as a function of long-run average weather ("climate") and other confounders varying across ZIP codes. The estimated marginal effect of climate on the slope of the short-run response function allows us to capture extensive margin adjustments to long-run changes in climate. We then use downscaled climate projections from 18 of the IPCC's most recent climate models to simulate future household electricity consumption at the ZIP code level under climate change, taking into account both intensive ("first-step") and extensive margin ("second-step") adjustments. We then compare the projected increases in electricity consumption to climate-driven reductions in natural gas consumption, which we estimate and project separately. We show that, in the case of California's residential sector, the natural gas savings are greater than the increases in electricity consumption in BTU terms.

The main advantage of the approach proposed here is that it does not require data on where air conditioners are installed. While there are a few surveys that record such data in the US (e.g., RASS, RECS), the spatial coverage is limited and the exact location of the household is masked for privacy reasons. Our approach circumvents this data limitation, which would be very costly to overcome, by relying on observed electricity consumption from billing data and weather only. The approach outlined here can be (and is starting to be) adopted for other sectors as well (e.g., health, agriculture).

2. Literature Review

The literature quantifying the economic impacts of climate change has experienced explosive growth over the past decade. Review articles by Carleton and Hsiang (2016), Hsiang (2016), and Dell et al.

(2014) provide up-to-date and comprehensive surveys of both methods and applications. The key challenge that still has not been adequately overcome is to estimate externally valid dose response functions between economic outcomes of interest (e.g., energy consumption, crop yields, mortality, water consumption, labor productivity, cognitive ability) and a long (e.g., 30 year) average of weather, which is commonly referred to as climate. This estimated long-run response is supposed to capture both adaptive behavior at the intensive margin (e.g., increased operation of existing air conditioners) and the extensive margin (e.g., installation of additional air conditioners). The coefficients parameterizing said dose response function should be estimated in a way that allows a causal interpretation. This is anything but straightforward. Below I provide a brief summary of the methodological approaches in existing papers, while listing examples with an energy focus.

The earliest literature relied on large-scale bottom-up structural simulation models to estimate future electricity demand under varying climate scenarios. The advantage of these models is that they can simulate the effects of climate change given a wide variety of technological and policy responses. The drawback is that they contain a large number of assumed response coefficients and make ad hoc assumptions about the evolution of the capital stock; there is little empirical guidance for either approach. The early papers in this literature suggest that climate change will significantly increase energy consumption (Cline, 1992; Linder et al., 1987, Baxter and Calandri, 1992; Rosenthal et al., 1995).

The recent literature has focused on providing empirical estimates of climate response functions for a large number of sectors. There are four empirical approaches using distinctly different sources of variation to parameterize climate response functions: (1) Time Series Regression (2) Ricardian Approach (3) Panel Estimation (4) Long Differences. Each of these approaches has distinct advantages and disadvantages.

A simple and commonly practiced approach employed to quantify the impact of climate on electricity consumption uses high frequency (e.g., daily or hourly) time series of electricity load and regresses these on population-weighted functions of weather. Franco and Sanstad (2008) use hourly electricity load for the entire California grid operator over the course of the year 2004 and regress them on average daily population-weighted temperature. They identify a highly nonlinear response of load to temperature. They show projected increases in electricity consumption and peak load of 0.9 to 20.3 percent and 1.0 to 19.3 percent, respectively. Crowley and Joutz (2003) use a similar approach for the Pennsylvania, [New] Jersey, Maryland Power Pool Interconnection. Auffhammer et al. (2017) estimate the response of peak load and average load to daily weather for 166 load-balancing authorities, covering the vast majority of the US electricity load. They show modest increases in consumption by the end of this century, yet significant increases in the intensity of annual peak load (15-21%) and a twelve- to fifteen-fold increase in the frequency of peak events by the end of century. The drawback of this approach is that it relies on short-term fluctuations in weather and hence does not estimate a long-run climate response but rather a short-run weather response. It simply cannot account for adaptation responses to climate change such as increased use and installation of air conditioners or increased incidence of demand-side management and energy efficiency programs.

The second strand of the literature is based upon the seminal work by Mendelsohn et al. (1994), who estimated the impact of climate change on agricultural yields by regressing yields or net profits on climate. This cross-sectional approach has the advantage that it estimates a true climate response. The method has been widely criticized, as any non-experimental cross-sectional regression is bound to suffer from omitted variables bias (e.g., Deschenes and Greenstone, 2007). Any unobserved factor correlated with climate and the outcome of interest will bias the coefficients on the climate variable. This approach has not been widely applied in the energy literature, yet Mansur et al. (2008) is one example of a cross-sectional approach, which endogenizes fuel choice, something that is usually assumed to be exogenous and provides one avenue of adaptation.

The third strand of the literature relies on panel data of energy consumption at the household, county, state or country level to estimate a dose response function. Deschenes and Greenstone (2011) were the first to use the panel approach to quantify the impacts of climate change on residential electricity demand. They study variation in residential energy consumption at the state level, using flexible functional forms of daily average temperatures. Their identifying assumption, which is credible, is that weather fluctuations are random conditional on a set of spatial and time fixed effects. As in the time series papers cited above, the authors find a U-shaped response function. They find that the impact of climate change on annual residential energy consumption for the Pacific Census Region (California, Oregon, and Washington) by 2099 is approximately nine percent - yet not statistically different from zero. Aroonruengsawat and Auffhammer (2012) use a panel of household-level electricity billing data to examine the impact of climate change on residential electricity consumption. They use within-household variation in temperature, which is made possible through variation in start dates and lengths of household billing periods. They can control for household fixed effects, month fixed effects, and year fixed effects. Their projected impacts are consistent with the findings by Deschenes and Greenstone (2011), ranging between 1% and 6%. The panel approach has the advantage that one can control for often extensive sets of fixed effects, which deal with the omitted variables issues from which the Ricardian model suffers. This comes at a cost. The estimated response is again a short-run weather response, not a long-run climate response, which fails to incorporate extensive margin adaptation. Further, the inclusion of large suites of fixed effects may amplify measurement error issues (Fisher et al., 2012).

A fourth approach, which due to data limitations has not yet been applied in the energy sector, is long difference estimation. Burke and Emerick (2016) take long differences (e.g., 10 or 20 years) of economic outcomes of interest (e.g., agricultural yields) and regress these on long differences of weather. This approach differences out unit-level unobservable cross-sectional differences. The advantage of this method is that it estimates a long-run climate response and is robust to the omitted variables issues raised in the Ricardian context. The data requirements are significant, as this approach requires a panel long enough to generate a difference in weather, which is long enough to be interpreted as climate.

In summary, the time series and panel approaches only capture intensive margin changes and are sensitive to time-varying confounders correlated with temperature. The Ricardian approach is sensitive to the confounding impact of unobservable factors correlated with the climate variables. The panel approach only estimates a short-run response. The long difference estimation approach is the most robust to the possible effect of confounding factors, yet the time series data requirements are significant. Finally, none of these approaches can separate the intensive and extensive margin effects empirically.

Davis and Gertler (2015) provide the only paper which combines a formal estimation of the extensive margin adoption decision with a more traditional panel data based intensive margin response function. They take advantage of a large database on household air conditioner ownership and electricity consumption for a large, rapidly developing country - Mexico. They characterize the temperature response on the intensive margin using electricity bills and observed temperature. To characterize their extensive margin impacts, they rely on a large cross-sectional survey of appliance ownership across households. They regress air conditioner ownership on contemporaneous Cooling Degree Days, not climate, which makes this a short-run extensive margin response. They link the two models to simulate impacts of growing income and warming weather on intensive and extensive margin consumption of electricity. They find significant impacts: For the worst case climate scenario and continued income growth, they estimate a 15.4 % increase in electricity consumption by end of century. Once they account for the extensive margin adjustment, the impacts grow to an 83.1% increase in consumption. The problem is that data on technology penetration and the outcome of interest (e.g., air conditioners and electricity consumption) do not exist for most developing or developed countries, which requires a different approach when one observes usage data only.

In this paper, we propose a simple method which endogenizes the shape of the temperature response function in the long run without ever observing the level and type of technology adopted by a household. This approach, CARE, uses fixed effects estimation to obtain causal estimates of the short-run (intensive margin) temperature response for a large number of relatively fine spatial aggregates (ZIP codes) with differing degrees of AC penetration. In a second regression, we estimate the sensitivity of the estimated slopes in the short-run temperature response across space as a function of long-run climate, which endogenizes the extensive margin response. The simulation then uses Global Climate Model (GCM) output to simulate the intensive margin impacts by moving along a given response function, as well as the extensive margin impacts by shifting the response function itself as climate changes. There is a literature which has shifted response functions in the long run (e.g., Bigano et al., 2006; Auffhammer and Aroonruengsawat, 2012b; Barreca et al., 2016; Dell, Jones, and Olken, 2012, 2014; Hsiang and Narita, 2012; Butler et al. 2013; Heutel et al. 2017). We build on the general insight of a climate-dependent response function and formalize an empirical approach to do so when one observes a large number of micro-level observations on outcomes. The application here is the perfect setting as we observe a large number of electricity bills across a significant amount of time (allowing for the inclusion of household fixed effects) and space (allowing for the cross-sectional variation in climate required for the second-step estimation). This approach allows any utility to estimate the business as usual impacts of climate change on consumption without having to engage in the costly collection of appliance stock and efficiency data.

3. Data

3.1 Residential Billing Data

As part of a confidential data sharing agreement with California's investor owned utilities (IOUs), we have obtained an extensive history of bills for all households serviced by the four IOUs in the state: Pacific Gas and Electric (PG&E), Southern California Edison (SCE), Southern California Gas Company (SoCalGas), and San Diego Gas and Electric (SDG&E). SDG&E and PG&E are gas and electric utilities, while SoCalGas only provides gas and SCE only provides electricity. Table (1) provides an overview of the temporal data coverage for the four utilities by energy source (electricity and natural gas).

The dataset contains the complete bill-level consumption and expenditure information for the population of single metered residential customers during the years for which we have data, as outlined in Table (1). Specifically, we observe an ID number for the physical location (e.g., residence), a service account number (e.g., customer), bill start date, bill end date, total electricity or natural gas consumption (in kilowatt-hours, kWh, or therms for gas), and the total amount of the bill (in $) for each billing cycle, as well as the five-digit ZIP code of the premise metered. Only customers who were individually metered are included in the dataset, hence we cannot say anything about multi-unit buildings with a shared meter. We also cannot reliably identify households who have moved and therefore refrain from using this as a source of econometric identification. For the purpose of this paper, a customer is defined as a unique combination of premise and service account number. We also can identify whether a customer receives a low-income subsidy on electricity pricing through a state program. Further, we can determine which homes are all-electric, meaning that they heat and cool using electricity and have their own electric water heaters. This is not mostly by the homeowners' choice, but is simply due to the fact that not all of California has natural gas infrastructure to serve residences.

It is important to note that each billing cycle does not follow the calendar month, as the beginning date and the length of the billing cycle vary across households, with the vast majority of households being billed on a 25-35 day cycle. We remove bills with average daily consumption less than 2 kWh from our sample, because we are concerned that these outliers are not regular residential homes, but rather vacant vacation homes. We also remove homes on solar tariffs from our data, since we do not observe total consumption from these homes, but only what they take from the grid, rendering these data useless for the purpose of this exercise. Hereafter, this dataset is referred to as "billing data."

For electricity, we observe a total of 964 million bills; for gas we have 928 million bills. We observe 658 million electric bills for "normal" households, which are neither on the subsidized tariff nor all-electric homes. In addition, we have 92 million bills for all-electric homes in the PG&E and SCE territories. The remaining bills are for households on the subsidized tariff in all four utility territories. We will treat these three classes of households separately in terms of estimation and simulation. It is important to note that we cannot match the electricity and gas data beyond the ZIP code level because we do not observe a customer's address and the account numbers were anonymized by the utility.

There is significant variation in bill-level consumption across and within households. Because across-household variation may be driven by unobservable characteristics at the household level (e.g., income, physical building characteristics, and installed capital), we will control for unobservable confounders at the household level using fixed effects, and we will use bill-to-bill within-household variation at the household level as our source of identifying variation. To proceed with estimation at the ZIP code level, we identify all ZIP codes across the four utilities' territories for which we have at least 1,000 bills. Our data cover 1,165 ZIP codes for which we observe such billing data.[2] The ZIP codes for which we have data represent approximately 80 percent of California's population.

3.2 Weather Data

The daily weather observations to be matched with household consumption data have been provided by the PRISM (2004) project at Oregon State University. This dataset contains daily gridded maximum and minimum temperature for the continental United States at a grid cell resolution of roughly 2.5 miles. We observe these daily data for California from 1980-2015. In order to match the weather grids to ZIP codes, we have obtained a GIS layer of ZIP codes from ESRI, which is based on the US Postal Service delivery routes for 2013. For small ZIP codes not identified by the shape file, we have purchased the location of these ZIP codes from a private vendor (zip-codes.com). We matched the PRISM grids to the ZIP code shapes from the census and averaged the daily temperature data across the multiple grids within each ZIP code for each day. For ZIP codes identified as a point, we simply use the daily weather observation in the grid at that point. This leaves us with a complete daily record of minimum and maximum temperature as well as precipitation at the ZIP code level from 1980 to 2015.

3.3 Other Data

Unfortunately, we only observe bill details about each household and are missing any sociodemographic observables. We do, however, observe the five-digit ZIP code in which each household is located. We purchased sociodemographics at the ZIP code level from a firm aggregating this

[2] See Figure A1 for a map of the spatial coverage of the electricity and gas data.

information from census estimates (zip-codes.com). We observe these data only for a single year (2016).

There are 1,640 five-digit ZIP codes in California that have non-zero population. Our sample of ZIP codes with more than 1,000 bills contains households for 1,165 of these. We do not have sufficient data for households in the remaining 475 ZIP codes. These remaining ZIP codes either are not served by the three utilities, or we do not have a sufficient number of bills for them. Table 2 shows summary statistics for both the ZIP codes in our sample and the ZIP codes for which we do not have billing data. The ZIP codes in our sample represent 80 percent of California's population. The ZIP codes in our sample are more populated, younger, richer, have more expensive homes, have slightly more persons per household, and have a lower proportion of Caucasians and a higher proportion of Hispanics and Asians. There is a small but statistically significant difference in summer and winter temperature, with the in-sample ZIP codes being slightly warmer. This is not surprising since most of the ZIP codes we are missing are in the northern part of the state and the mountainous Sierras. The big difference in elevation confirms this. Taking these differences into consideration is important when judging the external validity of our estimation and simulation results.

We will not make explicit use of this information in our first-step regression, but will control for the observable sources of variation in our cross-sectional second step, which by design does not allow for a fixed effects strategy. The variables we will use in the second stage are income, population density, and summer climate.

4. Econometric Estimation Strategy

4.1 Intensive Margin: The Usage Response to Temperature

Figure 1 visualizes our econometric estimation strategy. The figure displays stylized current intensive margin dose response functions between weather and electricity consumption for a moderate, a warm and a hot ZIP code. The horizontal axis displays the proportion of days annual temperature falls into discrete temperature bins. The moderate ZIP codes have more days in the 15-24 degree bin and fewer days in the 105-114 degree bin. Using billing data for a group of households in the moderate ZIP codes, one can econometrically recover an estimate of its response function by regressing billed consumption on the temperature controls, other observed confounders, and a suite of fixed effects. For each bin, one estimates a ZIP code-specific slope of the temperature response curve. One can do this for each ZIP code and recover a set of slope coefficients across the observed temperature spectrum for each ZIP code. One would expect that the slope of the temperature response in the warm ZIP codes for the bin 95-104 degrees would be steeper than the slope of the cold ZIP codes, yet flatter than the slope of the hot ZIP codes, as AC penetration is thought to be increasing in temperature. The second estimation step takes these β estimates for each bin and ZIP code in the upper portion of the temperature spectrum and regresses their cross section on long-run historical averages of observed temperature (climate). The estimated second-step coefficients can then be used to change the slope of each ZIP code's response curve as future climate changes.

Equation (1) below shows our main estimating equation, which is a simple log-linear equation estimated separately for each of the 1,165 ZIP codes indexed by j. This estimating equation has been commonly employed in climate change impacts estimation (e.g., Deschenes and Greenstone 2011, Davis and Gertler, 2015).

$$\log(q_{it}) = \sum_{p=1}^{14} \beta_{jp} D_{pit} + \gamma Z_{it} + \alpha_i + \phi_m + \psi_y + \varepsilon_{it} \tag{1}$$

where $\log(q_{it})$ is the natural logarithm of household i's daily average electricity (natural gas) consumed in kilowatt-hours (therms) during billing period t. D_{pit} are our binned measures of temperature, which we discuss in detail below. Z_{it} are observed confounders at the household level, α_i are time-invariant household fixed effects, ϕ_m are month of year fixed effects, and ψ_y are year fixed effects. ε_{it} is a stochastic error term. Because bills do not overlap perfectly with calendar months and years, ϕ_m and ψ_y are assigned as shares to individual bills according to the share of days in a bill for each month and year.

For estimation purposes, our unit of observation i is a unique combination of premise and service account number, which is associated with a household and structure. We thereby avoided the issue of having individuals moving to different structures with more or less efficient electricity consuming capital, or residents with different preferences over electricity consumption moving in and out of a given structure.

California's housing stock varies greatly in its energy efficiency and installed energy-consuming capital. Further, California's population is not randomly distributed across ZIP codes. We suspect that there may be differences in preferences for cooling, installed capital, quality of construction, and the associated demographics and capital across ZIP codes. The key novelty in this paper is that we causally estimate Equation (1) *separately* for each of the 1,165 ZIP codes in our data. The motivation for doing this is that we would expect the relationship between consumption and temperature to vary across these ZIP codes according to the penetration of air conditioners and the resident population's propensity to use these. One could of course estimate a pooled regression with interaction terms to limit the number of estimated coefficients. This is simply a weighted average of our disaggregated results. Because one of the main points of this paper is to account for the heterogeneity of impacts, we impose as little structure as possible, by estimating Equation (1) at the ZIP code level instead of pooling.

The main variables of interest in this paper are those measuring temperature. 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 - electricity consumption - in weather (e.g., Schlenker and Roberts 2006, 2009; Deschenes and Greenstone 2011, Davis and Gertler, 2015). We achieve this by sorting each day's mean temperature experienced by household i into one of 14 temperature bins. For the purposes of this study, we use the same set of bins for each ZIP code in the state. In order to define a set of temperature bins, we split the state's temperature distribution into a set of percentiles and use those to sort days into the bins. As a result, not all ZIP codes will have observations in each bin. The northern ZIP codes, for example, do not experience days in the hotter bins, while the southwestern parts of California have few or no days in the coldest bins.

We split the temperature distribution into deciles, and break down the upper and bottom deciles further to include buckets for the first, fifth, ninety-fifth, and ninety-ninth percentiles, to account for extremely cold/hot days. We therefore have a set of 14 buckets which we use for each household, independent of the climate zone in which the household is located. The cutoffs for the bins are 24, 35, 40, 46, 51, 55, 59, 63, 67, 72, 78, 83 and 92 degrees Fahrenheit mean daily temperature. For each household and bill, we count the number of days the mean daily temperature falls into each bin and record this as D_{pit}. The main coefficients of interest are the fourteen β_{jp} coefficients, which measure the impact of one more day with a mean temperature falling into bin p on the log of household daily electricity consumption in ZIP code j. For small values, β_{jp}'s interpretation is approximately the percent increase in daily average household electricity/natural gas consumption during a billing period, associated with experiencing one additional day in that temperature bin.

Panel (a) in Figure (2) displays the daily average temperature for the months of June, July and August, averaged over the years 1981-2015. This is a reasonable measure of summer climate (a 25 year average instead of the usual 30 year average). Figure (2) shows that the Central Valley non-coastal areas of Southern California are very warm during the summer months. We would expect these areas to have a significantly more temperature-sensitive electricity consumption response than the cooler coastal areas of Northern California and higher altitude settings in the Sierras. Panel (b) displays the winter months (December, January, February) average daily temperature. The spatial distribution is similar to that of the summer climate. This figure simply stresses that, due to its size and geography, California possesses significant heterogeneity in climate, which is necessary for our two-step approach to work.

Z_{it} is a vector of observable confounding variables, which vary across billing periods and households. There are two major confounders that we observe at the household level. The first is the average electricity price for each household for a given billing period. California utilities price residential electricity on a block rate structure. The average price experienced by each household in a given period is therefore not exogenous, because marginal price depends on consumption (q_{it}).

Identifying the price elasticity of demand in this setting is problematic (e.g., Hanemann 1984; Reiss and White 2005; Ito, 2014). We are not interested in estimating it, because it is simply impossible to write a better paper than Ito (2014), who uses the same electricity data we employ here.

However, the block rate pricing structure introduces an issue that has consequences for the later simulation. Higher temperatures in a given month will lead to higher electricity consumption. Block rate prices will force a share of households onto a higher pricing tier and raise average price, as is discussed in detail in Ito (2014). By design, this induces a positive conditional correlation between price and consumption. If we were to include price in Equation (1) as part of Z_{it}, we later would have to explicitly model the impact of higher temperatures on average price in a simulation framework, which would require us to make assumptions about a future pricing regime. An alternate approach would be to omit average price from Equation (1) and let the temperature coefficient capture both temperature channels. We opt for the latter strategy, because predicting climate change-driven changes in the block rate pricing schedule to the end of the century is not something any economist should do. In the absence of major technological change, which we discuss in the conclusion, one would expect retail prices to rise, pushing our modest impact estimates further toward zero.

The second major time-varying confounder is precipitation in the form of rainfall. We control for rainfall using a second-order polynomial in all regressions. A third confounder, which we do not observe, is humidity. Humidity is not a major issue in California, as most parts of the state are semi-arid. Our temperature coefficients hence capture the effects of humidity. Our simulations would become invalid if the correlation patterns between humidity and temperature in the future were projected to become different from the historical correlations, for which we could find no evidence in the literature.

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 $E[\varepsilon_{it} D_{pit} | D_{-pit}, Z_{it}, \alpha_i, \phi_m, \psi_y] = 0$. Because we control for household fixed effects, identification comes from within-household variation in daily temperature after controlling for confounders common to all households and for rainfall. We estimate Equation

(1) separately for electricity and natural gas for each of the 1,165 ZIP codes in our sample, using a least-squares fitting criterion and a household-level clustered variance covariance matrix. This approach is the first estimation step in our overall methodology and serves as the basis for our estimates of intensive margin adjustment due to climate change. We must make the assumption that the within-household response to slowly changing climate over this relatively short sample period is small, in order to be able to interpret our coefficients as the intensive margin adjustment to the changes in usage of existing equipment in response to changing temperature; we think this is reasonable.

4.2 Extensive Margin: The Long-Run Response to Temperature

In a warmer world, existing air conditioners will be run for more hours, which we call the intensive margin adjustment. The second margin of adaptation is the installation of additional air conditioners in existing homes and new construction. One can easily imagine that if San Francisco's future climate resembles that of current Fresno during the summer, the wealthy and no longer cool residents of San Francisco will install (additional) cooling equipment in their homes. To be clear, we are interested in the climate change-driven response, not an income- or price-driven response. We attempt to quantify the magnitude of this response. We estimate equations of the following form:

$$\beta_{jp} = \delta_1 + \delta_2 C_{pj} + \boldsymbol{\delta_3 Z_j} + \eta_{jp} \tag{2}$$

where β_{jp} is a measure of ZIP code j's temperature responsiveness in bin $p \; \epsilon \; [10; 14]$ as estimated in Equation (1). We would expect there to be a response only in the upper portion of the temperature response curve, where cooling occurs, which is why we limit the estimation of Equation (2) to bins 10-14. A common threshold for the uptick in the temperature response curve, which we will show is valid for our data, is 65 degrees Fahrenheit, which is also a commonly used base temperature for calculating cooling degree days (CDD).

The variable C_{pj} in Equation (2) is the share of days that ZIP code j experienced in temperature bin p during the sample years 1981-2000 from our ZIP code-level weather data produced from the PRISM data. C_{pj} is bounded by 0 and 1 and adds to one when summed across all temperature bins from 1-14. The variable(s) Z_j are any confounders that may affect the temperature response of the population in ZIP code j. One confounder we consider here is income, as higher-income households can more easily afford the capital expenditure of an air conditioner and its associated operating expense (Rapson 2011). We also include population density to proxy for the level of urbanization. While we will not use the estimated coefficients on income and population density in our simulation later, controlling for them ensures that we do not confound the temperature extensive margin adjustment by income. If individuals sort into climate according to income, failing to control for these factors would bias our estimated climate response. One could, of course, use the second-step estimates on income and population to simulate overall demand in a more populated, richer world.

In terms of estimation, we could estimate five separate equations of type (2) or estimate a pooled regression allowing for flexibility in the δ_2 coefficient for higher bins. We chose to estimate a pooled model, which restricts the coefficients on income and population density to be identical for all bins, yet controls for bin dummies. This provided more stable estimation results than estimating separate equations. The bin dummies control for the fact that each bin contains the response coefficients for a different collection of ZIP codes. This arises, as we mentioned above, because we do not have temperature coverage in all bins for all ZIP codes. Finally, we estimate Equation (2) via Ordinary Least Squares with heteroskedasticity robust standard errors, as the dependent variables are estimated coefficients and do not have constant variance. Running weighted least squares does not significantly change the results, yet the least squares estimates are more stable.

5. Estimation Results

5.1 Intensive Margin: The Usage Response to Temperature

As discussed in the previous section, we estimate Equation (1) for each of the 1,165 ZIP codes that have more than 1,000 bills. While we cannot feasibly present all of the estimated temperature response functions (which are comprised of up to 13 parameter estimates each), we can display the distribution of the temperature response curves in a fan plot, which is shown in Figure (3). The thick black line displays the median temperature response curve across the 1,165 ZIP codes. As the regression has average daily consumption on the left-hand side and the number of days out of a normalized 30 spent in each bin on the right-hand side, the coefficients indicate the percent change in average daily consumption from one additional day spent in a given bin relative to a day in the 65 degree bin. The curve has the expected U-shape with a steep positive slope above 65 degrees and a shallower negative slope at temperatures below 65 degrees. The trough of the U-shaped response curve is right near the omitted bin of 65 degrees. Figure 3 displays the significant heterogeneity in temperature response via the shaded fan areas. The palest grey fan indicates the bounds of the 5^{th} to 95^{th} percentile of the distribution. Each darker shade of grey increments the interval by 10%. What we see here is a significant number of ZIP codes with an extremely steep temperature response, as well as a significant number of ZIP codes with an almost flat temperature response. The bottom panel displays the temperature response when including average price in the regressions. As hypothesized, the response function flattens out significantly after controlling for price, which is consistent with the forced positive correlation between average price and consumption.[3]

Figure (4) displays the analogous results for the natural gas regressions, also excluding price from the regressions. Because space heating is the only major ambient temperature-sensitive use of natural gas in residences, we would expect a downward sloping line in temperature at low temperatures and a relatively flat response curve at higher temperatures. Figure (4) impressively

[3]Figure A2 produces analogous pictures for the subsidized households and Figure A3 for the all-electric households. The subsidized household distribution has a slightly shallower slope at both high and low temperatures. The all-electric distribution has slightly steeper slopes at higher and lower temperatures, which is to be expected because these houses tend to be older, with heating and cooling systems that use electricity, not natural gas.

displays exactly that. There is quite a bit of variation in slope across ZIP codes, yet the median response is exactly as expected and flattens out at almost exactly 65 degrees Fahrenheit.

5.2 Extensive Margin: The Long-Run Electricity Consumption Response to Temperature

As discussed in Section 4.2, we exploit the 1,165 estimated electricity temperature response curves and examine whether we can explain variation in temperature response at high temperatures through cross-sectional variation in "climate" as well as income and population density.

The left-hand side variable is our measure of temperature response of electricity consumption for each of the bins 10-14, which we estimated for each ZIP code j in the previous step, using Equation (1). On the right-hand side, we control for the percent of days spent in the respective bins during the years 1981-2000 (our predetermined proxy for summer climate), income, population density and bin dummies. These dummies are important because the bins contain very different sets of ZIP codes. Not all ZIP codes, for example, experience days in the hottest bin. The bin dummies hence control for unobservable difference across bins. We run a pooled regression, the results of which are shown in Table (3). Because the dependent variable is an estimated coefficient, we use White robust standard errors. Model (1) pools the climate response across all bins; it suggests a mildly positive impact of climate on the slope of the response function. Model (2) allows for a differential shift in the temperature response function for the three highest bins; as expected, the shift is significant and much larger than the pooled estimate. Models (3) and (4) run these models for the subsidized households and the all-electric households respectively. Both display a similar pattern.

We use the results from Models (4), (5) and (6) in Table (3) to simulate the impacts of climate change on the slope of each ZIP code's temperature response curve. In the next section, we will generate a large number of counterfactual climate futures from 18 General Circulation Models (the technical term for climate models) and two different scenarios of emissions. We will use these ZIP code-level climate futures to shift each ZIP code's temperature response curve for bins 10-14, using the estimates from Table (3). This simulated shift in the temperature response curve will allow us to quantify the extensive margin adaptation response.

6. Electricity and Natural Gas Consumption Simulations

In this section, we simulate the impacts of climate change on electricity and then natural gas consumption under two different emissions scenarios using 18 different climate models from the latest round of the IPCC assessments (AR5, CMIP5) in their downscaled form. For electricity, we conduct three different simulations. The first simulation holds population growth constant and only simulates electricity consumption per household using the first-stage estimates, which do not allow for changes in the extensive margin. In a second simulation, we incorporate the extensive margin adjustments from the previous section. In a final simulation, we allow for population growth. For each simulation, we can calculate the trajectory of aggregate electricity consumption from the residential sector until the year 2099, which is standard in the climate change literature. We provide simulated impacts for the periods 2020-2039, 2040-2059, 2060-2079 and 2080-2099.

In our simulations, we make one key assumption. For natural gas, we only use the intensive margin simulations, because one would not expect households to install more efficient or fewer heaters in response to climate change. We would expect existing equipment to be operated less frequently. But one would not install a more efficient and costly heater which is going to be used less due to climate change.

6.1 Temperature Simulations

The simulation for this section uses the climate response parameters estimated in Section 5.1. Using these estimates as the basis of our simulation has several strong implications. Using only the first stage parameters via Equation (1) implies that the climate responsiveness of consumption within climate zones remains constant throughout the century.

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's fifth assessment report (AR5) and applied in this study are based on the so-called "RCP4.5" and "RCP8.5" scenarios. The number after the RCP stands for the likely increase in forcing from the scenario by end of century relative to preindustrial values, in Watts per square meter. In terms more familiar to most economists, RCP4.5 is expected to result in warming of 1.8 °C, with a likely range of 1.1. to 2.6 °C. This is a very optimistic scenario, as attaining a goal of warming less than 2 degrees is unlikely. RCP 8.5 is the worst case scenario and is expected to result in warming of 3.7 °C, with a likely range of 2.6 to 4.8 °C.

We simulate consumption for each scenario using the 18 downscaled GCMs from the IPCC's CMIP5 database. The downscaled temperature scenarios were drawn from a statistical downscaling exercise based on the Coupled Model Intercomparison Project 5 (Taylor et al. 2012) utilizing a modification (Hegewisch and Abatzoglou, 2015) of the Multivariate Adaptive Constructed Analogs (Abatzoglou and Brown, 2012) method with the Livneh (Livneh et al., 2013) observational dataset as training data. These were provided to us by the MACA project at the University of Idaho. We matched the fine scale grids of the downscaled climate data to ZIP codes in the same fashion that we matched the PRISM weather grids. We calculated future climate by adding the predicted change in monthly temperature for each model, scenario and period to our baseline weather data, in order to avoid local biases, as the MACA project does not use the same weather data as its training data set.[4]

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:

$$\frac{q_{j,t+h}}{q_{j,t}} = \frac{exp(\sum_{p=1}^{14} b_{pj} D_{pj,t+h})}{exp(\sum_{p=1}^{14} b_{pj} D_{pj,t})} \tag{3}$$

To display the spatial variability in intensive margin impacts for the average household across

[4]A detailed description of the climate model output is available at http://maca.northwestknowledge.net/.

ZIP codes, we generate a map of average household-level impacts by ZIP code. Panel (a) in Figure (5) plots the predicted impact for the average household by end of century using the ensemble average prediction across all 18 GCMs for RCP8.5. What this graph shows is that the ZIP codes in the Central Valley and non-coastal Southern California are projected to experience the largest increases in household electricity consumption. This is due to the combination of the slope of the temperature response function and projected warming from the GCMs. These projections ignore potential extensive margin impacts, which we turn to next.[5]

For each ZIP code, climate model and scenario, we calculate the simulated shift of the temperature response curve using Model (2) in Table (3). As the temperature distribution shifts to the right for the vast majority of ZIP codes in California, a higher share of days in the higher bins is projected under both climate change scenarios for most models. It is impractical to show the almost 44,460 counterfactual response curves. Figure (6) collapses the temperature response curves across ZIP codes by projection period. The top panel displays the population-weighted statewide response curve in-sample in black and the projected future response curves in blue and red. As expected, the response curve tilts up more and more over time. The bottom panel repeats this exercise for RCP 4.5, which results in significantly less movement.

We now use the extensive margin adjusted response functions to simulate impacts of climate change on electricity consumption. Panel (b) in Figure (5) displays the impacts on the average household in a ZIP code using the ensemble average of GCMs and RCP 8.5 by end of century across the state for the extensive margin adaptation. It is important to note that this figure plots the "delta" from the intensive margin results. It indicates a noticeable increase in consumption across the state relative to the intensive margin only, shown in Panel (a). The right panel shows

[5]Figure A4 displays the projected increases in household residential electricity consumption across the approximately 1,200 ZIP codes for each of the four projection periods and the 18 GCMs for RCP8.5. The top panel displays this for intensive margin impacts only, while the bottom panel adds the extensive margin response. The box plots display tremendous variation across time (the box and whiskers plots for each model are shown in increasing temporal order for each model), across models, and within models. It is quite clear that median impacts are increasing over time and impacts range from the negative teens to increases approaching 50% for some ZIP codes. We trim the distribution of estimated impacts at the top and bottom because some point estimates are too large to be credible. This has to do with a lack of precision for some zip codes with very few observations in the extreme bins. We censor the slope coefficients to be less than 0.2 in absolute value and the projected impacts to be less than 50%.

that these extensive margin impacts will be felt most strongly in the Central Valley and non-coastal areas of Southern California.[6]

While these maps are instructive, it is hard to determine the size of the overall impact of allowing for extensive margin adjustment. Table (4) therefore shows the overall population-weighted increases in total electricity consumption averaged across the 18 climate models and for both RCPs - with and without extensive margin adjustments. The first thing to notice from this table is that accounting for the extensive margin adjustments results in a significant difference in simulated impacts, which is consistent with the findings in Davis and Gertler (2015) for Mexico. For RCP4.5 by the end of the century, accounting for extensive margin impacts increases the estimated impacts by 50%. The second noteworthy fact is that the estimated impacts for electricity consumption are relatively small even until 2059 - strictly less than 5% even for the worst case scenario incorporating extensive margin adjustment. In terms of the electricity planners' time horizon, the magnitude of the impacts falls within the noise. By the end of the century, the impacts are larger, yet their magnitudes are small enough that not overly optimistic assumptions about technological change related to energy efficiency should more than offset these gains. A 17.6% increase in electricity consumption from "normal" households - which is the largest effect we find - by end of century is about a 0.2% annual growth rate. The results for low-income households are even smaller: a 16.9% increase for the worst case scenario by the end of the century. The results for all–electric homes are much smaller. This makes sense because, for these homes, decreased heating will offset increases in air conditioning demand.

For natural gas, however, we see more significant decreases in consumption, even by mid-century. Under RCP8.5, consumption is expected to decrease by 10.4% by mid-century and by end of century by 20.5%. Again, the end of century is a long ways away and beyond the utility planners' horizon, but this raises the question of whether the savings from natural gas are bigger than the projected increases in electricity consumption in this counterfactual world. The EIA

[6] The bottom panel in Figure A4 displays the same box and whisker plots as we did for the intensive margin simulations earlier, but now incorporates the extensive margin changes. What stands out from this graph is an almost uniform upward shift in the medians across models and increased variability across models - especially at the high end.

states that California Homes used 0.287 quadrillion BTU of electricity and 0.439 quadrillion BTU of natural gas in 2009. If we use the projected percentage changes from Table (4), we arrive at the conclusion that climate change is simulated to lead to a 0.039 quad BTU net decrease in energy consumption for the residential sector in California. We will discuss the limitations of this simulation in the conclusions, but first it is instructive to put into perspective the impacts of other drivers of electricity consumption over the next century.

7. Conclusions

In the residential sector, one of the most widely discussed modes of adaptation to higher temperatures due to climate change is the increased demand for cooling and decreased demand for heating in the built environment. Due to its mild climate and heavy reliance on natural gas, California's residential sector uses relatively little electricity for heating. It is therefore expected that the demand for electricity will increase as households operate existing air conditioners more frequently, and in many regions will install air conditioners where there currently are few. This paper provides reduced form estimates of changes in electricity consumption due to increased use of installed cooling equipment under a hotter climate. The study adds to the literature by incorporating the change in temperature responsiveness due to likely increases in air conditioner penetration under climate change, using a two-stage method. The advantage of the proposed method lies in its relative simplicity and the fact that it only requires data on electricity consumption and not on installed cooling equipment.

We show that accounting for extensive margin adjustments will lead to statistically and economically significantly higher projections of electricity consumption. However, by estimating the response of natural gas consumption to higher temperatures, we also show that the projected increases in electricity consumption are more than offset by savings in natural gas, making climate change a net energy saving factor for the residential sector.

It is important to keep in mind several caveats. These are simulations, not forecasts. We think of the results provided in this paper as imposing end of century climate on a current day economy. Many other drivers of energy consumption will change. What our paper shows is the business as usual path, which mitigation strategy has to work against. We do not and cannot model changes in electricity consumption due to improvements in the efficiency of heating and cooling equipment and/or buildings. These effects will offset some or all of the increases in electricity consumption outlined in this paper and will amplify the natural gas savings. Further, the extensive margin adjustments in this paper cannot meaningfully control for changes in urban form, urban heat island effects, or other variables potentially leading to a higher response, which may be correlated with temperature. We leave the study of these effects to future work.

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Table 1: Electricity and Natural Gas Bills by Utility

Utility	Electricity Years	# of Bills	Gas Years	# of Bills
PG&E	2003-2009	342 Million	2004-2014	587 Million
SDG&E	2000-2009	153 Million	2008-2015	74 Million
SCE	1999-2008	469 Million		
SoCalGas			2010-2015	267 Million
Total		964 Million		928 Million

Notes: This table displays the total number of bills in our dataset. We drop electricity bills with average daily consumption less than 2kWh as well as solar homes. Further, the estimated models only include ZIP codes for which we have more than 1,000 bills.

Table 2: Summary Statistics for ZIP Codes In and Out of Sample

	In Sample	Out of Sample	p-value
Count	1,165	475	
Population (in thousands)	25.19	16.51	0.00
% White	70.07	72.35	0.04
% Black	5.13	5.31	0.67
% Hispanic	30.95	26.08	0.00
% Asian	10.87	10.10	0.26
% Male	50.14	50.93	0.00
Median Age (years)	38.90	40.31	0.00
Persons per Household	2.85	2.59	0.00
Average Home Value (in 100k US$)	4.14	3.98	0.39
Income per Household (in 10k US$)	6.52	5.99	0.00
Population Density	30.21	44.51	0.00
Elevation (in feet)	392.10	741.26	0.00
Mean Summer Temperature (F)	72.03	70.51	0.00
Mean Winter Temperature (F)	50.74	48.48	0.00
Mean Summer Precipitation (mm)	0.10	0.16	0.00
Mean Winter Precipitation (mm)	3.25	3.43	0.13

Notes: This table displays the mean observable characteristics of the ZIP codes in our sample and ZIP codes not in our sample with positive population. The t-test assumes unequal variances. The observable characteristics were purchased from zip-codes.com.

Table 3: Second Stage Regressions of Temperature Response Coefficients by Temperature Bin

	(1)	(2)	(3)	(4)
Historical Bin	0.0124***	0.0116***	0.0217***	0.0168***
Tavg Share	(0.000)	(0.000)	(0.000)	(0.000)
Interaction		0.0276***	0.0758***	0.0858***
Bin 12+		(0.000)	(0.000)	(0.000)
Special Customer	No	No	Subsidized	All-E
Income	Yes	Yes	Yes	Yes
Population Density	Yes	Yes	Yes	Yes
Bin Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,116	5,116	4,984	4,642

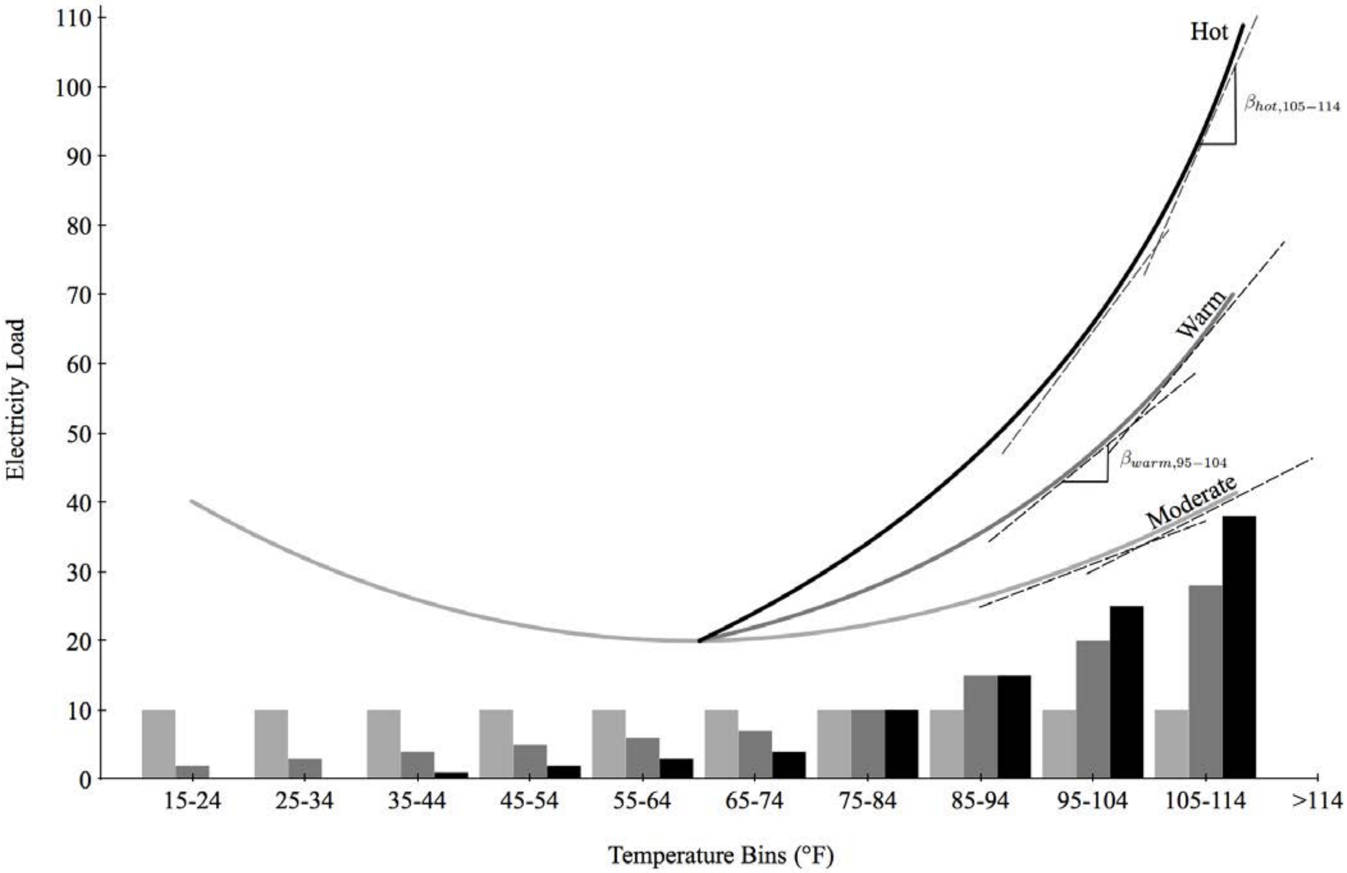
Notes: This table displays coefficients from a regression of the electricity slope coefficients estimated in equation (1) on the share of days in a given temperature bin the ZIP code has experienced over the period 1981-2000. The regression only includes the air conditioning relevant temperature bins 10-14. The standard errors are Huber-White. Regressions 1-2 are for "normal" households. Regression (3) is for households with subsidized energy bills. Regression (4) is for all-electric homes.

Table 4: Projected Percent Changes in Residential Electricity Consumption

Simulation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RCP	4.5	8.5	4.5	8.5	4.5	8.5	4.5	8.5
Special Customer	No	No	CARE	CARE	All-E	All-E	No	No
Fuel	Elec.	Elec.	Elec.	Elec.	Elec.	Elec.	Gas	Gas
Price Controls	No	No	No	No	No	No	No	No
Intensive Margin								
2020-39	0.8	1.1	0.8	1.1	-0.2	-0.2	-4.0	-4.9
2040-59	2.2	3.2	2.0	2.9	0.0	0.3	-7.9	-10.4
2060-79	3.2	6.7	2.9	6.0	0.3	1.9	-10.3	-16.1
2080-99	3.7	10.8	3.3	9.8	0.5	4.3	-11.3	-20.5
Extensive Margin								
2020-39	1.2	1.6	1.1	1.5	0.3	0.4	NA	NA
2040-59	3.2	4.8	3.0	4.5	1.2	1.9	NA	NA
2060-79	4.8	10.6	4.5	10.1	1.9	5.4	NA	NA
2080-99	5.6	17.6	5.3	16.9	2.4	10.2	NA	NA

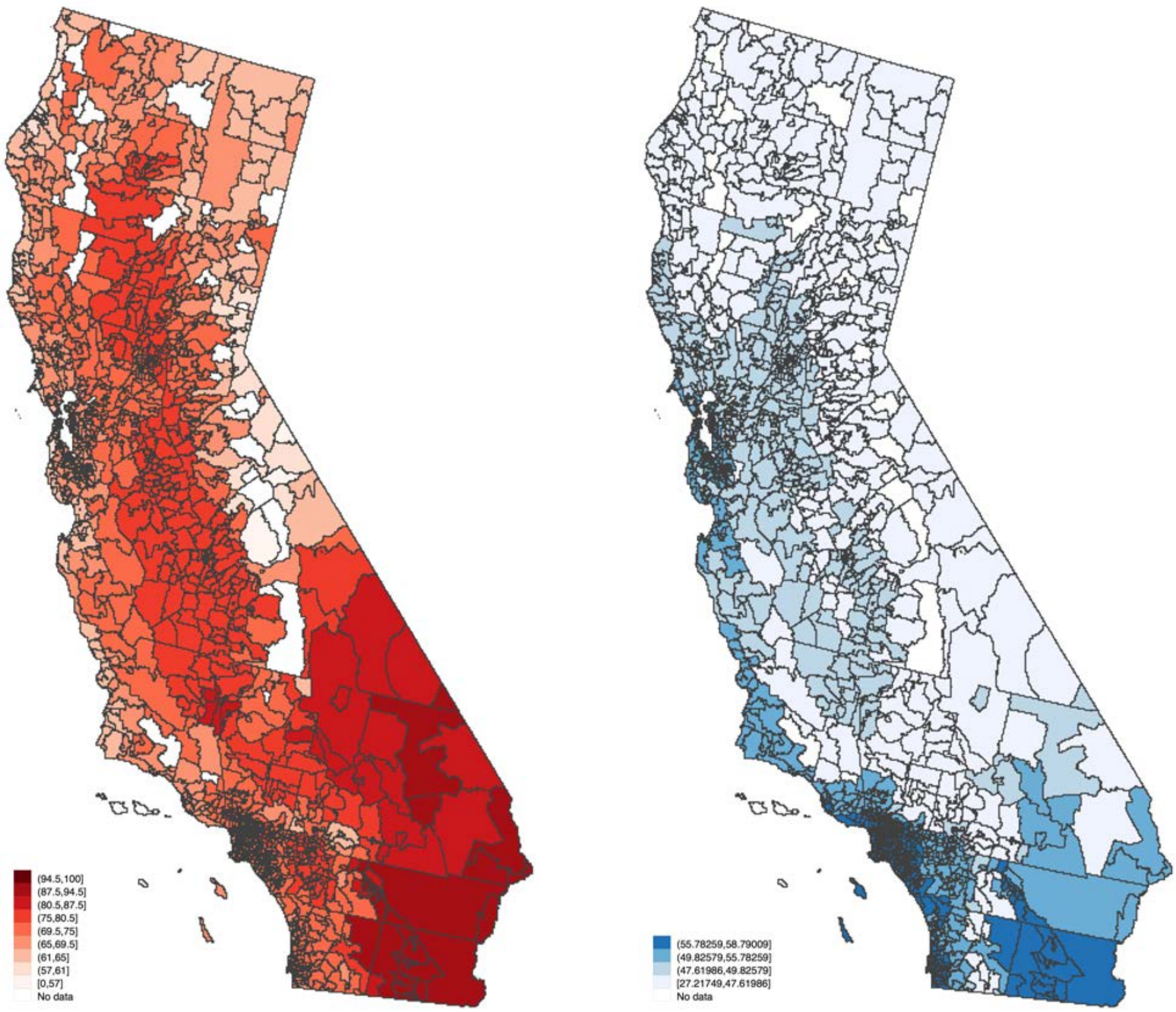
Notes: This table displays the simulated percent increase in total residential electricity consumption relative to 2000-2015 climate for the two IPCC Representative Concentration Pathways with low emissions (4.5) and high emissions (8.5). Columns (1) and (2), indicate simulated increases for normal households Columns (3) and (4) simulate increases for subsidized households. Columns (5) and (6) simulate changes for households which are all-electric. Columns (7) and (8) display the impacts on natural gas consumption for households with gas bills.

Figure 1: Conceptual Identification of Short and Long Run Response



Notes: This figure displays the temperature response of electricity consumption in three fictional ZIP codes with differing climates - moderate, warm and hot. The bars at the bottom display the temperature (weather) distribution for the three ZIP codes. The colors of the response functions match the colors of the weather distribution(s). The figure displays that the hot ZIP code has a steeper temperature response at higher temperatures than the warm and moderate ZIP codes. The first step in the estimation identifies the ZIP code specific temperature response curves using household level data. The second estimation step estimates the effect of climate (average time spent in a portion of the temperature spectrum) on the slope of the response curves across ZIP codes for the air conditioning relevant portion of the temperature spectrum.

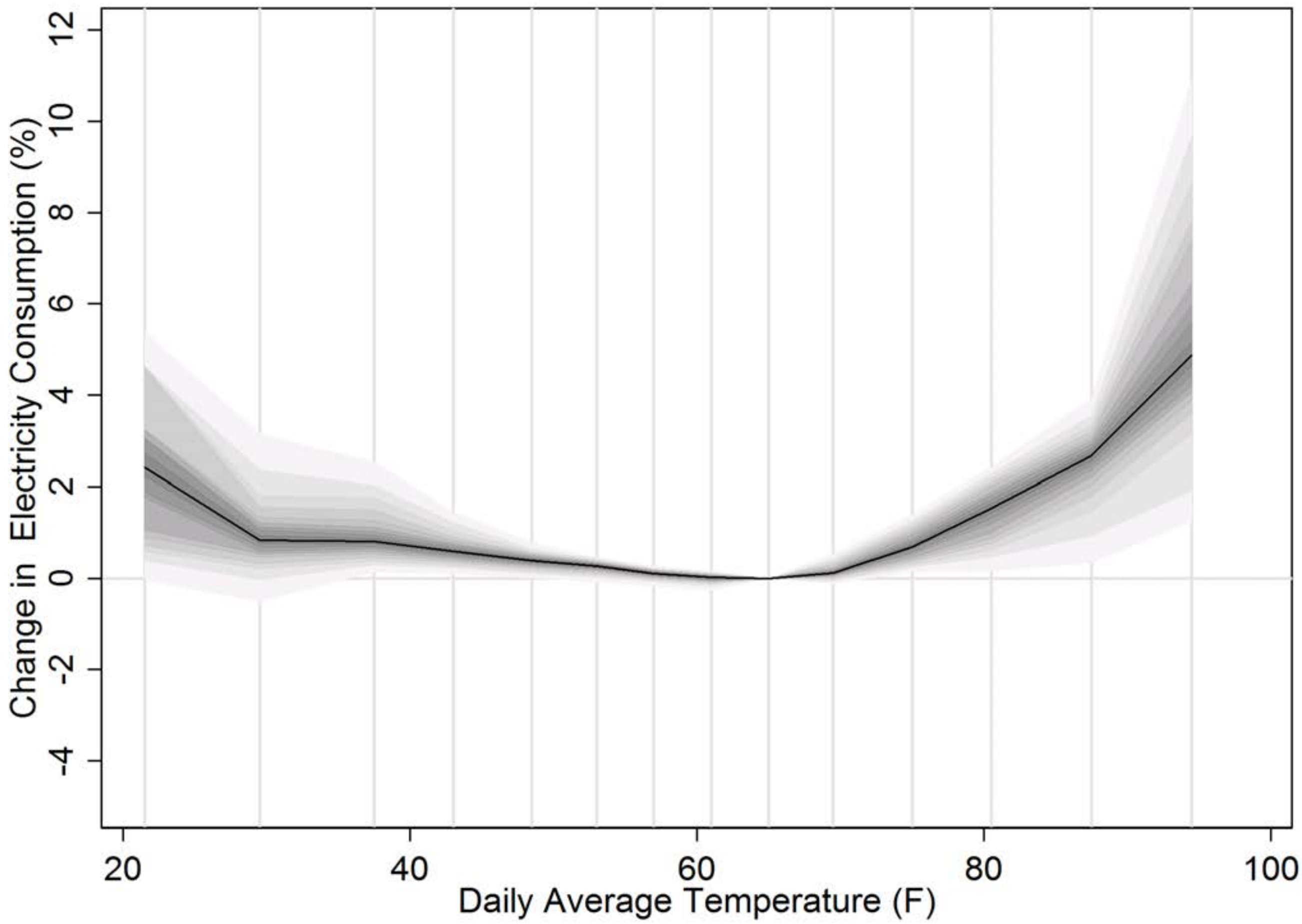
Figure 2: CALIFORNIA'S SUMMER (JUNE-AUGUST) AND WINTER (DECEMBER-FEBRUARY) CLIMATE: AVERAGE DAILY TEMPERATURE 1981-2015



(a) Summer

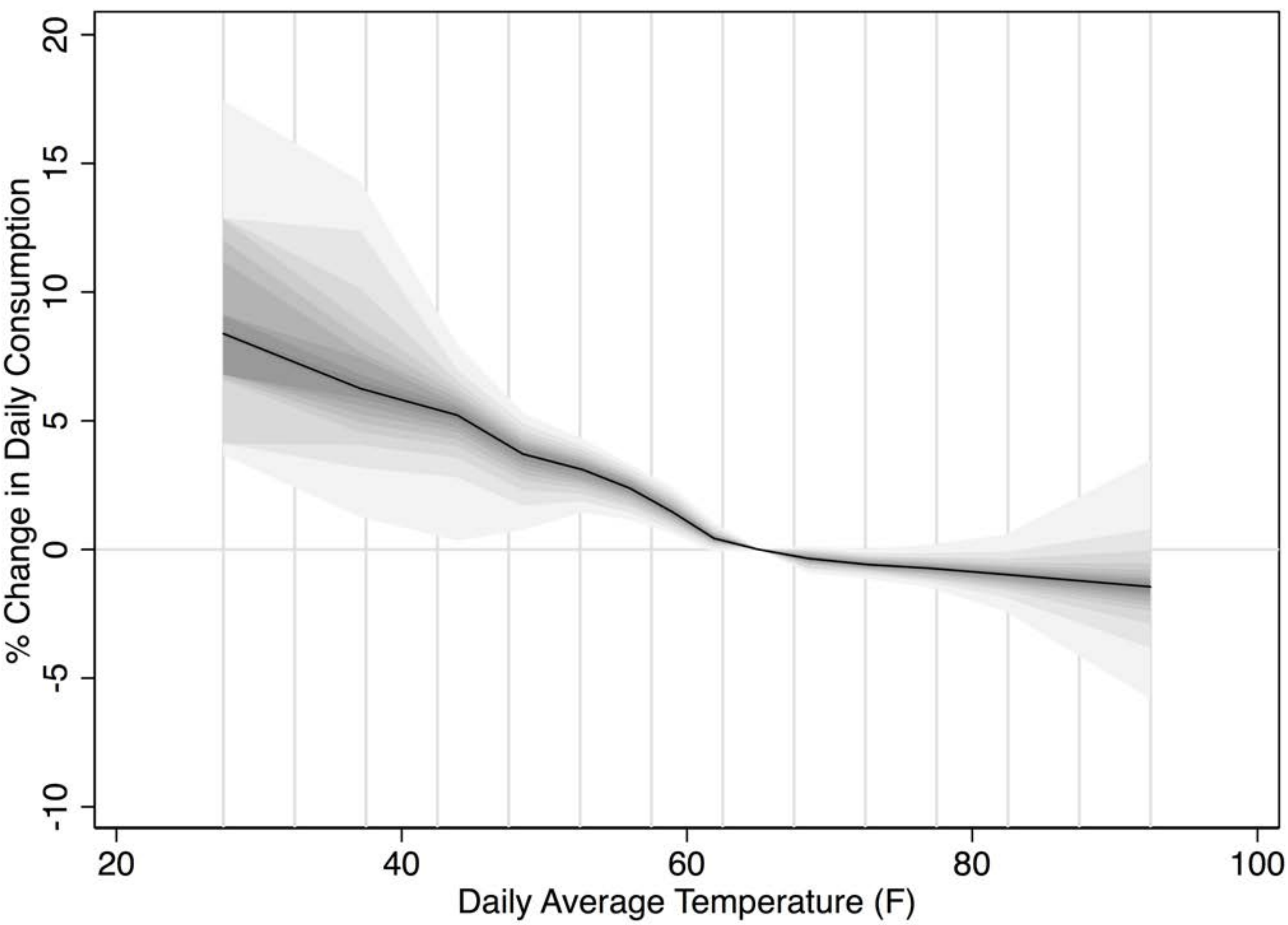
(b) Winter

Figure 3: Distribution of Estimated Electricity Temperature Response Coefficients across ZIP Codes



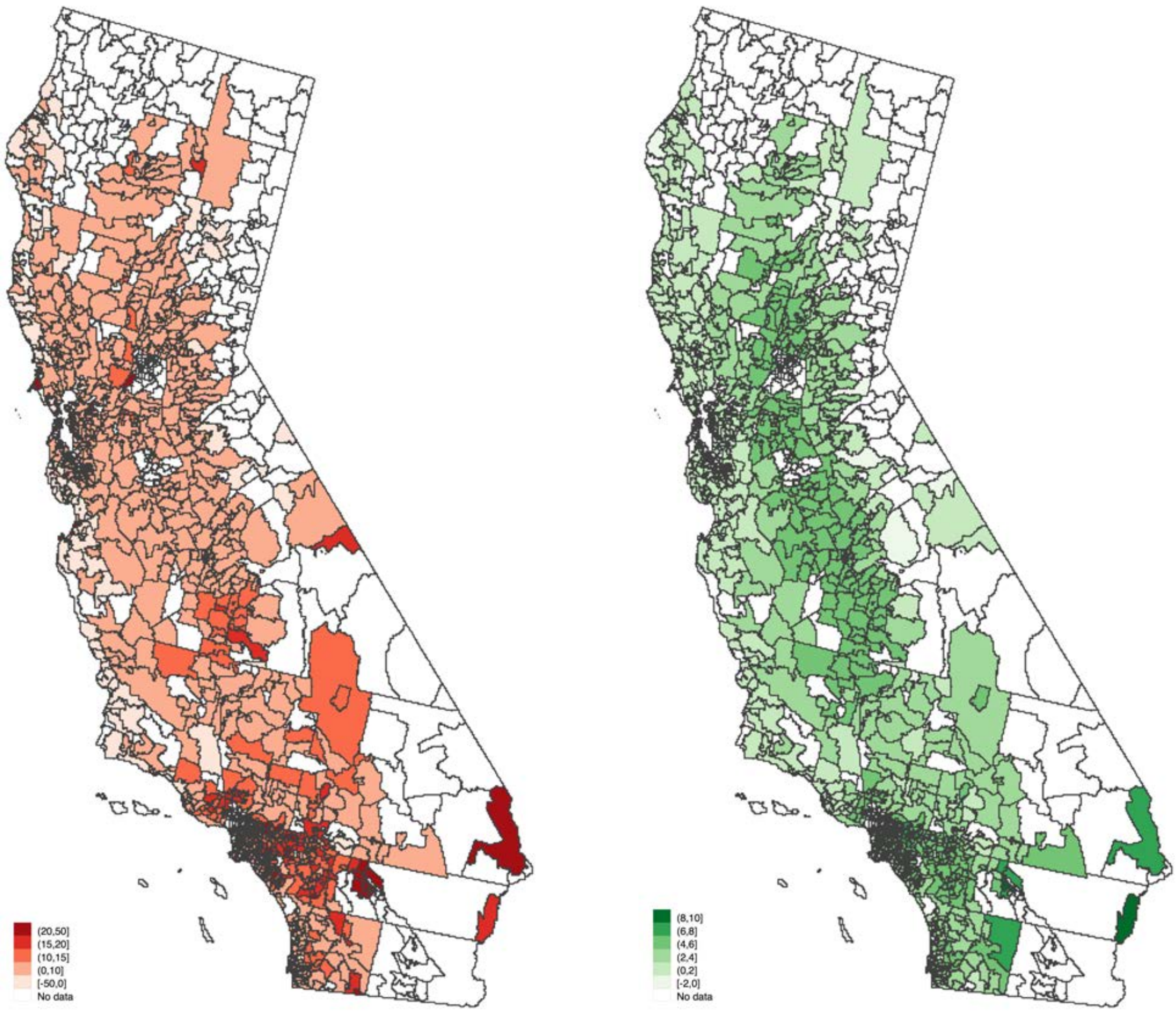
Notes: This figure displays the empirical distribution of the estimated electricity temperature response function across ZIP codes in the sample across percentile temperature bins. The lightest grey shading indicates the range of the 5^{th} to 95^{th} percentile. Each darker shading represents a 5% increase in the percentile. The solid black line represents the median temperature responsiveness. The vertical grey lines indicate the cutoffs of the temperature bins.

Figure 4: Distribution of Estimated Natural Gas Temperature Response Coefficients across ZIP Codes



Notes: This figure displays the empirical distribution of the estimated natural gas temperature response function across ZIP codes in the sample across percentile temperature bins. The lightest grey shading indicates the range of the 5^{th} to 95^{th} percentile. Each darker shading represents a 5% increase in the percentile. The solid black line represents the median temperature responsiveness. The vertical grey lines indicate the cutoffs of the temperature bins.

Figure 5: Intensive and Extensive Margin Adjustment: Projected Percent Increases in Average Household Electricity Consumption 2080-2099 over 2000-2015 for RCP 8.5

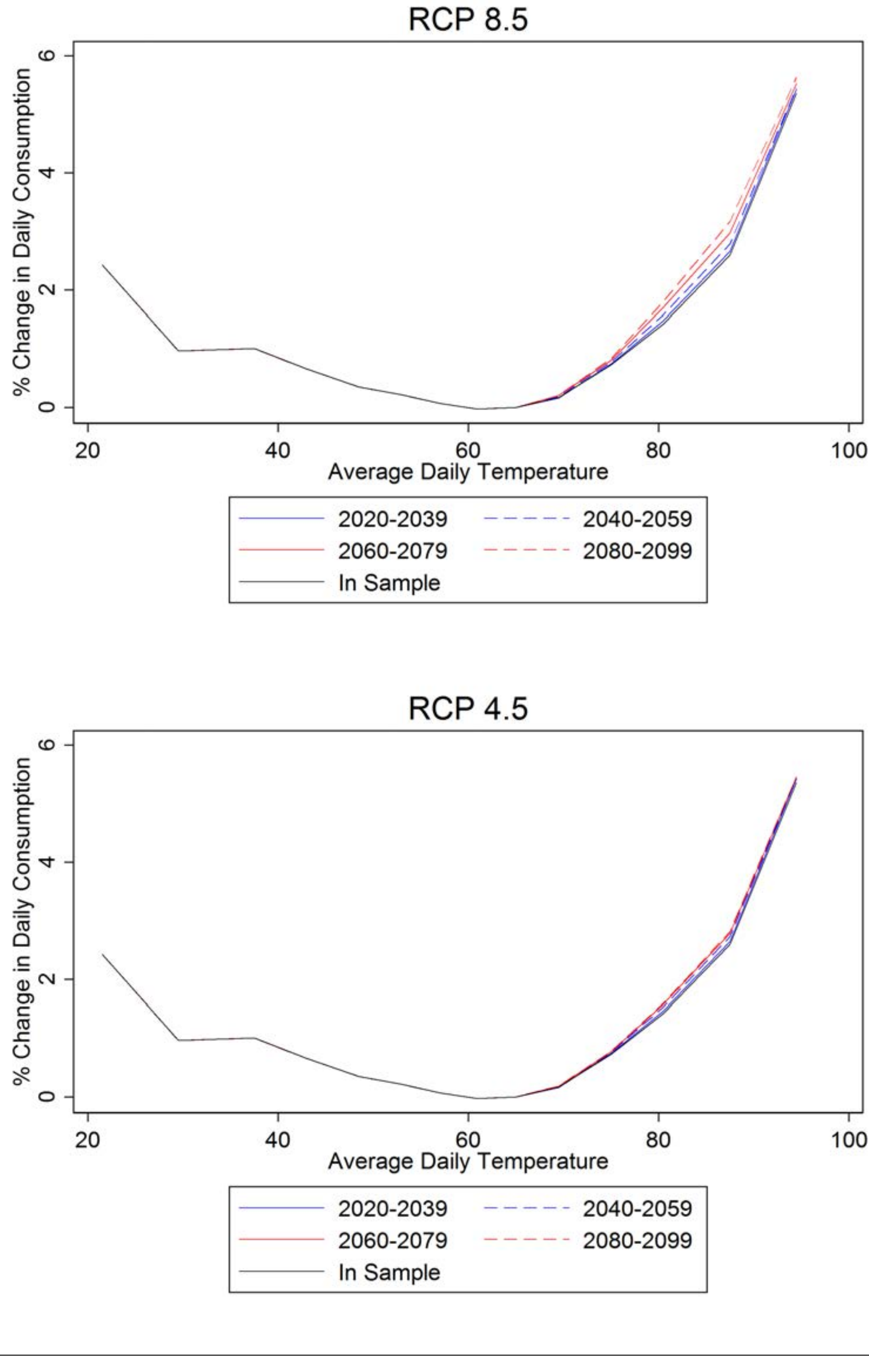


(a) Intensive Margin

(b) Extensive Margin Delta

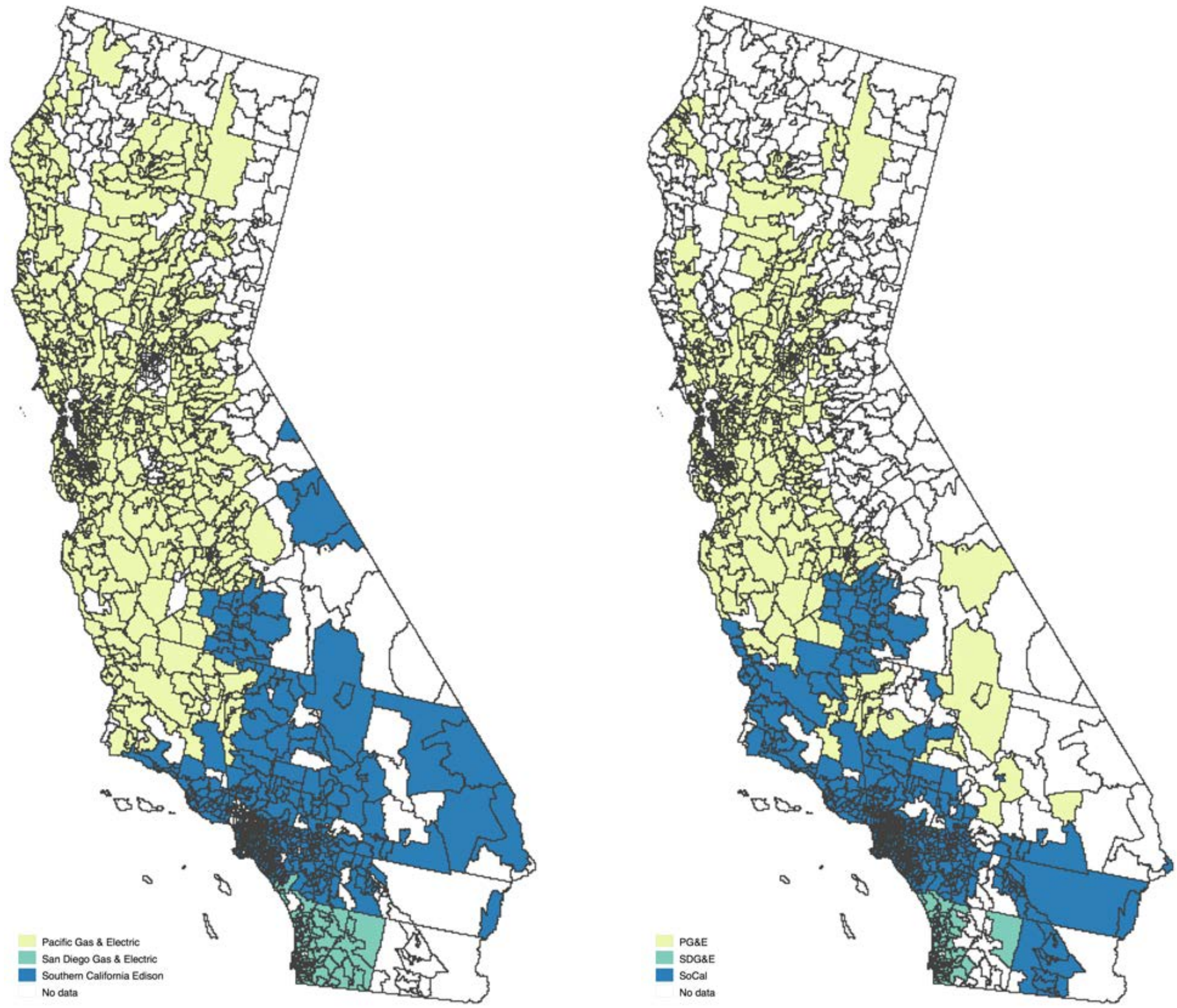
Notes: This figure plots the average per household increase across all 18 GCMs for RCP8.5 for the last two decades of this century over the years 2000-2015. Panel (a) holds the temperature response curve fixed at the values estimated in-sample. Panel (b) allows for the empirically guided extensive margin adjustment.

Figure 6: In–Sample and Simulated Future Population-Weighted Temperature Response Curves.



Notes: This figure plots the population weighted average of the temperature response curves across all 18 GCMs (climate models) in blue and red. The solid black line displays the in-sample estimated population weighted average across all zip codes.

Figure A1: California's Summer (June-August) and Winter (December-February) Climate: Average Daily Temperature 1981-2015

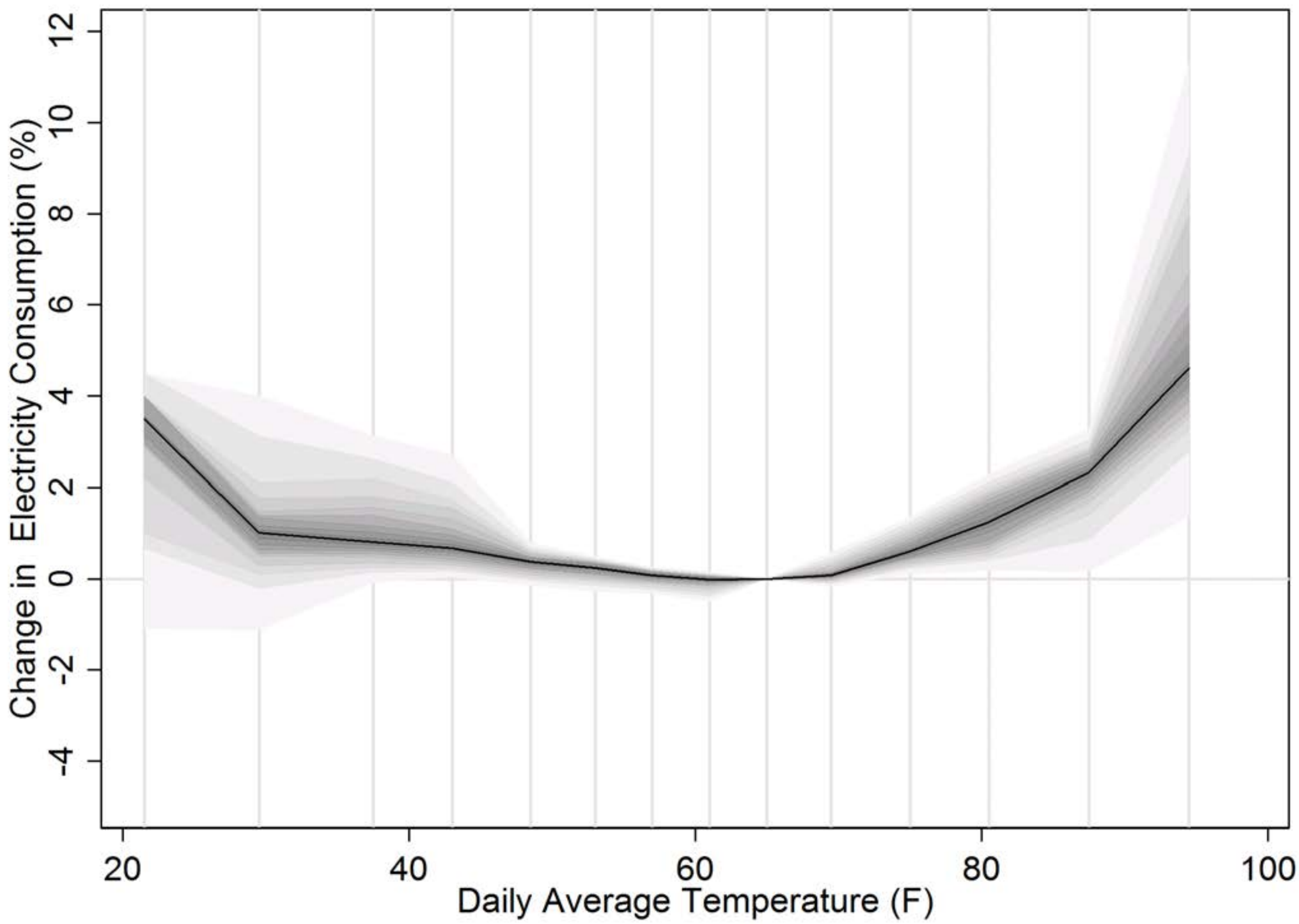


(a) Electricity

(b) Natural Gas

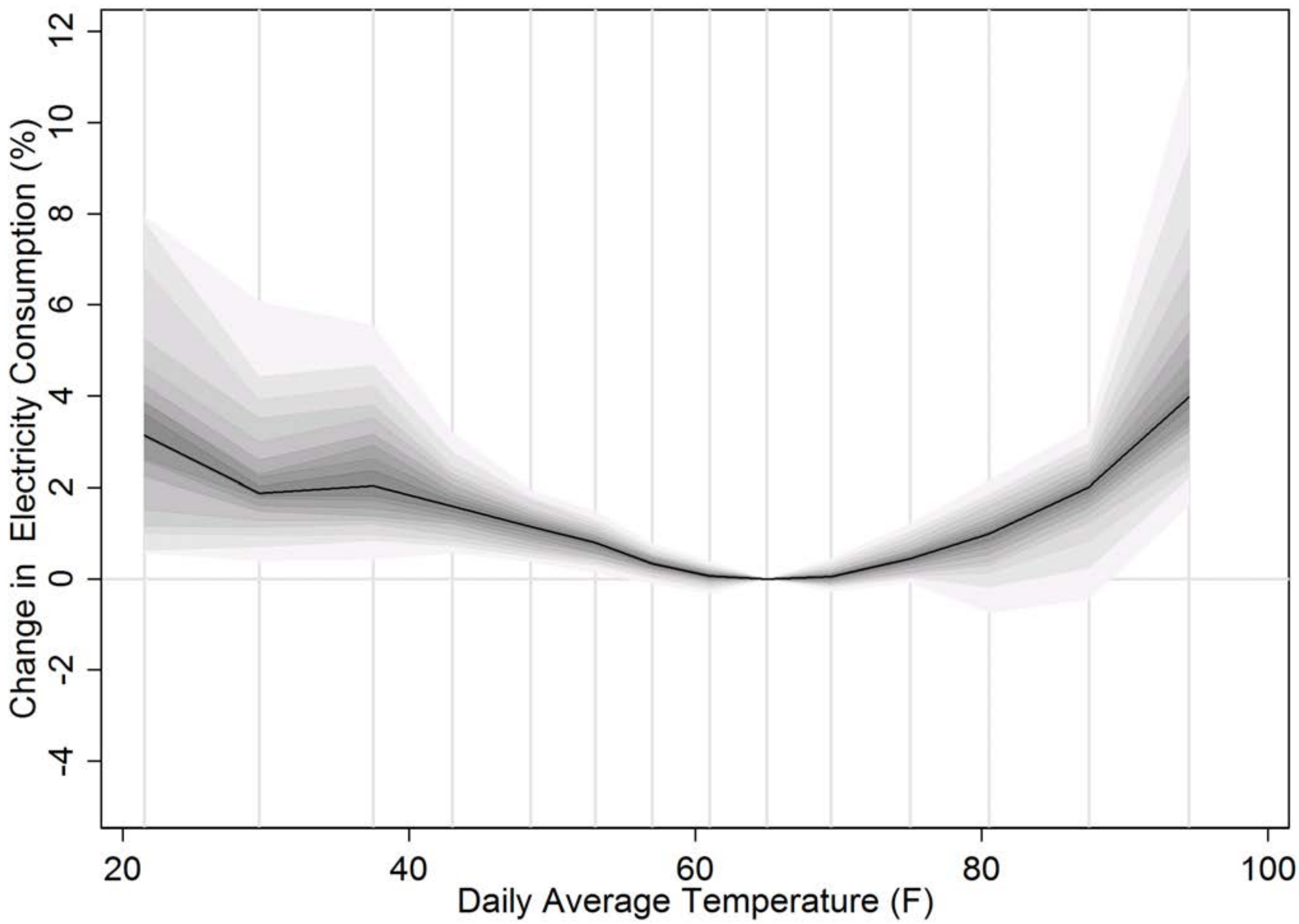
Notes: Notes: The maps above display the five-digit ZIP codes for which we have more than 500 bills over the estimation period from either PG&E, SCE, SCG or SDG&E. Zip codes with no data either have fewer than 500 bills total or are served by one of California's many municipal utilities. Panel (a) displays coverage for our electricity data. Panel (b) displays coverage for our natural gas data.

Figure A2: Distribution of Estimated Electricity Temperature Response Coefficients across ZIP Codes for Subsidized Households



Notes: This figure displays the empirical distribution of the estimated electricity temperature response function across ZIP codes in the sample across percentile temperature bins. The lightest grey shading indicates the range of the 5^{th} to 95^{th} percentile. Each darker shading represents a 5% increase in the percentile. The solid black line represents the median temperature responsiveness. The vertical grey lines indicate the cutoffs of the temperature bins. This figure is estimated for the subset of households receiving a 20% discount on their utility pricing due to their low income status.

Figure A3: Distribution of Estimated Electricity Temperature Response Coefficients across ZIP Codes for All-Electric Households



Notes: This figure displays the empirical distribution of the estimated electricity temperature response function across ZIP codes in the sample across percentile temperature bins. The lightest grey shading indicates the range of the 5^{th} to 95^{th} percentile. Each darker shading represents a 5% increase in the percentile. The solid black line represents the median temperature responsiveness. The vertical grey lines indicate the cutoffs of the temperature bins. This figure is estimated for the subset of households identified as all–electric by the utilities.

Figure A4: Intensive margin [Top Panel] and Extensive Margin [Bottom Panel] per household impacts across ZIP codes and Climate Models.