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Building Vintage and Electricity Use: Old Homes Use Less Electricity In Hot Weather

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This paper studies whether electricity use in newer or older residential buildings rises more in response to high temperature. Peak electricity demand occurs at the highest temperatures which are predicted to increase due to climate change. Understanding how newer buildings differ from older buildings improves forecasts of how peak electricity use will grow over time. Newer buildings are subject to stricter building energy codes, but are larger and more likely to have air conditioning; hence, the cumulative effect is ambiguous. This paper combines four large datasets of building and household characteristics, weather data, and utility data to estimate the electricity-temperature response of different building vintages. Estimation results show that new buildings (1970-2000) have a statistically significantly higher temperature response (*i.e.*, use more electricity) than old buildings (pre-1970). Auxiliary regressions with controls for number of bedrooms, income, square footage, central air conditioning, ownership, and type of residential structure partially decompose the effect. Though California has had extensive energy efficiency building standards that by themselves would lower temperature response for new buildings, the cumulative effect of new buildings is an increase in temperature response. As new buildings are added, aggregate temperature response is predicted to *increase*.

JEL Codes: Q41, Q48

keywords: Electricity, Temperature Response, Demand Forecast, Climate Change Impacts, Vintage-Differentiated Regulation, Building Standards, California, Load Factor, Rosenfeld Effect

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1. Introduction

Understanding the relationship between electricity usage and temperature, *i.e.* temperature response, is important for climate change policy and long-range electricity infrastructure planning. Residential buildings are a substantial contributor to CO2 emissions. In the US, residential buildings account for 21% of 2008 CO2 emissions (Environmental Protection Agency 2010), with about 50% of residential energy going to space heating and air conditioning (Energy Information Administration 2009). Furthermore, temperature increases from CO2 emissions will affect electricity demand through increased cooling loads, *i.e.*, air conditioning use. Electric power plant construction and infrastructure decisions are strongly driven by peak electricity demand which in California occurs during periods of highest temperature.

If new buildings have higher temperature response[1], then the average temperature response will increase as new buildings are added. Peak demand per household will also increase. Policies to reduce greenhouse gas emissions or reduce energy use often aim to decrease peak and total electricity demand.

Temperature response is better than total electricity use as a measure of the performance of buildings. As the component of electricity usage that varies with temperature, temperature response isolates factors such as the thermal performance of the building, the size of the building, and the thermostat preferences of occupants. In contrast, total electricity use conflates these factors with appliance ownership (e.g., more televisions) and other factors that don't depend on the building.[2]

Whether newer or older residential buildings in California have higher temperature response has not been studied using field data. California has had the most extensive energy efficiency standards in the United States applied to new buildings. Engineering models (e.g., Marshall and Gorin (2007); Abrishami, Bender, Lewis, Movassagh, Puglia, Sharp, Sullivan, Tian, Valencia and Videvar (2005)), predict strong reductions in energy use (both peak and total

[1]In this paper, temperature response is defined as the percentage increase (relative to usage on a 65°F day) in electricity use due to a 1°F increase in temperature. Higher temperature response means more incremental electricity use.

[2]Though I focus on temperature response, I also present comparisons of the total electricity use across vintage in Appendix A. Unsurprisingly, new homes use more electricity, principally because they are larger.

use) due to these standards, *ceteris paribus*, but other factors can offset these increases. The sign of the cumulative effect, measured as the difference between new and old buildings, is ambiguous. I use field data to estimate the temperature response across houses of different vintages.

This paper uses (household, monthly) field panel data on electricity use linked to building vintage and other building and household characteristics. Household electricity usage (quantity) data in Riverside County, California, USA, is regressed on time series variation in temperature to estimate temperature response. Cross sectional variation in building vintage and other characteristics at the Zip9-level or census block group-level identifies the temperature response by vintage.

The main finding is that each successive decade since 1970 has statistically significantly *increased* temperature response compared to older buildings (built prior to 1970). Hence, average peak load is expected to increase due to population growth and ensuing new construction. This exacerbates the impact of climate change on electricity use. Auxiliary regressions add controls for bedrooms, income, sqft, central air conditioning ownership, and type of residential structure. These differ across vintage and partially explain the increase in temperature response for newer buildings. With controls, 1990s homes are estimated to have a temperature response of 8% less to 6% more than pre1970s homes in the most unrestrictive specification.

The organization of the paper is as follows. Section 2 presents existing related studies. Section 3 presents a description of the data. Section 4 presents an econometric model. Section 5 estimates the model. Section 6 discusses results and potential mechanisms. Section 7 concludes.

2. Related Work

2.1. **Temperature Response and Building Vintage in Field Evidence and Forecasting.** Several papers have focused on temperature response of buildings using field evidence but ignore how buildings have changed across vintage. Aroonruengsawat and Auffhammer

(2009) examine the variation in the non-linear relationship between temperature and electricity use by sixteen climate zones in California, showing that the strongest relationships are in hotter inland areas. Earlier work on temperature response with (annual, state)-level data by Deschênes and Greenstone (2008) predicts that climate change scenarios generate a 33% increase in residential energy consumption nationwide *with the current set of buildings*. New buildings, if they perform worse than older buildings, may exacerbate this predicted increase.

By ignoring vintage effects, such studies would underestimate the impact of new buildings. Baxter and Calandri (1992) use an engineering model to estimate the impact of a 1.9°C temperature increase, finding a 2-4% increase in electricity use, but the study holds the building stock fixed. More recent work suggests that newer buildings are more temperature responsive. Every two years, the California Energy Commission runs a detailed simulation model to construct its demand forecast that includes a large mix of econometrically estimated parameters and engineering estimates. In a recent revision, they find that air conditioning saturation for newer buildings increased unexpectedly for both hotter (inland) and cooler (coastal) areas (Marshall and Gorin 2007). [3]

A limitation of engineering studies is uncertainty about whether engineering parameters represent actual field performance. Joskow and Marron (1992) describe many factors that contribute to overstatement of program effectiveness. In particular, a rebound effect may exist where occupants demand more services by responding to a decrease in the price due to efficiency (Greening, Greene and Difiglio 2000), interventions may imperfectly translate to the field, or unexpected confounding effects could diminish or accentuate savings. Although only a small portion of their broader critique, they highlight the difficulty of extrapolating from the laboratory to the field. In Joskow and Marron (1993), they find that the ratio of measured to estimated savings are 0.31-0.42 for two 1980s retrofit programs; that is, engineering predictions overstated savings by a factor of 2 to 3. As more current evidence that field measurements and engineering estimates differ, Larsen and Nesbakken (2004) compare

[3]Their large simulation model reports aggregate result but does not explain how they model differences between new and old homes. They use an alternate but related concept of load factor, which is defined as average demand relative to peak demand. Load factor and average temperature response are inversely related. They project that load factor will decrease.

an econometric decomposition approach to the predictions of engineering models in Norway. They find that the two approaches decompose end uses quite differently. Hirst (1990) surveys the broader question of program evaluation. Nadel and Keating (1991) summarize results of a large number of field evaluations and find generally positive, but usually smaller, savings than what engineers predict. Use of field data, like that done in this paper, can produce more realistic forecasts or provide ways to validate engineering estimates. If engineering parameters overstate energy savings, then demand forecasts will be biased downward.

Two very recent papers use field data to test the impact of building vintage, both using monthly utility data. Jacobsen and Kotchen (2009) analyze one building standard code change in Florida using a sharp regression discontinuity. They estimate a 4-6% reduction is energy use. Costa and Kahn (2010) estimate the differences in total electricity use by building vintage for buildings in a community in California using cross-sectional variation and show that homes built after 1983 had lower total electricity use. My research looks at the differences for homes over three decades and focuses on differences in temperature response.

2.2. **The Rosenfeld Curve and Energy Efficiency.** Per capita total electricity sales for California have been relatively flat since the mid-1970s, when landmark legislation for energy efficiency was passed. Comparatively, sales for the rest of the United States have gone up by 50% (Figure 1). Explanations of this time series phenomenon, commonly referred to as the Rosenfeld Curve, vary widely. The obvious explanation points to California's policies, especially the establishment of building and appliance standards unique to California, as major contributors. However, correlation is not causation. The visual remarkableness of this curve is tempered when looking at comparable curves for nearby states. A look at analogous "Rosenfeld Curves" of *residential* electricity per capita over time for eight Western States (Figure 2) presents a quick visual contrast to California's impressive performance relative to the United States (Figure 1). Three other states (NV, OR, and WA) have had flat residential electricity per capita profiles, though they had weaker building standards.[4]

[4]Historical information for all states on building energy standards comes from the Building Codes Assistance Project (n.d.). Nevada implemented a mandatory building energy code in 1978 but "between 1983 and 1986,

Avoiding many of the problems of state-level analyses, my research uses rarely available microdata at the household-level with covariates at the 5-10 household-level. State-level analyses are problematic because they assume comparability across states. The identifying assumption in such studies is that changes in per-capita electricity load across states would have been the same in the absence of energy efficiency policies. This assumption is embedded in several state-level analyses: Aroonruengsawat, Auffhammer and Sanstad (2009) and Horowitz (2007) use state-level panel data; Sudarshan and Sweeney (2008) make a comparison between the US and California; and Loughran and Kulick (2004) and Auffhammer, Blumstein and Fowlie (2008) use utility-level panel data. These analyses typically find evidence that energy efficiency programs reduce energy consumption. Comparability across states can be violated for many reasons. The evolution of a state's aggregate energy efficiency (as measured by residential electricity per capita) will depend on changes in the composition of the type of housing (urban vs rural, single family vs condominiums), growth in the size of housing, changes in geographic/climatic composition (e.g. coastal vs. inland), and differences in the adoption of air conditioning.

This analysis makes an important contribution to studies of policies aimed at reducing residential energy. In the context of "energy intensity" measures, such as electricity per capita or per GDP, my research identifies the *new and counterintuitive* empirical fact that households in new buildings use more electricity per household, both in total use and in response to temperature. It runs counter to what one might expect from looking at the Rosenfeld Curve, where per capita electricity has been flat, but the Rosenfeld Curve is an aggregate-level result that may conflate other factors.[5] Explaining what causes this empirical fact is important for understanding the effectiveness of building energy use policy in the context of many *simultaneous* changes.

the state did not support or enforce this energy code". Oregon implemented a building energy code in 1978 that did not apply to residential buildings. A residential code was adopted in 2003. Washington adopted a voluntary energy code in 1977, with a mandatory code established in 1986.

[5]Given that households in new buildings use more electricity than those in older buildings, if older buildings have not changed, it follows logically that the average household use would go up. Since this contradicts the flat average electricity use (Rosenfeld Curve), the inference is that households in old buildings use significantly less electricity, to the point that the average use is flat.

3. Description of the Data

Three investor-owned utilities (Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric) gave researchers at the University of California Energy Institute the complete billing history for all residential household bills in these electricity service territories. Time coverage for utilities varies, but the longest period of data are from 1998 to part of 2009 for Southern California Edison (SCE). Information includes billing start date, billing end date, total electricity used (kWh), total bill, an account id, a physical location id, and the zip code (usually at the nine digit level). This paper currently focuses on one county, Riverside County, where there are over 20 million observations for SCE customers.

Riverside County was chosen because it is an inland area with a wide range of temperatures, there is considerable variation in the building vintage, Aroonruengsawat and Auffhammer (2009) found this region to have substantial average temperature response, and detailed county assessor's property information is available. It is important to restrict to one county or area because housing design, climate, and building standards differ strongly across the state. For cleaning, bills with 25 days or less or 35 days or more were dropped (about 5%). Bills with less than 2kWh/day or more than 80kWh/day are outliers were also dropped (about 4%).

The billing data lacks housing and household information; two data sets of different spatial resolution are used to provide this information. County assessor's data (County of Riverside Assessor's Office 2010) was obtained for single family homes identifiable to the address. Because SCE billing includes both bills for single family and multifamily (e.g., apartments), I condition on census block groups where more than 95% of households are in single family homes. Bills are next matched to assessor data via the zip9. Zip9s are very small, with an average of 4.8 assessor records per zip9. For each zip9, the proportion constructed in each vintage category, the median of square footage, and the proportion of houses with central air conditioning for each zip9 is associated with all the bills in that zip9.

The second source of housing information is the US Census. The 2000 US Census's Summary File 3 (United States Census Bureau 2009) has at the census block group-level proportions of the vintage of housing, proportions of type of structure (single family vs multifamily vs mobile home), the number of rooms, and the income distribution. A census block group has a size on the order of 500 housing units. Figure 3 has a map of part of Riverside County by census tract.[6]. The shading corresponds to the proportion of housing in a tract that was built after 1980, with darker meaning more new construction. Hence, within this county, there is substantial spatial variation in the age of housing which is needed for estimating vintage differentiated temperature response; *i.e.* temperature response is compared between dark and light areas of the figure. Because of the large number of observations and computing limitations, a 1-in-5 subsample was used to reduce the sample to 5.3 million observations when using census data.

Daily maximum (Tmax) and minimum (Tmin) temperature at a 4km x 4km grid are generated according to the algorithm used by Schlenker and Roberts (2009) which has been used for estimating the relationship between crop yields and temperature. The reader is directed there for a more full description of the algorithm as well as diagnostics that show the methodology is reliable. Billing data are then matched via Zip9 to the gridded temperature data and to the census block group. The average of Tmax and Tmin is then taken as the daily temperature. These are then translated into cooling degree days (CDD) and heating degree days (HDD) with a reference temperature of 65°F. In a more flexible approach which follows Aroonruengsawat and Auffhammer (2009), the daily temperature is binned into 10 bins with approximately equal number of observations. Temperature bin ranges are listed in Table 1.

To give a better sense of the data, Figure 4 gives plots of average daily electricity use versus time from the monthly billing data for one household. Peaks for electricity use correspond to summer months. This data is then replotted as average daily electricity use versus

[6]On average, a census tract is 3 census block groups.

average cooling degree days in Figure 5. As temperature increases, the electricity use for this household increases.

Summary statistics of the data (using assessor's data which is restricted to single family homes at the zip9 level) are in Table 2. Most single family homes (88%) have central air conditioning overall; the newest homes almost always have central air conditioning, but less than half of older homes have central air conditioning.

Summary statistics of the data (using census block groups) are in Table 3. The top section reports information from the billing data. The average household use per day is 25.5kWh, or 9307kWh per year. This is slightly lower than the national average of 11,500 kWh per year (Energy Information Administration 2009). The second section of the summary statistics corresponds to building and household characteristics from the Census data at the level of the census block group. 20% of observations were built in 1970-1979, 36% in 1980-1989, and 21% in 1990-2000, and 23% before and including 1969. The min and max of these variables are close to zero and one, which means there is substantial variation across census block groups in building vintage. The vintage variables differ from the previous table because this data set includes non-single family homes. The average number of bedrooms and rooms are 2.57 and 5.23, and the average household income is $48,200.

An extended data discussion with additional detail on data cleaning and matching is in Appendix D.

4. Econometric Model

The average temperature response for subareas of California has been estimated by Aroonruengsawat and Auffhammer (2009) and nationally by Deschênes and Greenstone (2008). A similar estimating equation is given by Equation 1. This flexibly estimates the average temperature response in log terms within the sample area after controlling for a household fixed effect.[7] Temperature is binned. D_{pit} is a scalar $[0, 1]$ that denotes the fraction of days where

[7]Studies relating energy use and temperature have varied in the functional forms used. I discuss this in Appendix B. In the robustness checks and the auxiliary regressions, I include alternative functional forms.

a household is exposed to the pth temperature bin.

$$ln(kWh\_useperday_{it}) = \sum_{p=1}^{BINS} \rho_p * D_{pit} + \alpha_i + \varepsilon_{it} \quad (1)$$

An alternative specification is to parameterize the temperature response in terms of cooling degree days and heating degree days[8]. Following Reiss and White (2008), I include linear and squared terms for CDD and HDD which results in Equation 2.

$$\begin{aligned} ln(kWh\_useperday_{it}) &= f(CDD, HDD) + \alpha_i + \varepsilon_{it} \\ &= \beta_1 CDD_{it} + \beta_2 CDD_{it}^2 + \beta_3 HDD_{it} + \beta_4 HDD_{it}^2 + \alpha_i + \varepsilon_{it} \quad (2) \end{aligned}$$

I have estimated both temperature parameterizations. The degree day parameterization is the main specification presented. A limited number of binned results will be presented.

I next estimate the heterogeneity of temperature response by vintage. The vintage of each household is not known, but the proportion of buildings of each vintage in an area is known, either at the Zip9- or census block group-level. The temperature response of each vintage is estimated via the cross sectional variation in vintage across areas. Equation 3 uses the degree day parameterization, while Equation 4 estimates the average response by vintage using binning.

$$ln(kWh\_useperday_{ijt}) = \sum_{v=1}^{VINTAGES} V_{jv} * \left(\beta_{1v} CDD_{it} + \beta_{2v} CDD_{it}^2 + \beta_{3v} HDD_{it} + \beta_{4v} HDD_{it}^2\right) + \alpha_i + \varepsilon_{it} \quad (3)$$

$$ln(kWh\_useperday_{ijt}) = \sum_{v=1}^{VINTAGES} \left(\sum_{p=1}^{BINS} [\beta_{pv} V_{jv}] \right) * D_{pit} + \alpha_i + \varepsilon_{it} \quad (4)$$

[8] Degree days are referenced to 65°F. For a given day, $CDD = max(Tmean - 65, 0)$ and $HDD = max(65 - Tmean, 0)$

where

- i, j, t index households, zip9 or census block groups, and time (monthly billing period), respectively
- $BINS$ represents the number of temperature bins, p indexes them.
- $VINTAGES$ represents the number of building vintage categories. v indexes them.
- V_{jv} is in [0,1] and represents the proportion of buildings in j for vintage v
- D_{pit} is in [0,1] and is the measure of the proportion of days for household i in the billing cycle t where the average temperature is in the pth bin

In both regressions, the mean temperature-invariant consumption is captured by the household fixed effect, α_i. Importantly, this will flexibly capture temperature invariant factors such as variation in appliance ownership and usage patterns. In Equation 4, the parameters of interest are the β_{pv} that represent the temperature response for the pth temperature bin for the vth vintage[9]. The set of β_{pv} plotted against the p temperature bins yields the temperature response. Electricity use should increase with increasing temperature, represented by $\beta_{p^*v} > \beta_{p'v}$ when p^* is hotter than p' in the air conditioning range of temperatures for a given v.[10] If new buildings have higher temperature response than older buildings, then $\beta_{pv^*} > \beta_{pv'}$ when v^* is newer than v' for any p in the air conditioning range of temperatures. In Equation 3 with the degree day parametrization, the β_{1v} and β_{2v} determine the temperature response to hotter temperatures. Temperature response is higher when these coefficients are larger. In the degree day parameterization, the comparison of interest is the analogous differences in predicted temperature response across vintages.

Estimation of Equations 4 and 3 determines the average temperature response by vintage but does not identify the causal effect of building standards. Over time, buildings have changed in numerous ways, such as building standards on insulation and glazing, efficiency standards on appliances, the likelihood to have air conditioning, the square footage, and

[9]One of the temperature bins, 62.7°F – 66.4°F is left out wlog as the reference temperature bin, otherwise the rank condition is violated.

[10]The heating range of temperatures is estimated but not discussed in this paper. Heating fuel varies across vintage, with newer homes more likely to have natural gas as their primary heating fuel. In contrast, electricity is almost universally the energy source for cooling.

building design. The standard practice of using $ln(kWh\_useperday)$ as the dependent variable is one way to controls for square footage and size as discussed in Appendix B, but the other factors are captured by the vintage effect. Building standards do vary by vintage and are predicted via engineering estimates to have an impact on temperature response. However, building standards cannot be isolated from the other changes.[11] Hence, I interpret the estimate to Equations 4 and 3 as the cumulative impact of multiple changes.

In order to aid interpretation of the cumulative effect, available covariates can be added which can isolate some factors of the cumulative impact of vintage, but the remaining factors cannot be isolated. County assessor's data provide additional covariates for central air conditioning ownership and square footage at the zip9-level but only for areas almost entirely composed of single family homes. Using this data, the following auxiliary specifications can be run, the first with the degree day parameterization and the second with temperature bins. Importantly, building standards are not controlled for and would be part of the vintage effect.

$$
\begin{aligned}
ln(kWh\_useperday_{izt}) \;=\; & \sum_{v=1}^{VINTAGES} V_{zv} * (\beta_{1v}CDD_{it} + \beta_{2v}CDD_{it}^2 + \beta_{3v}HDD_{it} + \beta_{4v}HDD_{it}^2) \\
& + CentralAC_z * (\varphi_1 CDD_{it} + \varphi_2 CDD_{it}^2 + \varphi_3 HDD_{it} + \varphi_4 HDD_{it}^2) \\
& + SquareFootage_z * (\theta_1 CDD_{it} + \theta_2 CDD_{it}^2 + \theta_3 HDD_{it} + \theta_4 HDD_{it}^2) \\
& + \alpha_i + \varepsilon_{it} \qquad (5)
\end{aligned}
$$

$$
\begin{aligned}
ln(kWh\_useperday_{izt}) = \; & \textstyle\sum_{p=1}^{BINS} \Big(\displaystyle\sum_{v=1}^{VINTAGES} [\beta_{pv} V_{zv}] + \qquad (6) \\
& \varphi_p CentralAC_z + \\
& \theta_p SquareFootage_z \Big) * D_{pit} + \\
& \alpha_i + \varepsilon_{it}
\end{aligned}
$$

[11] There are two potential methods of estimating the causal impact of building standards. First, a regression discontinuity (RD) design may be possible if the treatment is discontinuous. However, building standards implementation could be slow and gradual, which would not be picked up by an RD design. Jacobsen and Kotchen (2009) apply an RD approach which assumes a sharp change in standards implementation. Second, cross state comparisons can be made, but the limitations of cross-state analyses has been discussed.

where

- i, z, t index households, zip9, and time (monthly billing period), respectively,
- V_{zv} is in [0,1] and represents the proportion of buildings in z for vintage v
- $CentralAC_z$ is the proportion of buildings with central air conditioning in z, and
- $SquareFootage_z$ is the median square footage for buildings in z.

With the census data, three variables are interacted with temperature response that vary at the census block group-level: (1) average ln(income), (2) average number of bedrooms (a proxy for size), and (3) the type of structure, *i.e.* Single Family or Multifamily or Mobile/Other. Equation 7 presents this auxiliary specification with the degree day parameterization.

$$
\begin{aligned}
ln(kWh\_useperday_{ijt}) \quad = \quad & \sum_{v=1}^{VINTAGES} V_{jv} * (\beta_{1v} CDD_{it} + \beta_{2v} CDD_{it}^2 + \beta_{3v} HDD_{it} + \beta_{4v} HDD_{it}^2) \\
& \sum_{s=1}^{STRUCTURES} STR_{js} * (\rho_{1s} CDD_{it} + \rho_{2s} CDD_{it}^2 + \rho_{3s} HDD_{it} + \rho_{4s} HDD_{it}^2) \\
& + AvlnIncome_j * (\gamma_1 CDD_{it} + \gamma_2 CDD_{it}^2 + \gamma_3 HDD_{it} + \gamma_4 HDD_{it}^2) \\
& + AvBedrooms_j * (\delta_1 CDD_{it} + \delta_2 CDD_{it}^2 + \delta_3 HDD_{it} + \delta_4 HDD_{it}^2) \\
& + \alpha_i + \varepsilon_{it} \qquad (7)
\end{aligned}
$$

STR_{js} is in [0,1] and represents the proportion of buildings in j for the type of structure, s. $AvlnIncome_j$ is the average of ln(income) per household in j. $AvBedrooms_j$ is the average bedrooms per household j. j indexes census block groups. Importantly, building standards and measures of air conditioning ownership are not available as covariates in this specification.

An important property of estimates of temperature response is that they are immune to many types of omitted variable bias. In order for omitted variable bias to bias temperature response results, two conditions must be met. First, the omitted variable must vary across vintage. Second, the omitted variable must be correlated with temperature. A variable, such as price, that does not vary within this region nor by temperature, would not bias results, except if price elasticities for cooling varied across vintages. Aroonruengsawat and Auffhammer (2009) included price as a regressor in estimating regional temperature response and found that it did not affect results.

5. Results

5.1. **Main Results: Degree Day Parameterization With County Assessor's Data.**

Results presented in this subsection use the degree day parameterization and county assessor's data. Alternative specifications follow this subsection.

I first estimate the average temperature response across all households given earlier by Equation 2. Column A1 of Table 4 and Figure 6 present the results of the estimation using fixed effects panel regression with standard errors clustered at the zip9 level. This shows the strong increase in electricity in response to temperature for both higher and lower temperatures, relative to 65°F.

Next, I estimate temperature response *by vintage* as given earlier by Equation 3. Column A2 of Table 4 and Figures 7 to 10 present the results of the estimation. The omitted vintage variable is pre1970s, so the coefficients on the remaining variables are differences from the temperature response of pre1970s buildings. Figure 7 is the temperature response for pre1970s buildings. Figures 8 to 10 are for each other vintage relative to pre1970s buildings. Each figure has a horizontal line at zero to indicate what would result if there were no difference between vintages. To interpret these results, the 1970s, 1980s, and 1990s vintage of buildings have statistically significantly higher temperature response than pre1970s buildings. The highest temperature response is for 1990s buildings, followed by 1980s buildings, 1970s, and then pre1970s buildings.

Lastly, I estimate temperature response by vintage with some controls interacted with temperature response, as given by Equation 5. These controls capture variation in temperature response that is correlated with central air conditioning and square footage. Results are in Column A3 of Table 4 and Figure 11 which combines the graphs. Central air conditioning strongly positively increases temperature response and is more prevalent in newer buildings. Square feet negatively impacts CDD; this means that the percentage increase in electricity on a hot day is *less* for larger buildings. As discussed in the Appendix B, the main econometric specification assumes comparability across households of different size by comparing percent changes. In the figure, all of the temperature response curves shift downward because new buildings more often have air conditioning. 1970s buildings are not statistically significantly different from pre1970s buildings after adding controls. 1980s and 1990s buildings are still more temperature responsive after adding controls.

5.2. **Robustness checks.**

To guard against the possibility that some of these results are driven by parametric assumptions on size, I re-estimate the previous regression and restrict square footage to 1300 to 1600 square feet which reduced the observations by about two-thirds. Estimation results are presented in Column A4 of Table 4 and Figure 12. The signs of the Square Foot $\times$ CDD and Square Foot $\times$ CDD^2 variables change, but it is also less statistically significant. Even with this change, cumulative responses by vintage with controls are similar to the main results.

The degree day parameterization may be overly restrictive. I run analogous regressions but with temperature binning instead of the degree day parameterization. Equation 4 presents the regression without controls. Results are given in Figure 13. Equation 6 presents the regression with controls. Results are given in Figure 14.[12] Results are similar to the main results. Without controls, all vintages have statistically higher temperature response for bins higher than 65°F. With controls, 1970s buildings are not statistically significantly different from pre1970s buildings for all bins, and 1980s and 1990s buildings are more temperature responsive.[13]

In each of these cases, the $ln(kWh_{perday})$ specification compares households in terms of the percent change in electricity use relative to each house's fixed effect, *i.e.* their temperature invariant mean usage. An alternative approach is to compare each household's temperature response in levels (as opposed to percentages) and control explicitly for size. This alternative is discussed and estimated in Appendix B. Referring to Figure 15, this parameterization

[12] Regression tables available upon request.

[13] Note that caution should be used when looking at the lowest and highest temperature bins. These bins contain outliers and the intra-bin temperature distribution across vintages is quite large. Newer buildings have more data points in the highest temperature bin.

shows that the predicted temperature response for all vintages of buildings are not statistically significantly different from the reference group of pre-1970s buildings. Standard errors are larger.

An alternative data source is census data which offers some advantages. Census data is not restricted to single family homes and includes income and other socioeconomic information. The disadvantage is that census block groups are larger geographically, so there is less spatial variation and more potential for bias from aggregation, as discussed in Appendix C. Regressions are run with census block data. Figure 16 shows the temperature response by vintage after estimating Equation 3. 1980s and 1990s homes hive a higher temperature response that is not statistically significantly different from pre1970s homes, but 1970s homes have a lower temperature response. Standard errors are much larger due to the decrease in number of areas. There are 372 census block group areas compared to 9316 Zip9's areas. Figure 17 shows the the results of estimating temperature response by vintage with controls for income, size, and type of structure, as described in Equation 7. Note that air conditioning is not available at this spatial resolution and is not used as a control. With controls, results change dramatically. 1970s buildings have a higher temperature response that is not statistically significant. 1980s and 1990s buildings have a higher temperature response that is statistically significant. The reason for the upward shift is that 1970s and 1980s buildings had a higher proportion of apartments which have lower temperature response. After controlling for this, both curve shifted upward. For the 1990s buildings, income has a negative effect on temperature response and households in newer building have higher income. After controlling for this, the the 1990s curve shifts upward.

Total usage is another way to compare electricity use across households. This research focuses on temperature response under the argument that temperature response isolates elements of the building and household preferences only for cooling and heating services. In contrast, total usage captures many other differences across vintages, such as the number and type of appliance. Appendix A discusses this in more depth. The results, as presented in Table 5, shows that new homes use statistically significantly more electricity than older homes in total electricity use (Column T1). This is expected since new homes are larger. After adding controls for square footage and central air conditioning (Column T2), new houses use statistically significantly less electricity. Further adding controls for temperature across vintages (Column T3), new homes still use less electricity, and the coefficient on central air conditioning without temperature interactions becomes statistically insignificantly different from zero.

6. Policy Significance and Potential Mechanisms

6.1. **Policy Significance.** The results show that, in Riverside County, the cumulative temperature response for buildings has been stronger for newer buildings (1980s and 1990s) than for older buildings (1970s and pre1970s). This has two main policy impacts, one for load forecasting and one for the impacts of climate change given that the composition of the building stock is changing to something more temperature responsive.

First, in conducting load forecasts, these results suggest that new construction will increase the average temperature response and increase peak load on the hottest days. As a calibration, the population forecasts of RAND (RAND California 2010) predict an average annual population increases of 2.6% for Riverside County. Applying this growth to Riverside County and assuming that new construction has the same temperature response as 1990s buildings, Figure 18 predicts the increase in average temperature response on a 75°F day to go from 48.8% to 52.3% from today to 2020. Peak demand will increase proportionately as well. This is comparable to the estimated 3.7% increase in peak demand due to a 1.9°C increase in temperature as estimated by Baxter and Calandri (1992).

Looking at the issue of air conditioning statewide potentially could have an even greater effect. This is because coastal areas have historically had a lower amount of air conditioning, but the CEC revised forecast commented that there was an unexpected increased air conditioner saturation in cooler areas. Table 6 presents air conditioning saturation for old versus new housing by forecast climate zones from KEMA-XENERGY (2004) data. Figure 19 gives a map of the zones. Coastal areas that have very low ownership of air conditioners for older buildings have dramatically increased air conditioner ownership for newly built buildings.

Second, climate change impacts will be exacerbated with the increased temperature response from newer houses. Using the same calculation as given in Figure 18 above, I can predict the difference in climate change impacts adjusting for the estimate that new buildings are more temperature responsive. In 2050, Riverside's population is predicted to more than double. For a 5°F increase due to climate change, temperature response will be about 2-3%higher with the addition of new buildings compared to the current building stock.

6.2. **Potential Mechanisms.** As previously discussed, it is not possible to separate out the mechanism of the vintage-differentiated temperature response. The heterogeneity by vintage was first estimated, and then controls for observables were included, which captured some of the heterogeneity. The remaining temperature response is from the other factors.[14] One of the remaining factors that are part of the vintage temperature response coefficients were policy developments. This would include building standards implemented in 1975, 1979, 1984, and 1992 and appliance standards implemented in 1978 and 1987.

After controlling for differences in air conditioning, the remaining differences across households of different vintages is smaller and depends on the specification used. In the main log specification with controls for central air conditioning ownership, new buildings had statistically significantly higher temperature response by a small amount (Figure 11). Using a level specification and restricting the sample to houses of similar size, new homes performed slightly better, but not statistically significantly so (Figure 15).

Engineering estimates provide a prediction of the impact of buildings standards absent any other changes. Building standards have also varied by vintage and are predicted to reduce temperature response significantly by 34-56% for new versus old buildings. The CEC identifies four significant changes in building standards and estimates the savings from those standards with engineering models (Marshall and Gorin (2007) and Abrishami et al. (2005)). I summarize and report the savings from in Table 8. Total load reduction is about 6% from engineering estimates. However, to make this result comparable to my estimates, two adjustments must be considered. First, building standards only affect new construction

[14]This relies on the assumption that the other factors are uncorrelated. Otherwise, the included controls would pick up other factors through correlation with omitted variable.

and major renovation; these are represented in the fourth column which has the population increase since the standard went into effect as a proportion of the current population. Also, building standards only affect the temperature response component of electricity use. I calculate the implied reduction in Temperature Response, -34% to -56% from each building standard in the last column.

The juxtaposition of similar temperature response across vintages and a large predicted decrease in temperature response due to building standards suggests that other factors have had a large positive effect for new houses. There are multiple potential mechanisms, none of which the data can separate out. Behavioral responses, such as those driven by the rebound effect (Greening et al. 2000) can increase temperature response. This would mean that part of the increase is due to an increase in comfort from using more cooling services. New buildings may differ in their thermal design in that they may have taller ceilings, more structural complexity, or a higher window-to-wall ratio; all of which may increase the electricity needed to cool a building. It is also possible that there is sorting, where people who favor more cooling services are more likely to live in new buildings. Another possibility is that standards may not have been as effective as they have claimed, following the logic of Joskow and Marron (1992). These are factors that would need to be carefully considered when designing and evaluating of building standards.

6.3. **Future Work.** Billing data are available for a large portion (about 80%) of California and future work will estimate this specification across the entire state. Though the average temperature response in coastal areas is low, according to Aroonruengsawat and Auffhammer (2009), the CEC reports suggest that new construction in lower temperature areas on the coast has had higher than anticipated air conditioning ownership. In fact, Table 6 shows that air conditioning ownership has increased strongly in both coastal and inland areas. Estimation of the entire state would enable me to aggregate county-level estimates to a statewide average cumulative temperature response.

This research also presents a puzzle about the causes of the Rosenfeld Curve, shown in Figure 1. Since the mid 1970s, per capita electricity consumption for California has been flat while it has increased 50% for the United States. The breakpoint in the 1970s coincided with the establishment of aggressive energy efficiency policies. The Rosenfeld Curve coupled with engineering estimates suggest that California's policies have been very effective, but this research suggests that, in terms of temperature response, the net effect has been that newer buildings increase temperature electricity use more than older ones in response to high temperatures in Riverside County, one of California's hottest counties. Several other drivers (most notably, population growth biased toward hotter areas which have higher electricity use) would also increase aggregate per capita electricity consumption. The resulting puzzle is why California has had a flat per capita electricity profile despite these drivers that would strongly push electricity use upwards. To try to understand the aggregate effect, I will look at patterns of population growth, housing size (square footage), and changes in heating fuel in addition to the heretofore studied differences between new and old residential buildings in temperature response.

7. Conclusion

The contribution of this paper is to focus on the relationship between building vintage and temperature response in residential buildings in California. The main finding is that temperature response for buildings varies by vintage: new buildings (1970-2000) have a statistically significantly higher temperature response (*i.e.* use more electricity in response to higher temperature) than old buildings (pre-1970). This is robust to many specifications. The cumulative positive effect for temperature response in new buildings means that increased air conditioning ownership and other factors have outweighed other energy-saving impacts, such as building standards applied to new residential buildings.

This result has two main implications, one for electricity demand forecasting and one for climate change impacts. First, since new residential buildings have higher temperature response, this means that the average temperature response is expected to go up as new buildings are added. Peak electricity load will also increase, even with climate held constant. Second, if temperatures increase due to climate change, the new residential buildings will exacerbate the increase in peak load.

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Appendices

Appendix A. Total electricity vs temperature response

This appendix provides estimates that compare the differences in the total electricity use across households of different vintages. Note that because the variation in age of housing does not vary over time, this precludes the use of household fixed effects. Vintage effects will include differences across households that are not related to the building, such as increases in the amount of appliances or televisions.

Regression results are shown below using a random effects specification with clustering at the ZIP9 level in Table 5. The first column shows that newer buildings have larger utility bills, with no clear pattern across decades. The second column two adds a control variable for square footage. Size increases total electricity use, as expected, but the estimates have 1990s and 1980s buildings using less energy after controlling for size, whereas 1970s buildings use slightly more than pre1970s buildings. The third column adds controls for temperature interacted with all variables; the signs of the vintage coefficients are unchanged.

Though interesting empirical regularities, the coefficients on the vintage variables are hard to interpret. They can be rationalized both by increasing efficiency of appliances in new buildings or fewer appliances in new buildings of comparable size.

It is important to note that newer buildings have a larger temperature invariant component (Column T1), which means that the same percentage increase in new buildings and old buildings (due to temperature difference) also means a higher change in kWh for the new buildings.

Appendix B. Functional Form

The function form used in electricity regressions varies across studies, with the literature split between have $ln(kWh_{useperday})$ (dubbed "ln") or $kWh_{useperday}$ (dubbed "levels") as the LHS variable. In many cases, the choice is ad hoc, justified on the grounds that the ln specification compares percent changes across observations which roughly controls for size.

In KEMA-XENERGY (2004), a conditional demand analysis framework is used that is motivated by the concept of summing up the loads of each appliance separately, in which case levels are the appropriate regressand and temperature response is scaled by some measure of the size of a house.

First, I present a mathematical justification for the ln specification. Second, I present some results using levels as the regressand after making appropriate adjustments. The results across vintage are similar.

$$
\begin{aligned}
kwhperday_{it} &= base_i + heat_{it} + cool_{it} && (8)\\
kwhperday_{it} &= base_i + f(weather) \times f(size) \times f(other) && (9)\\
kwhperday_{it} &= base_i + Z && (10)\\
ln(kwhperday_{it}) &= ln(base_i) + \frac{1}{base_i} * Z && (11)\\
&\quad \text{via Taylor approximation around Z=0} && \\
ln(kwhperday_{it}) &= ln(base_i) + \frac{1}{base_i} * f(weather) \times f(size) \times f(other) && (12)\\
&\quad \text{assuming } \frac{f(size_i)}{base_i} = Q, \text{ a constant} && \\
ln(kwhperday_{it}) &= ln(base_i) + Q * f(weather) \times f(other) && (13)
\end{aligned}
$$

The derivation above begins with a partition of energy use into a base usage that is temperature and time invariant followed by heating and cooling loads that vary by time through weather's variation over time. The next step takes the natural log and then expands via a Taylor expansion. Under the maintained hypothesis that a function of size enters multiplicatively and that the ratio of base usage to the function of size is constant, size can then be omitted. Intuitively, this specification assumes that percent changes of bills are the comparable metric across buildings of different size. The $f(other)$ term would include vintages, housing characteristics, and household characteristics. [15]

[15] A reasonable alternative approach would be to use Box-Cox transformations to estimate nonlinearly the impact of size and choosing the model with the best fit.

Alternatively, one could directly estimate Equation 9 by choosing a functional form for $f(weather) \times f(size) \times f(other)$ when such data is available at a fine spatial resolution. My data at the Zip9-level, which on average has 5-10 households, is spatially more disaggregated than most other data. Weather was parameterized as a function of CDD and HDD and its squares.

A natural assumption to make is that cooling and heating loads scale by size, so that $f(size) = sqft$. This turns out to not be a good assumption, as shown below. I first estimate the cumulative temperature response across vintages without other controls as described in Equation 14.

$$\begin{aligned} kWh\_useperday_{ijt} \;=\; & \sum_{v=1}^{VINTAGES} V_{jv} * (\beta_{1v} SQFT \times CDD_{it} + \beta_{2v} SQFT \times CDD_{it}^2 + \\ & + \beta_{3v} SQFT \times HDD_{it} + \beta_{4v} SQFT \times HDD_{it}^2) \\ & + \alpha_i + \varepsilon_{it} \end{aligned} \tag{14}$$

The results in Figure 20 show that new buildings are much less temperature responsive, contrary to other specifications. I then re-estimate this constrained to areas where the sqft variable is between 1300 and 1600 sqft which is a range of sqft with substantial overlap for all vintages. The results in Figure 21show that new buildings perform worse, as is expected because they have much more air conditioning. The reason the two results differ is because the density of the sqft variable is larger for new houses and cooling and heating loads scale less than proportionately to sqft. Hence, the assumption that $f(size) = sqft$ overcorrects for size.[16]

While still using levels, I estimate a less functionally constrained version of $f(weather) \times f(size) \times f(other)$ in Equation 9. Size is restricted to sqft between 1300 and 1600. $f(size) = (\alpha_0 + \alpha_1 * sqft)$ which is a first order approximation applied to this narrow range of sqft. A similar first order approximation is used for air conditioning, and vintage is given by an

[16]KEMA-XENERGY (2004) models cooling load as scaling by external surface area. If a building doubles in size, the external surface area will less than double. For example, a cube on the ground has 5 external faces (one exposed to the ground), but two cubes side by side only have 8 external faces.

indicator variable, similar to the main specification. The final specification has 64 parameter estimates.

$$
\begin{aligned}
kwhperday_{it} &= base_i + f(weather) \times f(size) \times f(other) \\
&\quad \text{where} \\
f(weather) &= \gamma_1 CDD + \gamma_2 CDD^2 + \gamma_3 HDD + \gamma_4 HDD^2 \\
f(size) &= \alpha_0 + \alpha_1 * sqft \\
f(other) &= \sum_{v=1}^{VINTAGES} \delta_v * VintageDummy_v * (\delta_0 + \delta_{CAC} * CentralAirConditioning)
\end{aligned}
\tag{15}
$$

Figure 15 shows the results of the regression by predicting the value of electricity consumption $kwhperday_{it}$, for a reference 1500sqft house with central air conditioning for each vintage. Because of the large number of covariates, the regression results are omitted. The results show that the 1990s and 1970s buildings may have lower temperature response after controlling for air conditioning and size, but that the difference is not statistically significant. Focusing just on the 1990s buildings, the range of the difference at 75°F is -2 to +1.5 kwhperday. This translates into an -8% to +6% which is lower than the range given by the main specification.

Appendix C. Aggregation

The aggregation issue can be described by referring to the discussion of Blundell and Stoker (2005) which focuses on aggregation issues in demand systems and other scenarios. Aggregation presents biases when the underlying data generating process has cross-terms and there are non-zero covariances. For example, the following data generating process has no cross terms and could be estimated by data aggregated spatially across j.

$$
\begin{aligned}
y_{ij} &= \beta_0 + \beta_1 * x_{ij} + \beta_2 * z_{ij} + \varepsilon_{ij} && (16)\\
E_j[y_{ij}] &= \beta_0 + \beta_1 * E_j[x_{ij}] + \beta_2 * E_j[z_{ij}] + E_j[\varepsilon_{ij}] && (17)\\
y_j &= \beta_0 + \beta_1 * x_j + \beta_2 * z_j + \varepsilon_j && (18)
\end{aligned}
$$

In the presence of a cross term, the aggregation presents bias if there are covariances. In the example below, the relationship between the individual level coefficient, β_3, and the aggregate regression parameter, γ_3, is $\beta_3 = \gamma_3 \times \frac{E_j[x_{ij}]*E[z_{ij}]}{E_j[x_{ij}*z_{ij}]}$. The two equal if an only if the covariance, $Cov(x_{ij}, y_{ij})$, is zero.

$$
\begin{aligned}
y_{ij} &= \beta_0 + \beta_3 * x_{ij} * z_{ij} + \varepsilon_{ij} && (19)\\
E_j[y_{ij}] &= \beta_0 + \beta_3 * E_j[x_{ij} * z_{ij}] + E_j[\varepsilon_{ij}] && (20)\\
E_j[y_{ij}] &= \beta_0 + \beta_3 * (E_j[x_{ij}] * E[z_{ij}] + Cov(x_{ij}, y_{ij})) + E_j[\varepsilon_{ij}] && (21)\\
y_j &= \beta_0 + \gamma_3 * x_j * z_j + \varepsilon_j && (22)
\end{aligned}
$$

Aggregation problems are less likely with county assessor's data than with census block group data. County assessor's data is matched at the Zip9-level, which is about 5-10 households. Hence, it is hoped that covariates in a Zip9-level are relatively homogeneous in terms of house size, vintage of year built, and ownership of air conditioning. Census block groups, at 300-700 households each are much more likely to have these issues.

I have not done aggregation of bill to the census block or zip code level. Aggregation of all bills within a census block group can be done only if the panel is balanced; otherwise some bills exist in some years but not in others. A large proportion of properties have occupant turnover. If occupant turnover were random, dropping unbalanced observations would not present bias, but it is plausible that certain homes are more likely to have occupant turnover.

Appendix D. Extended Data Discussion

There are two datasets depending on the building characteristic information used. The first dataset uses ZIP9-level data from county assessor's information. The second dataset uses census block group-level data from the 2000 Census.

The billing data was cleaned. Bills with 25 days or less or 35 days or more were dropped (about 5%). Bills with less than 2kWh/day or more than 80kWh/day are outliers were also dropped (about 4%).

For the ZIP9 data, assessor's data primarily includes complete records of square footage, year built, and air conditioning ownership for single family homes. Records were dropped if there was more than 10 bedrooms, square footage less than 200 or greater than 10000, missing ZIP code, or the structure was built before 1850 or after 2000. Many of these were obvious data errors because they contained internally inconsistent values, such as many bedrooms but very little square footage. Census block group information was used to identify areas where more than 95% of the households were in single family structures and decreases the sample to this area. Next, at the ZIP9-level, the proportion of houses with central air conditioning, the median structure size, and the proportion of buildings built in each vintage category were attributed to each bill in that associated ZIP9.

For the census block group data, a 1-in-5 subsample of observations was used to enable the estimation to be run on a Linux server with 8GB of RAM and an Intel Quadcore processor, running Stata 10.0 MP.

The spatial matching of weather, census block groups, and ZIP9s merits some description. Weather data is available on a 4km x 4km grid. Census block groups are given as polygons. ZIP9s are given as points, but the ZIP9 are ranges of street addresses. Typically opposite sides of the street will have different ZIP9s. To describe the matching from the perspective of the bill, the bill's ZIP9 is matched to the census block group and 4km by 4km grid square that contains the Zip9 point.

FIGURE 1. The "Rosenfeld" Curve. Per capita electricity sales for California and the United States, annually from 1960-2006. Source: California Energy Commission (2007).

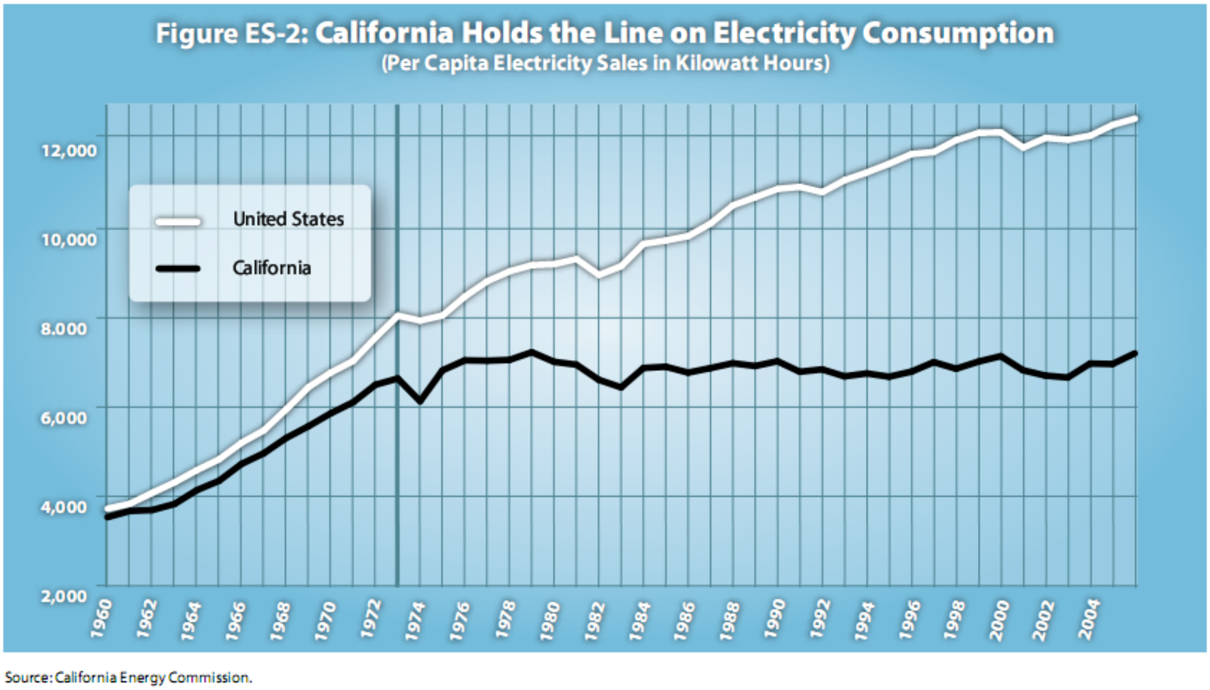


FIGURE 2. Per capita *residential* electricity sales for eight western states, 1963-2004 . Source: Energy Information Administration (2007).

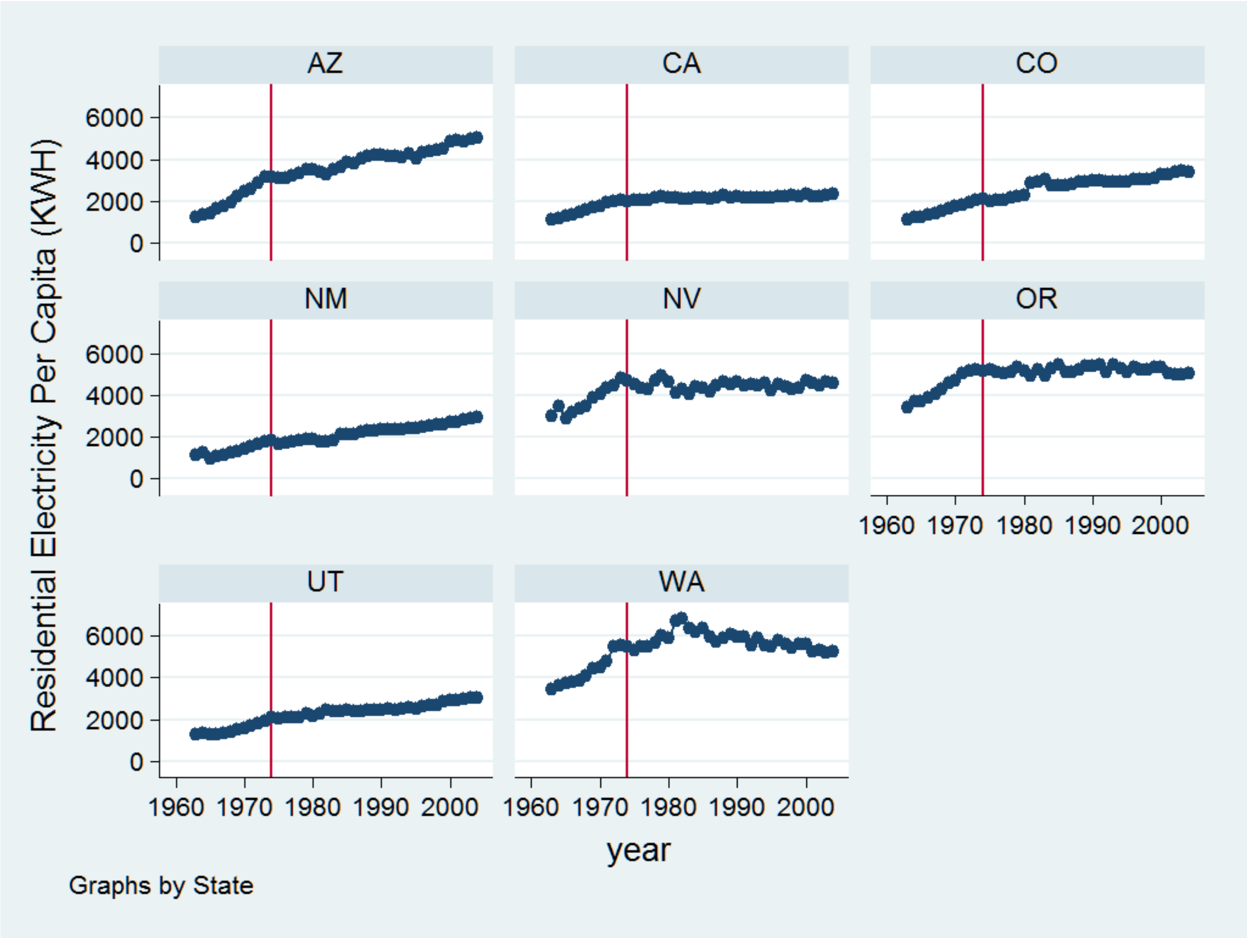


FIGURE 3. Variation in building vintage in Riverside County, California, USA. Shading represents proportion of buildings built since 1980. Darker means higher proportion of new buildings.

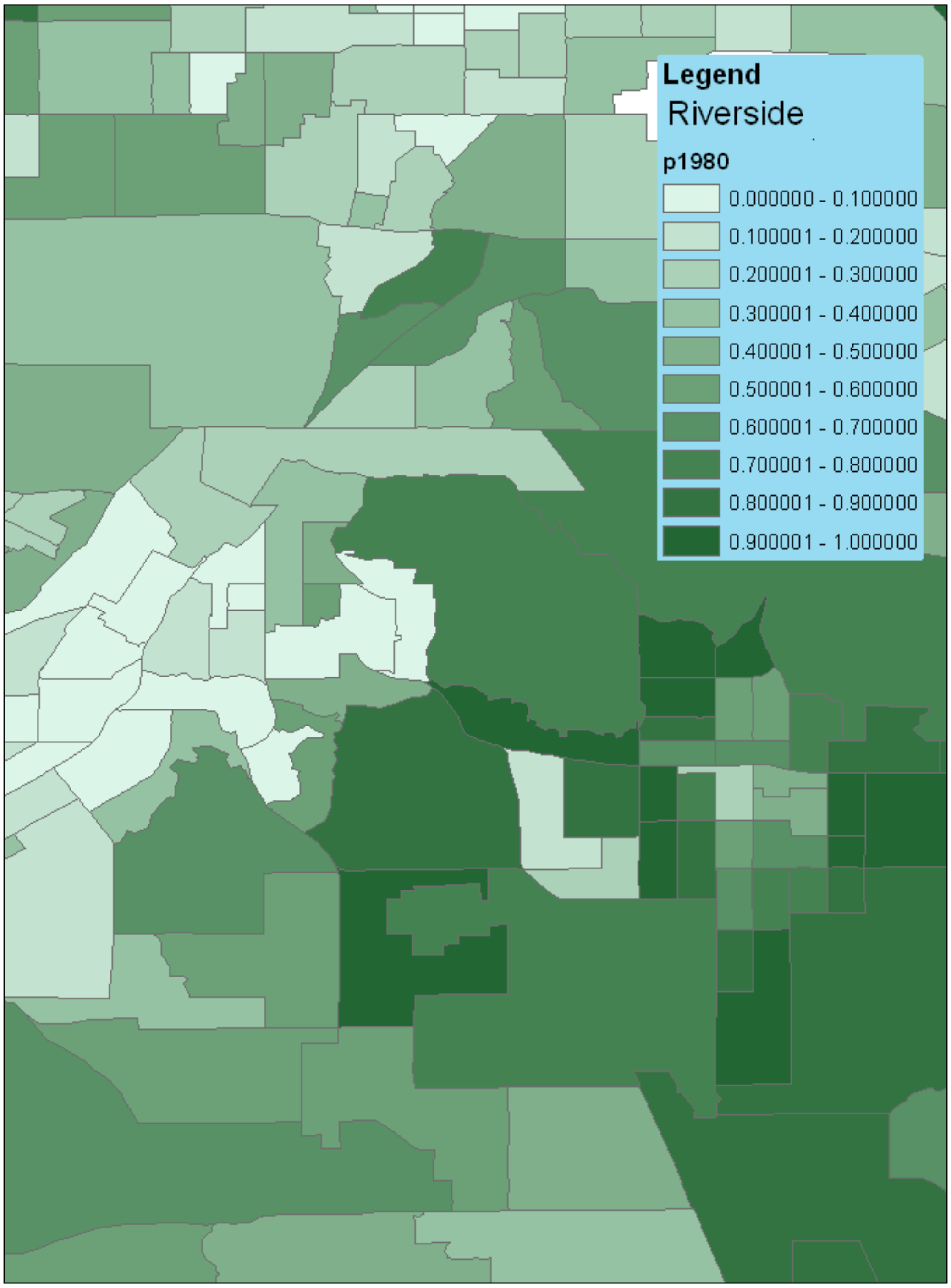


Table 1. Temperature bins.

Bin Number	Temperature Range
bin0	0-51.96°F
bin1	51.96-55.89°F
bin2	55.89-59.25°F
bin3	59.25-62.70°F
bin4	62.70-66.39°F
bin5	66.39-70.54°F
bin6	70.54-74.37°F
bin7	74.37-78.30°F
bin8	78.30-84.02°F
bin9	84.02-130°F

FIGURE 4. Electricity Use (KWH) vs time for one sample household. Source: Author's data.

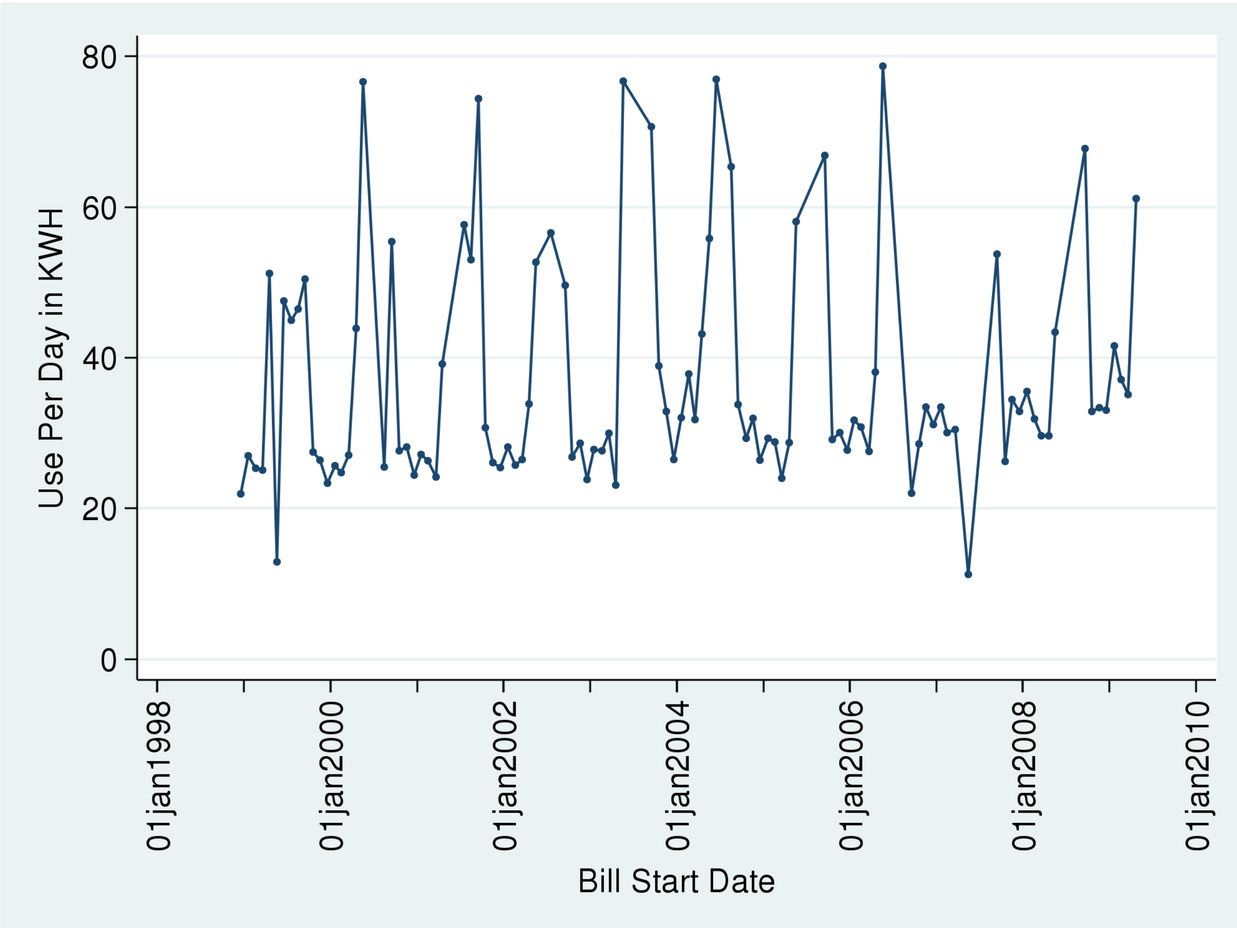
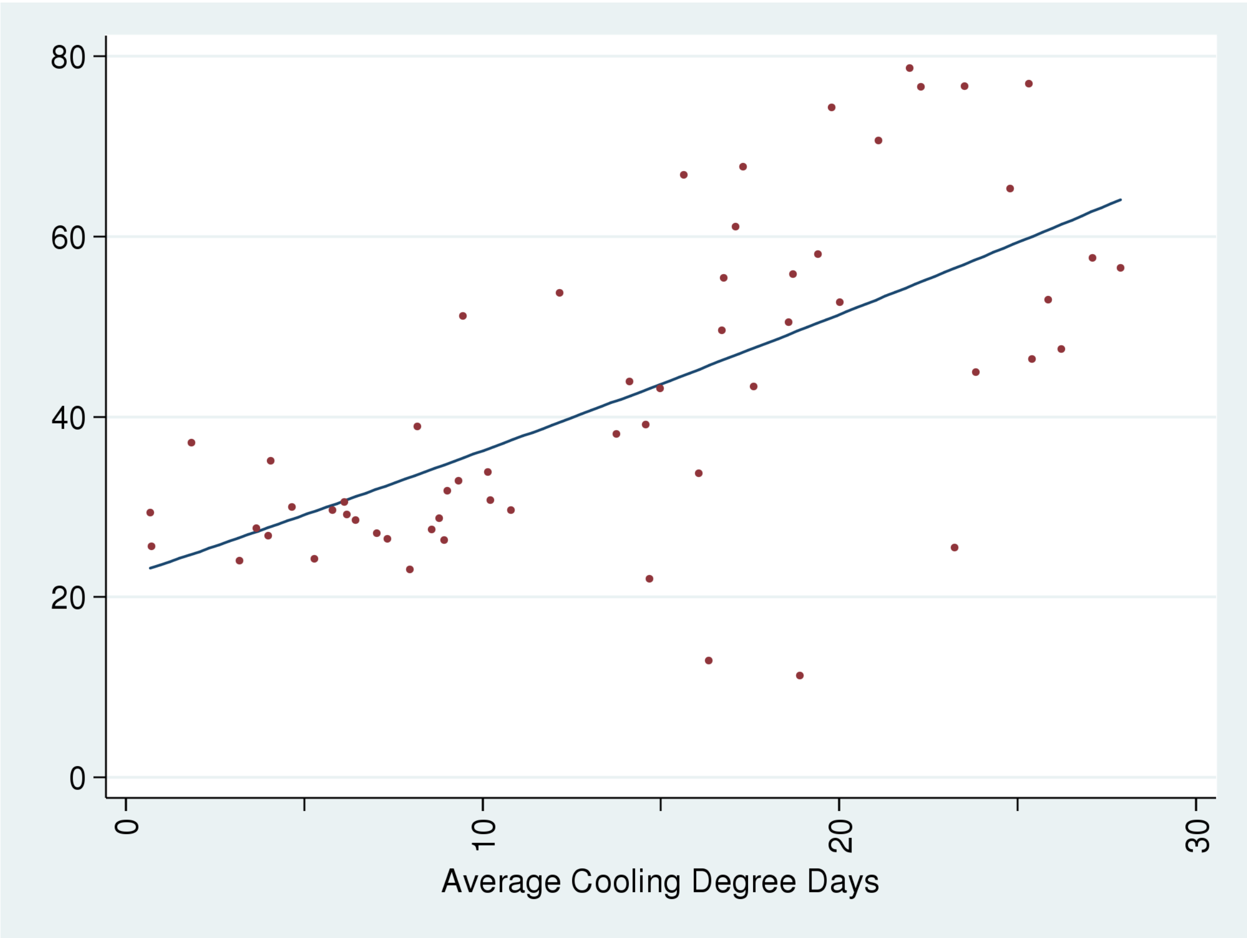


FIGURE 5. Electricity Use (KWH) vs cooling degree days for one sample household. Source: Author's data.



Note: Days with heating degree days were omitted.

Table 2: Summary Statistics.

Variable	Mean	Std. Dev.	Min	Max
BILLING DATA				
useperday	24.73	14.20	2.03	79.97
days	30.43	1.50	26	34
ASSESSOR'S DATA				
Building Age				
proportion built prior to 1970	0.15	0.36	0	1
proportion built in 1970s	0.16	0.36	0	1
proportion built in 1980s	0.54	0.50	0	1
proportion built in 1990s	0.15	0.36	0	1
Other Characteristics				
Square Feet	1750	480	360	7138
Has Central Air Conditioning?	0.88	0.28	0	1
for pre1970s	0.407			
for 1970s	0.847			
for 1980s	0.986			
for 1990s	0.995			
Observations (no subsampling)	5,106,398			

Table 3: Summary Statistics.

Variable	Mean	Std. Dev.	Min	Max
BILLING DATA				
useperday	21.61	14.56	2.03	79.97
days	30.43	1.52	26	34
CENSUS DATA				
Building Age				
proportion built prior to 1970	0.23	0.24	0	1
proportion built in 1970s	0.20	0.16	0	1
proportion built in 1980s	0.36	0.22	0	0.94
proportion built in 1990s	0.21	0.21	0	0.98
Type of Structure				
proportion SingleFamily	0.64	0.30	0	1
proportion MultiFamily	0.28	0.28	0	1.00
proportion MotorOther	0.073	0.15	0	0.84
Other Characteristics				
Average Bedrooms	2.57	0.62	0.89	4.36
Average Rooms	5.23	1.01	2.31	8.00
Average Income	$48,200	$16,600	$13,000	$108,900
Observations (1-in-5 subsample)	5303019			

TABLE 4. Estimation results, temperature response with CDD and HDD parameterization, assessor's data.
Dependent variable is $ln(KWH\_perday)$

VARIABLES	(A1)	(A2)	(A3)	(A4)
CDD	0.0553*** [0.000330]	0.0460*** [0.000930]	0.0355*** [0.00149]	0.0476*** [0.00321]
HDD	0.0274*** [0.000268]	0.0293*** [0.000905]	0.0231*** [0.00132]	0.0326*** [0.00286]
CDD^2	-0.000283*** [1.61e-05]	-0.000185*** [4.44e-05]	0.000234*** [8.27e-05]	-0.000270* [0.000164]
HDD^2	-0.000590*** [1.87e-05]	-0.000743*** [6.64e-05]	-0.000260*** [8.93e-05]	-0.000802*** [0.000191]
Built in 1990×CDD		0.0149*** [0.00121]	0.0108*** [0.00160]	0.00871*** [0.00300]
Built in 1980×CDD		0.0117*** [0.00103]	0.00482*** [0.00141]	0.00827*** [0.00246]
Built in 1970×CDD		0.00393* [0.00201]	0.000171 [0.00210]	0.000292 [0.00371]
Built in 1990×HDD		-0.00049 [0.00109]	-0.00306** [0.00139]	-0.00364 [0.00248]
Built in 1980×HDD		-0.00195** [0.000976]	-0.00502*** [0.00125]	-0.00359* [0.00208]
Built in 1970×HDD		-0.00800*** [0.00161]	-0.00980*** [0.00169]	-0.00984*** [0.00295]
Built in 1990× CDD^2		-0.000242*** [5.61e-05]	-0.000151** [6.81e-05]	-3.00E-05 [0.000116]
Built in 1980× CDD^2		-0.000130*** [5.00e-05]	7.86E-05 [5.98e-05]	-2.47E-05 [9.66e-05]
Built in 1970× CDD^2		7.56E-05 [0.000114]	0.000147 [0.000113]	0.000384** [0.000195]
Built in 1990× HDD^2		0.000128* [7.71e-05]	0.000114 [9.32e-05]	0.000201 [0.000154]
Built in 1980× HDD^2		0.000156** [7.02e-05]	0.000263*** [8.61e-05]	0.000261* [0.000133]
Built in 1970× HDD^2		0.000674*** [0.000106]	0.000737*** [0.000109]	0.000598*** [0.000186]
Central Air Conditioning×CDD			0.0160*** [0.00186]	0.00803** [0.00318]
Central Air Conditioning×HDD			0.00822*** [0.00164]	0.000798 [0.00275]
Central Air Conditioning× CDD^2			-0.000554*** [8.98e-05]	-0.000287* [0.000151]
Central Air Conditioning× HDD^2			-0.000534*** [0.000110]	-0.00014 [0.000181]

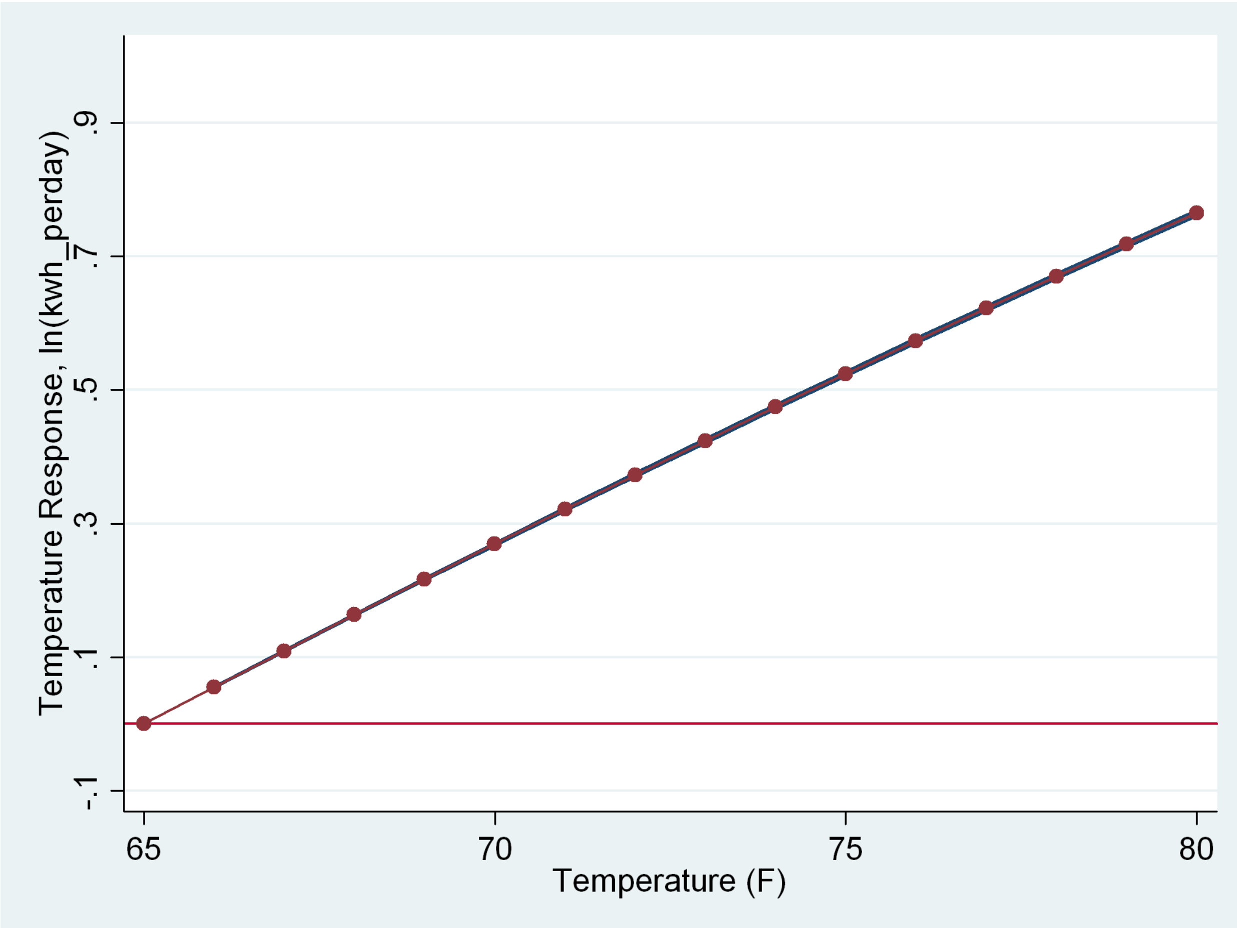
regression results continued

continuation of regression results

VARIABLES	(A1)	(A2)	(A3)	(A4)
Square Feet×CDD			-0.00516*** [0.000482]	0.00621** [0.00295]
Square Feet×HDD			-0.00239*** [0.000360]	0.00540** [0.00257]
Square Feet× CDD^2			0.000241*** [2.66e-05]	-0.000235* [0.000134]
Square Feet× HDD^2			0.000243*** [2.16e-05]	-4.91E-05 [0.000164]
Constant	2.704*** [0.00122]	2.705*** [0.00138]	2.710*** [0.00151]	2.597*** [0.00244]
Observations	5,625,517	5,625,517	5,625,517	1,652,525
R-squared	0.363	0.366	0.367	0.414
Number of aididlong	118,252	118,252	118,252	37,984

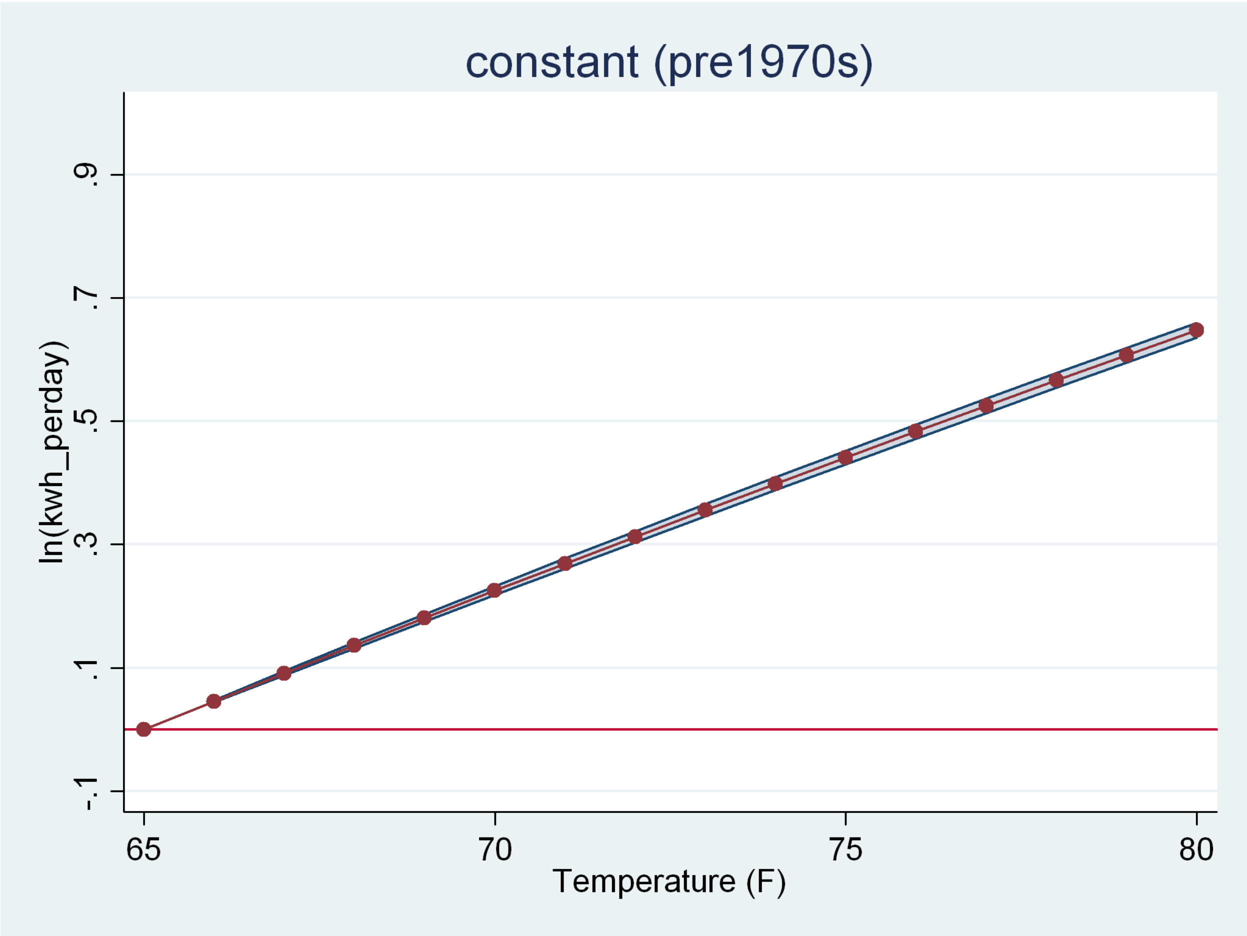
Includes household-level fixed effects. 5,303,019 observations over 159,819 households. *,**,*** represent 10%, 5%, and 1% statistical significance, respectively. Robust standard errors clustered at the Zip9-level. †The square feet variable has been demeaned (1750 square feet) and rescaled by the population standard deviation (480 square feet).

FIGURE 6. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, average across all vintages
Dependent variable is $ln(KWH\_perday)$



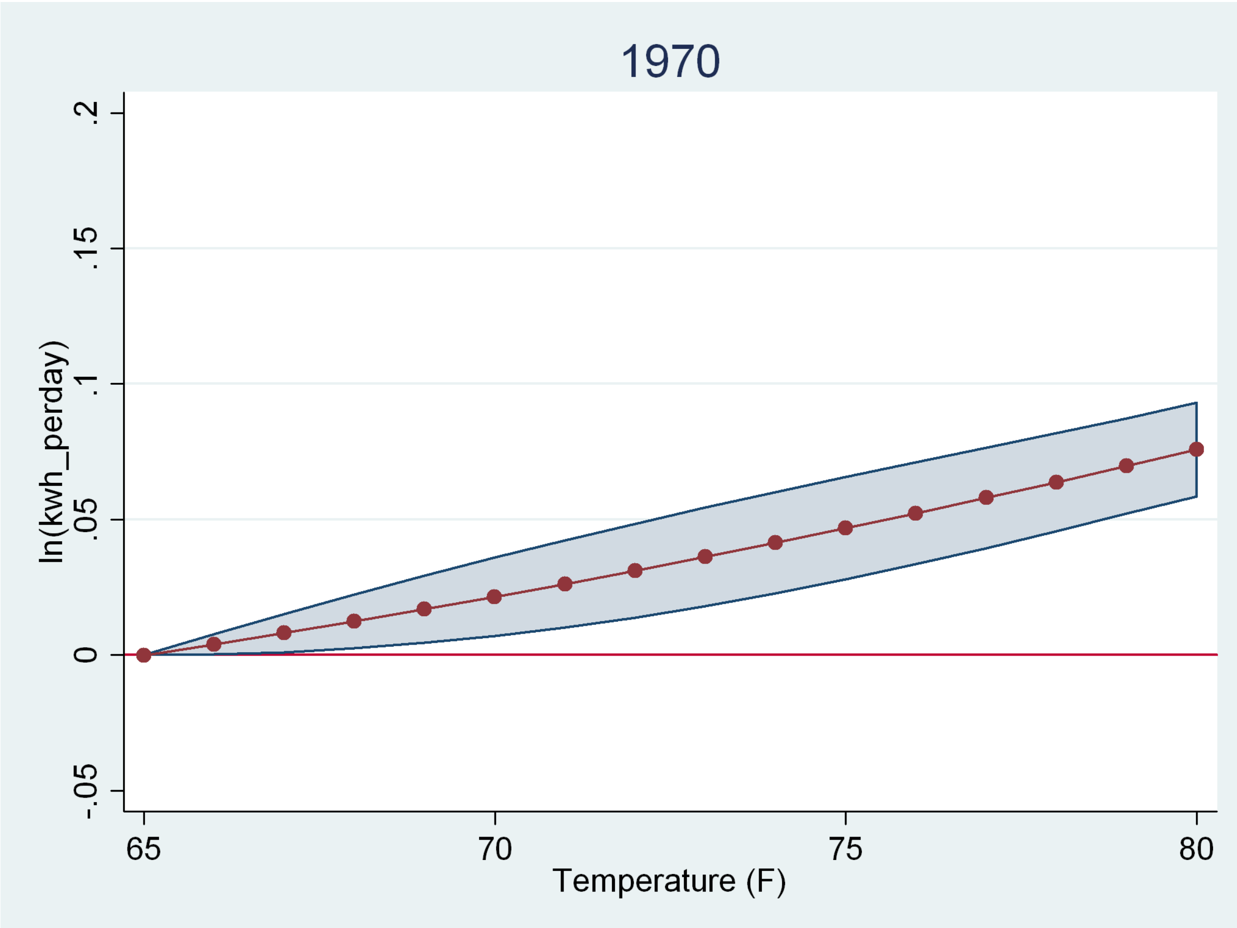
The range represents the 95% confidence interval.

FIGURE 7. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage. pre1970s reference curve. Dependent variable is $ln(KWH\_perday)$



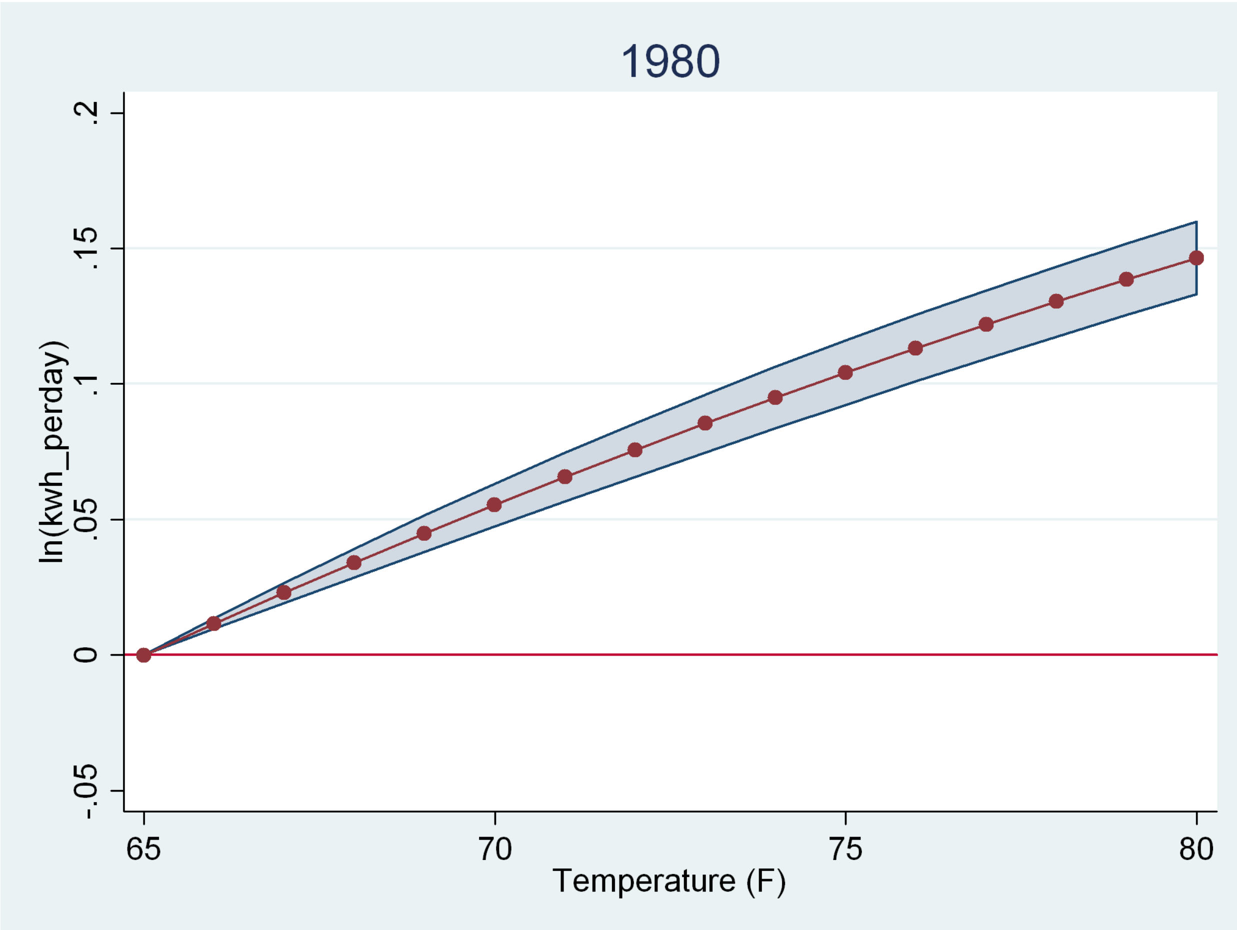
The range represents the 95% confidence interval with robust standard errors.

FIGURE 8. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage. 1970s relative to pre1970s curve. Dependent variable is $ln(KWH\_perday)$



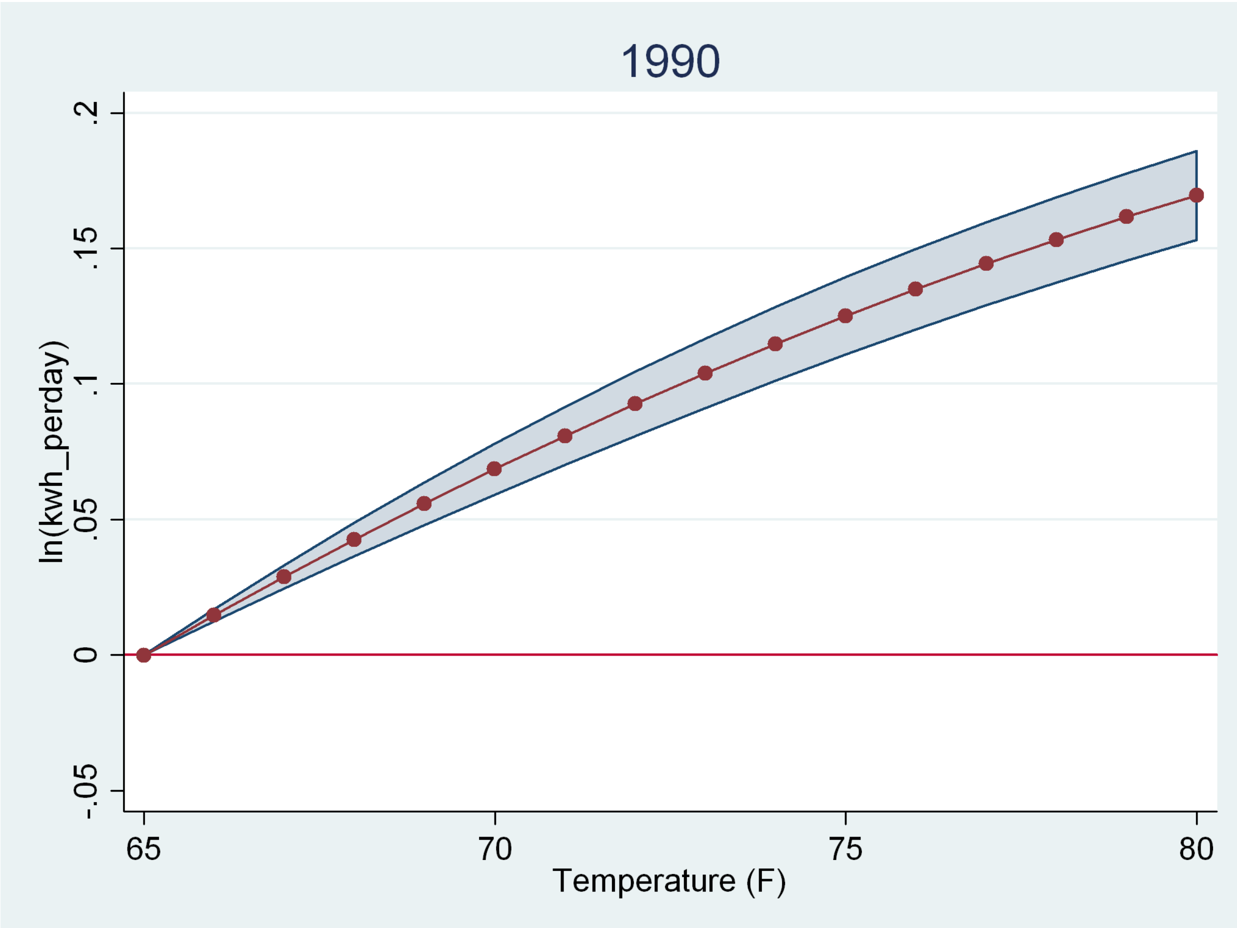
The range represents the 95% confidence interval with robust standard errors.

FIGURE 9. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage. 1980s relative to pre1970s curve. Dependent variable is $ln(KWH\_perday)$



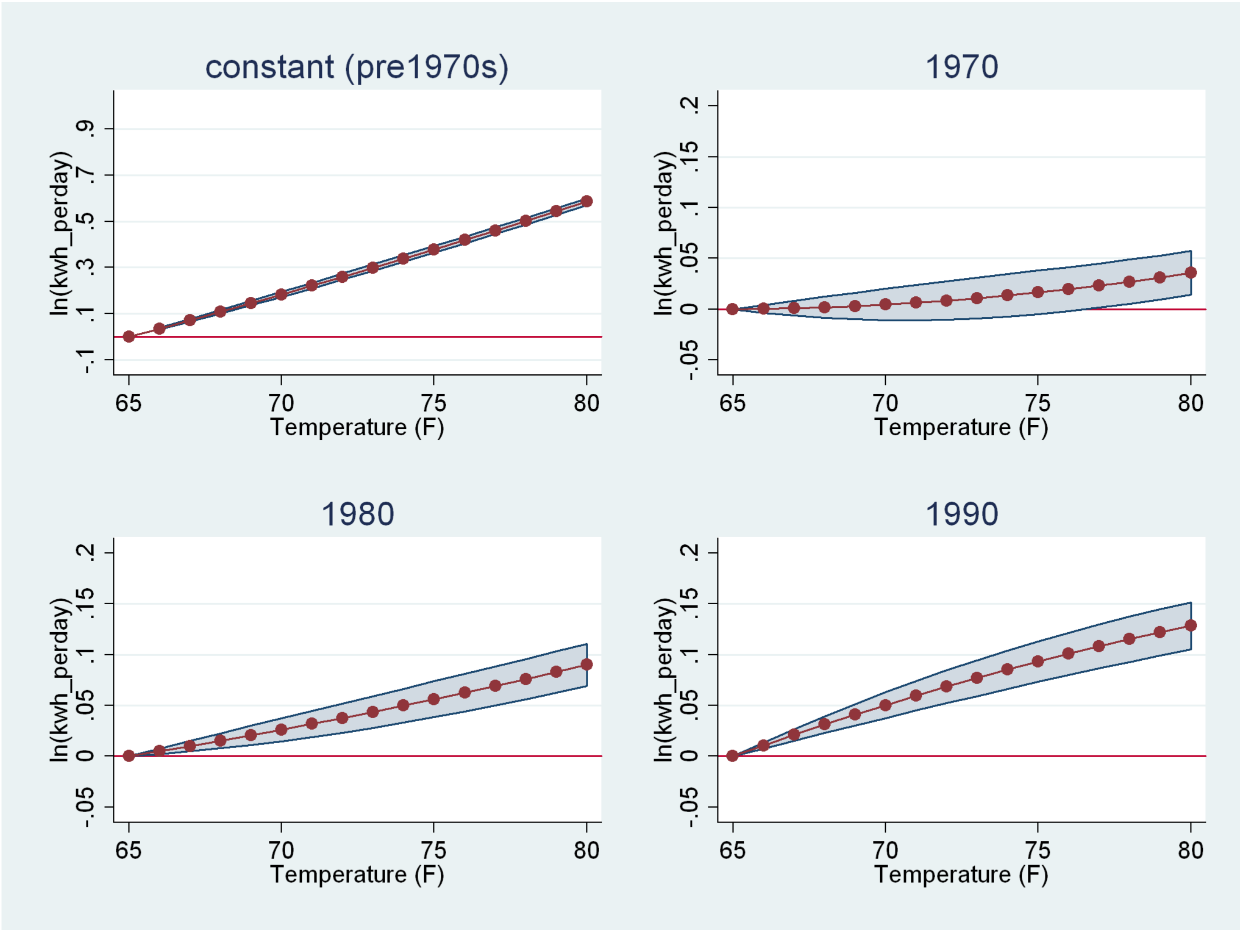
The range represents the 95% confidence interval with robust standard errors.

Figure 10. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage. 1990s relative to pre1970s curve. Dependent variable is $ln(KWH\_perday)$



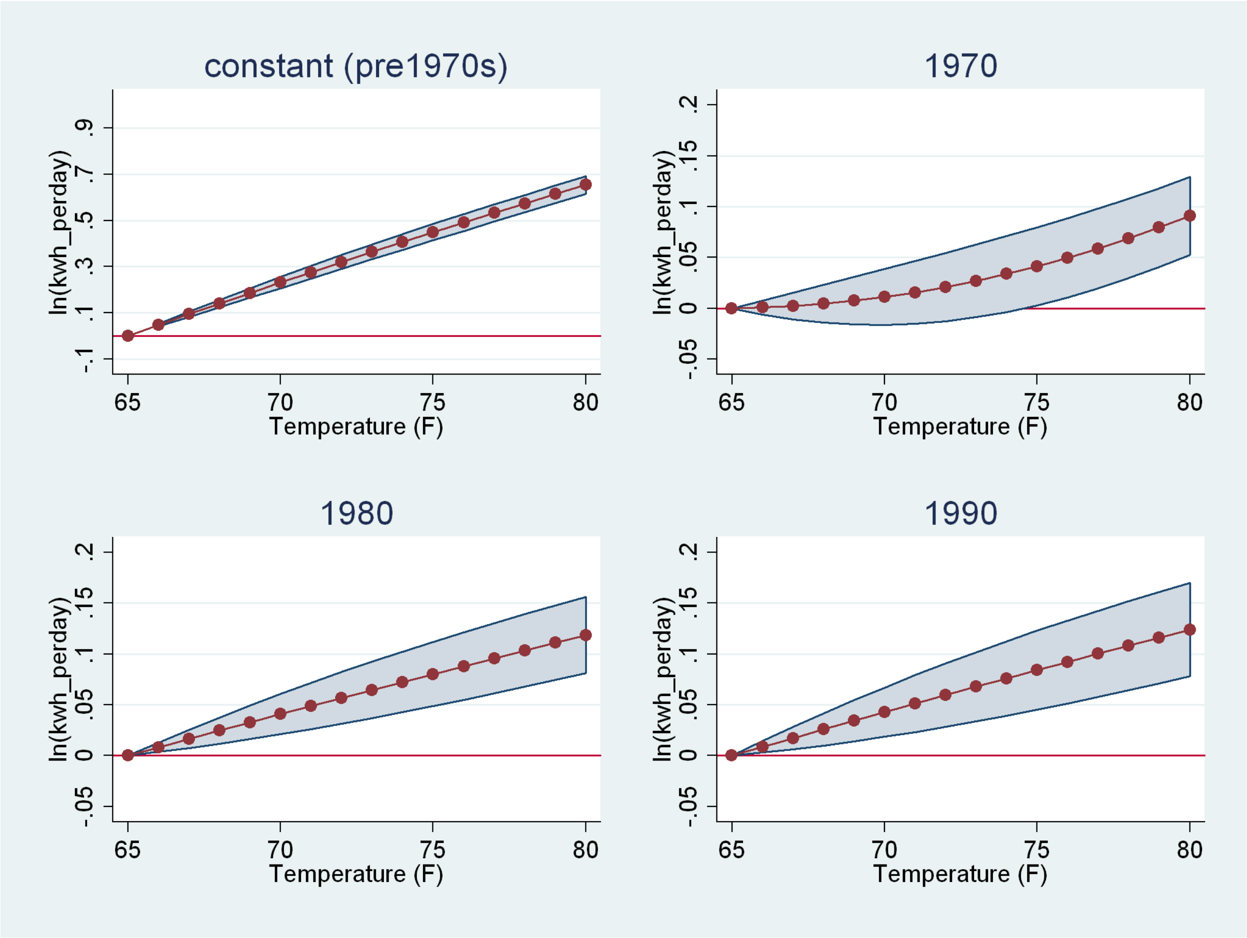
The range represents the 95% confidence interval with robust standard errors.

Figure 11. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage, with controls.
Dependent variable is $ln(KWH\_perday)$



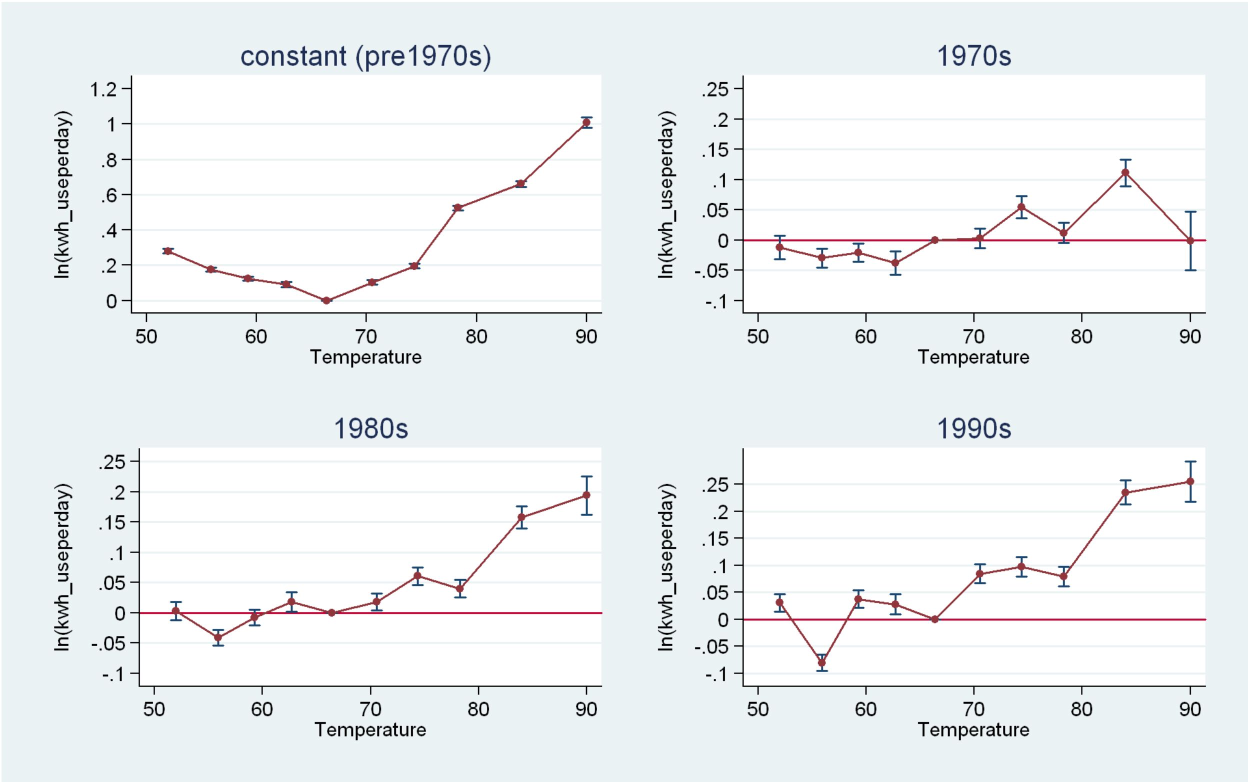
The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The remaining curves are the relative temperature responses of the other vintages.

FIGURE 12. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage, with controls. Home size restricted to 1300-1600sqft.
Dependent variable is $ln(KWH\_perday)$



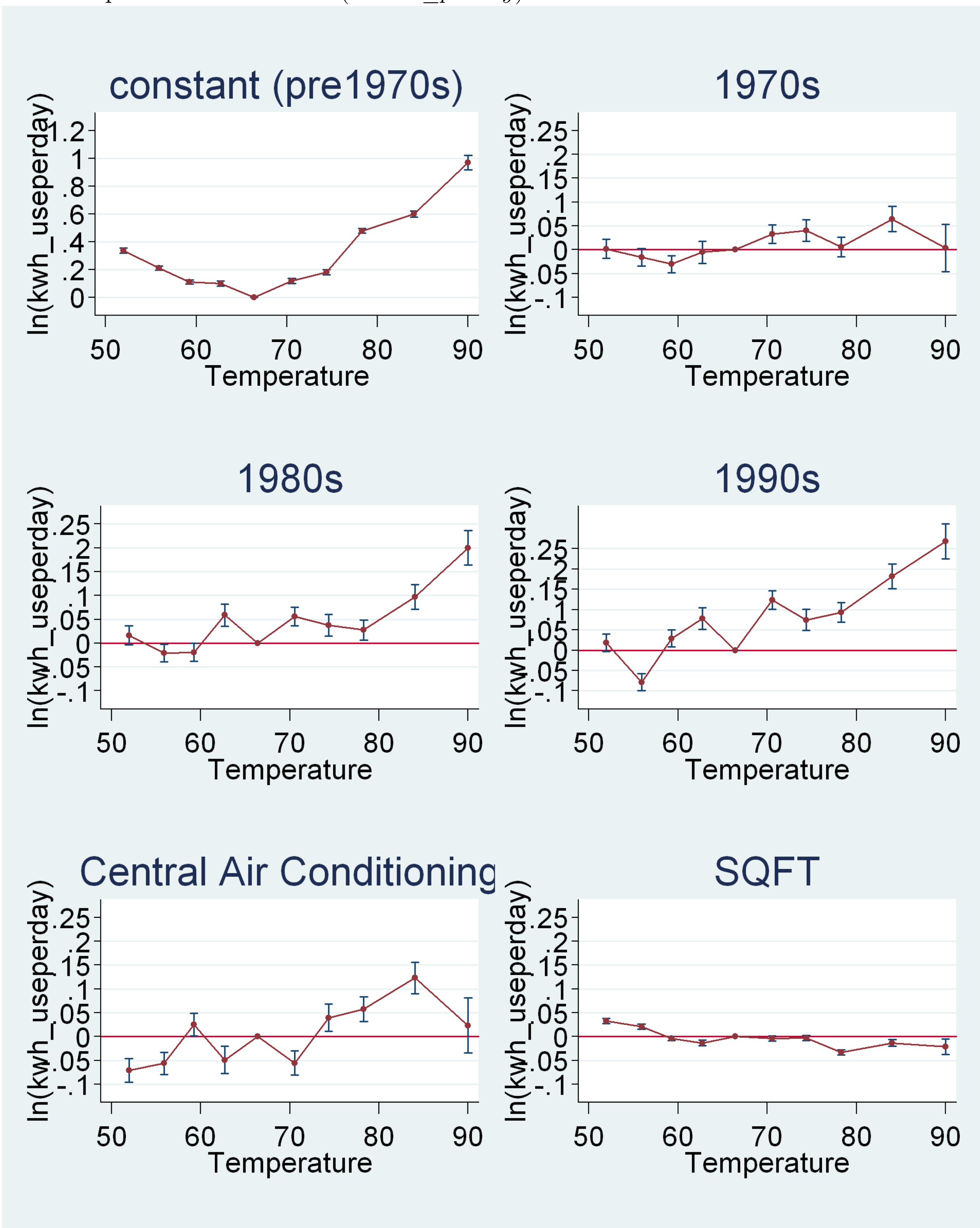
The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The remaining curves are the relative temperature responses of the other vintages.

Figure 13. Estimation results, temperature response with binning, assessor's data, by vintage, no controls.
Dependent variable is $ln(KWH\_perday)$



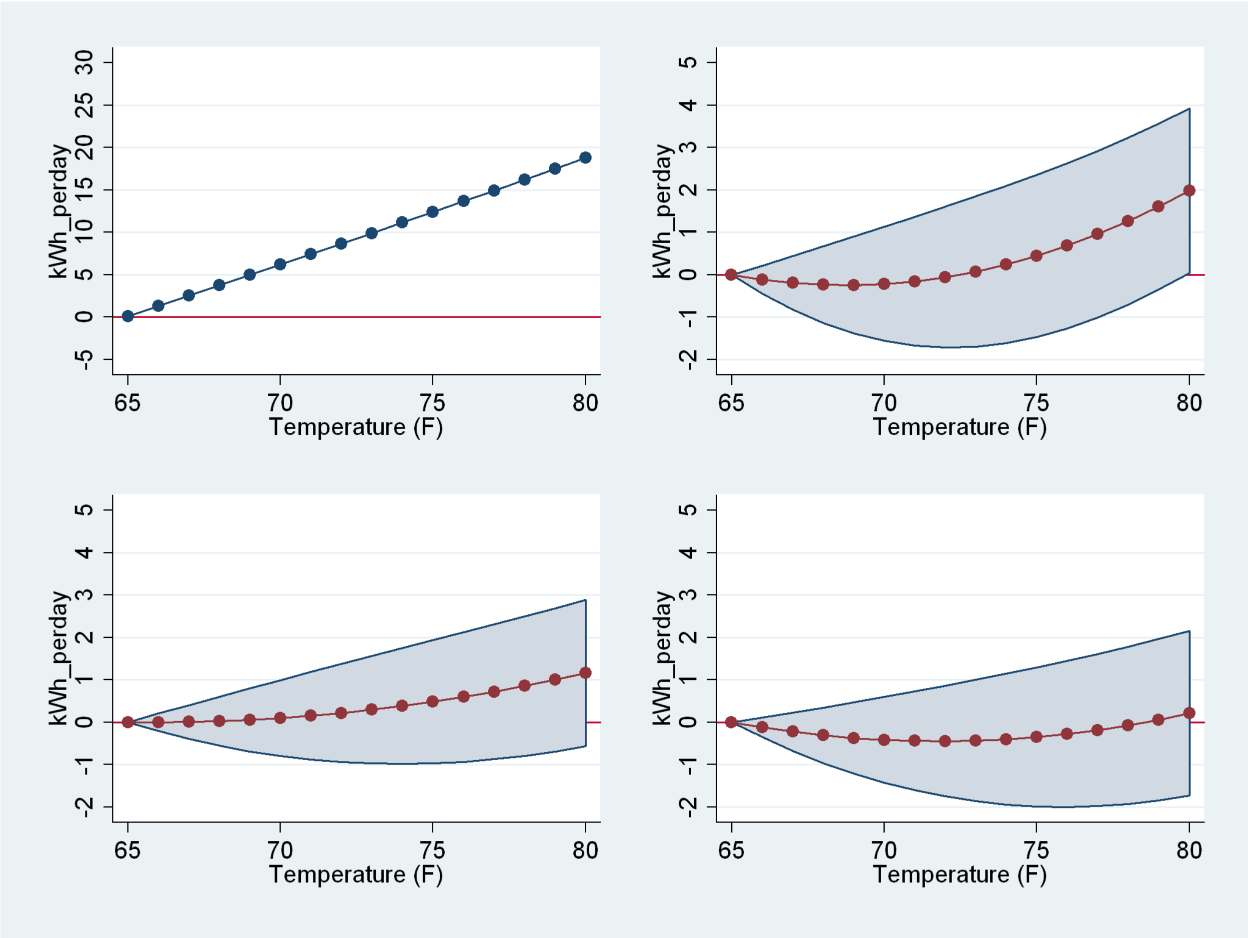
The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The remaining curves are the relative temperature responses of the other vintages.

Figure 14. Estimation results, temperature response with binning, assessor's data, by vintage, with controls.
Dependent variable is $ln(KWH\_perday)$



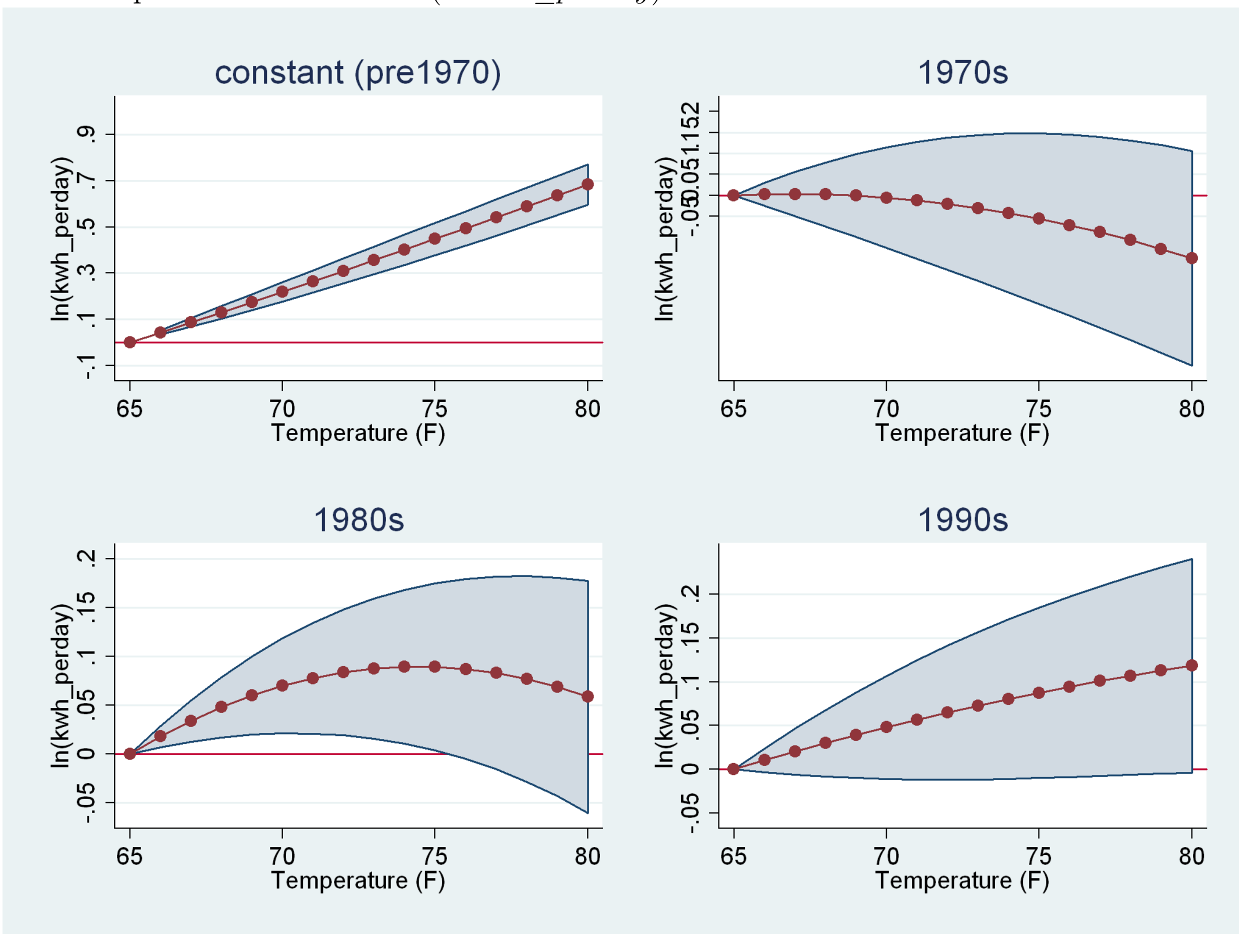
The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The next three curves are the relative temperature responses of the other vintages. The bottom curves plot the impact of central air conditioning and square footage.

Figure 15. Estimation results, temperature response with CDD and HDD parameterization, assessor's data, by vintage, with controls. Home size restricted to 1300-1600sqft.
Dependent variable is KWH_perday



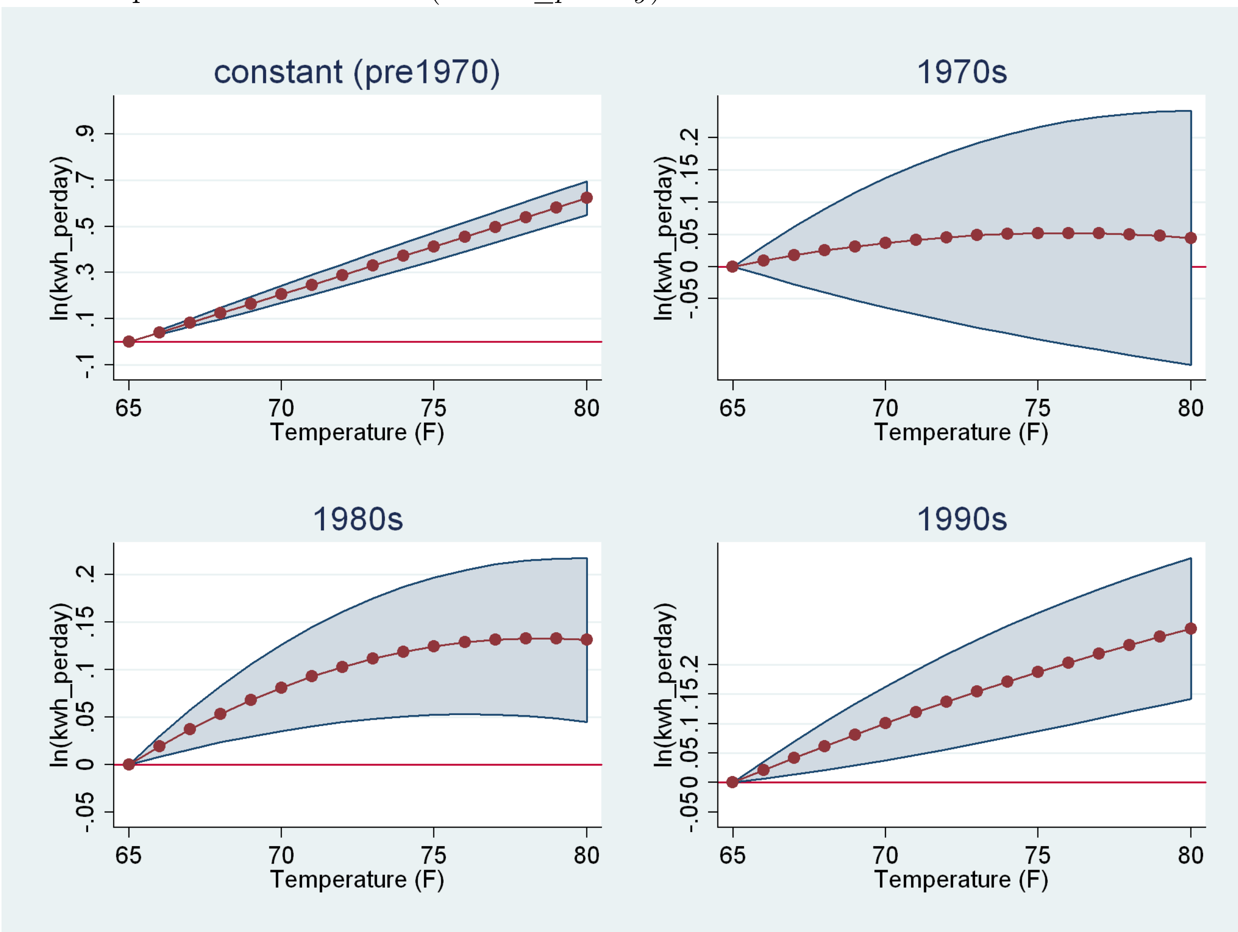
The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The remaining curves are the relative temperature responses of the other vintages.

FIGURE 16. Estimation results, temperature response with binning, census data, by vintage, no controls.
Dependent variable is $ln(KWH\_perday)$



The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The next three curves are the relative temperature responses of the other vintages. The bottom curves plot the impact of central air conditioning and square footage.

Figure 17. Estimation results, temperature response with binning, census data, by vintage, with controls for type of structure, bedrooms, and income. Dependent variable is $ln(KWH\_perday)$



The range represents the 95% confidence interval with robust standard errors. Top left graph is the reference curve for pre1970s buildings. The next three curves are the relative temperature responses of the other vintages. The bottom curves plot the impact of central air conditioning and square footage. Variation in temperature response by the three controls (structure, bedrooms, and income) are omitted.

TABLE 5. Estimation results, Differences across vintage for total usage
Dependent variable is $ln(KWH\_perday)$

VARIABLES	(T1)	(T2)	(T3)
Built in1990s	0.145***	-0.156***	-0.196***
	[0.0124]	[0.0137]	[0.0149]
Built in1980s	0.0459***	-0.126***	-0.133***
	[0.00959]	[0.0120]	[0.0130]
Built in1970s	0.177***	0.0118	0.0445***
	[0.0139]	[0.0133]	[0.0146]
Square Feet†		0.158***	0.189***
		[0.00341]	[0.00381]
Central Air Conditioning		0.0980***	-0.00343
		[0.0147]	[0.0157]
Constant	2.833***	2.928***	2.681***
	[0.00858]	[0.00963]	[0.0108]
random effects	yes	yes	yes
controls for Temperature Response	no	no	yes
Observations	5,625,517	5,625,517	5,625,517
Number of aididlong	118,252	118,252	118,252
Robust standard errors in brackets			
*** p<0.01, ** p<0.05, * p<0.1			

*,**,*** represent 10%, 5%, and 1% statistical significance, respectively. Robust standard errors clustered at the Zip9-level. Temperature response controls include square feet, central air conditioning, and vintage dummies interacted with the quadratic degree day parameterization. †The square feet variable has been demeaned and rescaled by the population standard deviation.

FIGURE 18. Simulation of Riverside average temperature response in 2020, with and without new building stock. Source: Author's calculations.

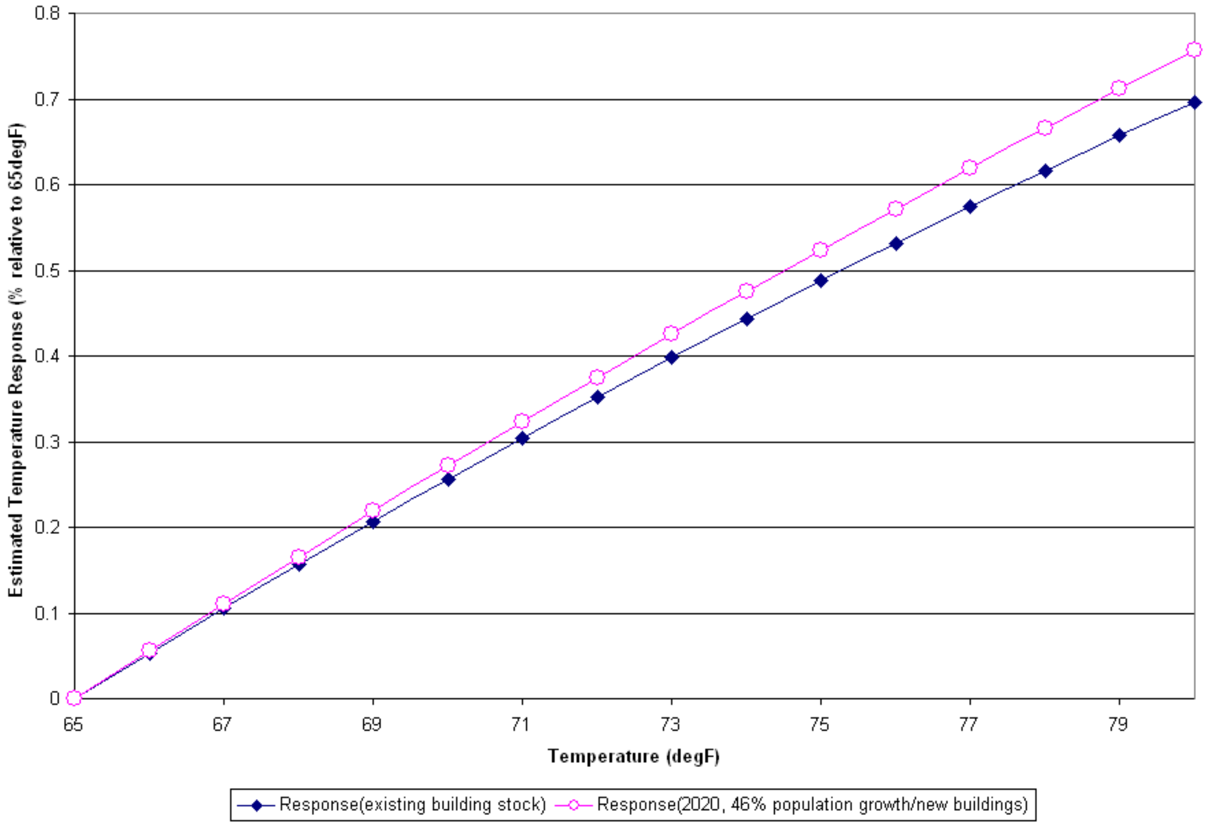


Table 6. Comparison of Air Conditioning Saturation by Climate Zone for Old and New Homes. SOURCE: RASS 2004

		Central Air		Central or Room Air	
Zone	Geography	1990s	pre1970s	1990s	pre1970s
1	Inland	56%	23%	63%	37%
2	Inland	96%	55%	97%	78%
3	Inland	93%	61%	95%	79%
4	Coastal	69%	30%	72%	41%
5	Coastal	27%	4%	29%	8%
7	Inland	93%	59%	93%	73%
8	Coastal	77%	21%	80%	32%
9	Inland	84%	39%	85%	59%
10*	Inland	94%	53%	96%	76%
11	Coastal	60%	12%	68%	25%
12	Coastal	75%	51%	82%	81%
13	Coastal	68%	22%	69%	32%

Note: Zone refers to Forecast Climate Zones as determined by the California Energy Commission. Zone 10 includes Riverside County. A map of the zones is given below in Figure 19.

FIGURE 19. California Energy Commission Forecast Climate Zones. Source: California Energy Commission (2007), page 24.

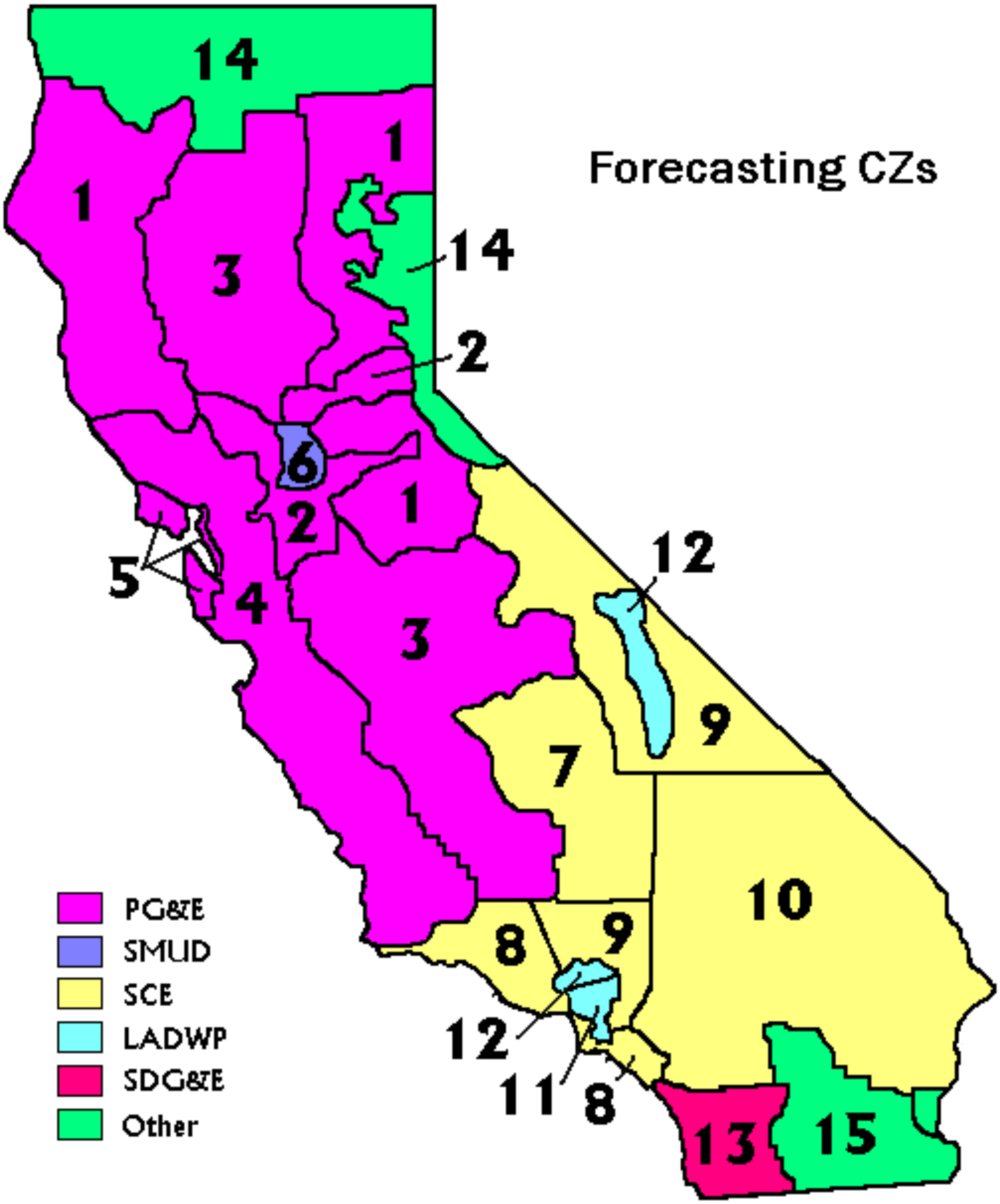


Table 7. Comparison of Air Conditioning Saturation by Vintage in Forecast Climate Zone 10. SOURCE: RASS 2004

Vintage	Central Air	Room Air	Central or Room
pre1970s	53%	22%	76%
1970	80%	9%	88%
1980	89%	2%	91%
1990	94%	1%	96%

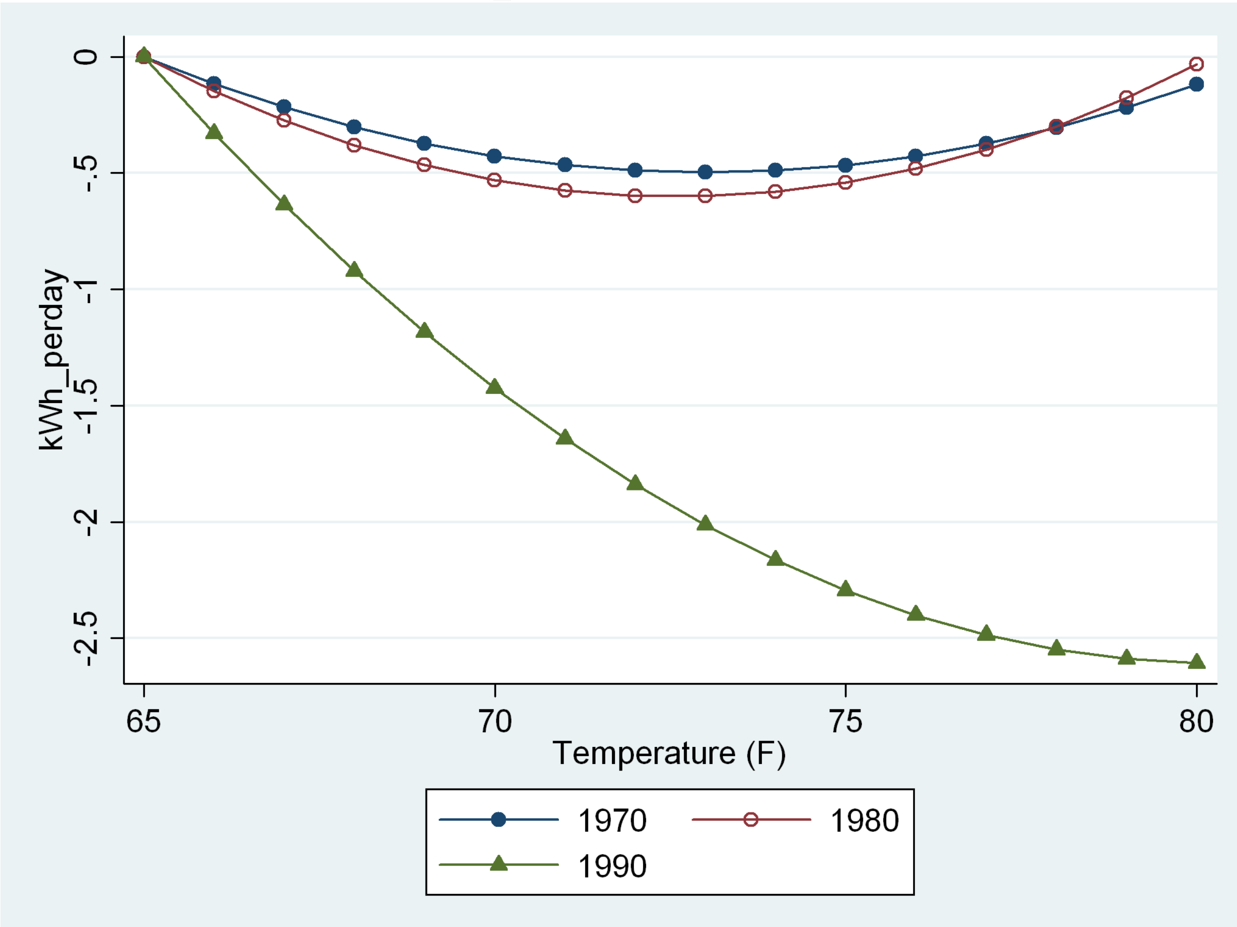
Note: Forecast Climate Zone 10 includes Riverside County.

Table 8. Savings from Building Standards in 2005 and the Implied Reduction In Temperature Response. SOURCE: California Energy Commission reports, author's calculations

Standard	Estimated Savings (GWH)	Percent of Total Load	Population Increase Since Standard	Implied Impact on Temperature Response (Cumulative Standards)
Building Standard1992	310.7	0.4%	15%	-34 to -56%
Building Standard1984	1074.8	1.3%	29%	-31 to -53%
Building Standard1979	878.7	1.1%	36%	-25 to -45%
Building Standard1975	3166.9	3.8%	41%	-20 to -38%

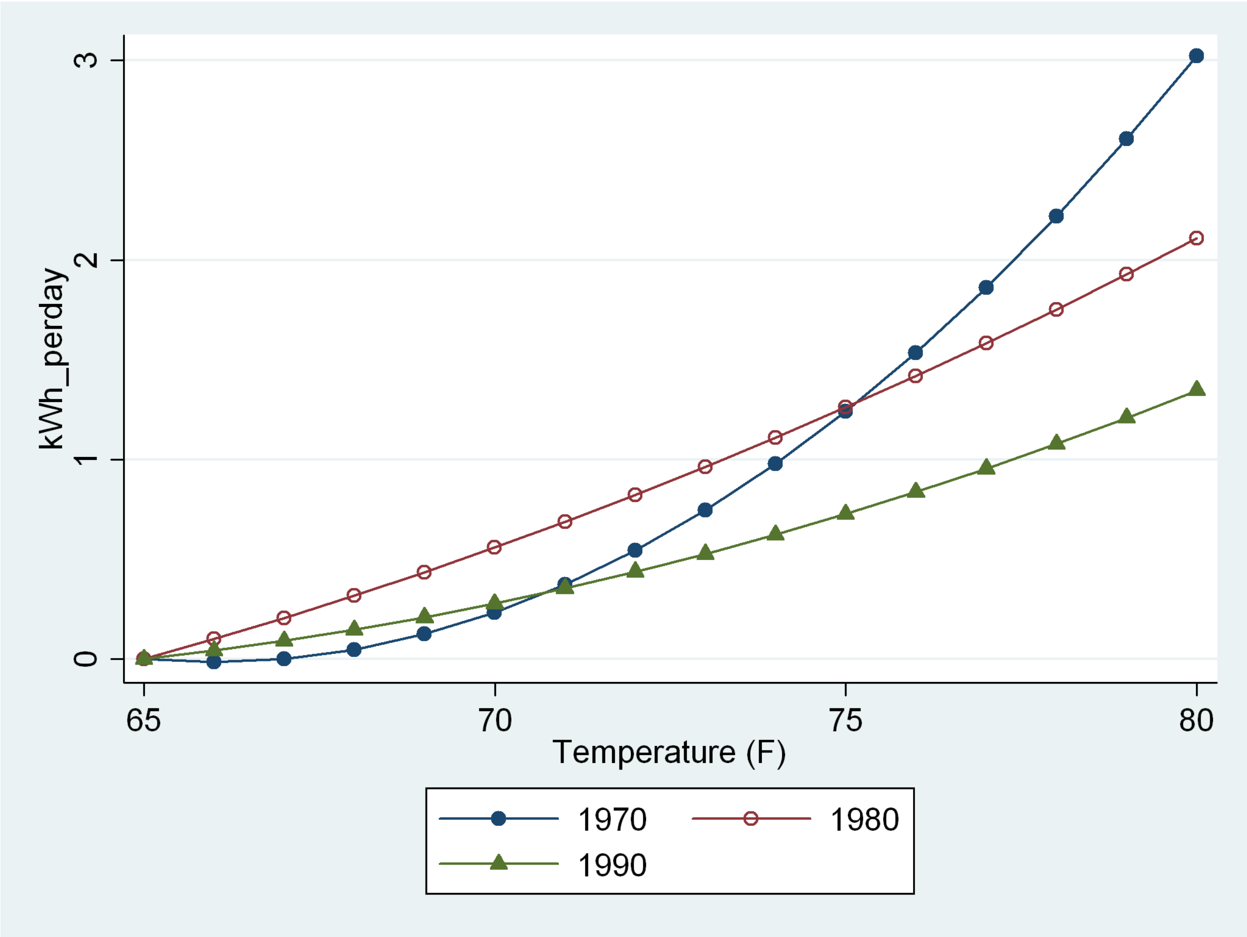
Notes: These values include only the top 5 utilities: PG&E, SDG&E, SCE, LADWP, and SMUD. These utilities supply electricity to a wide majority of the state's population. Total residential load is 83600 GWH for these utilities. To interpret columns 4 and 5 in the second to last row, 36% = (change in population from 1979 to 2005)/(population in 2005) and -25 to -45% is the implied percent reduction from all standards prior to and including the 1979 standards. The calculation range is given by a low and high assumption, 0.1 and 0.25, of the proportion of load that is temperature response. An adjustment factor of 50% was also used to crudely account for the fact that growth has been faster in hotter inland areas and that new homes are larger. These numbers should be treated as speculative because the details of how the estimated savings were calculated are not fully known beyond that which is described in the two CEC reports referenced in the text of my paper.

FIGURE 20. Estimation results, difference in temperature response with CDD and HDD parameterization, assessor's data, by vintage.
Dependent variable is KWH_perday



This uses the assumption that $f(size) = sqft$.

FIGURE 21. Estimation results, difference in temperature response with CDD and HDD parameterization, assessor's data, by vintage, restricted to sqft in [1300,1600].
Dependent variable is KWH_perday



This uses the assumption that $f(size) = sqft$, but for a narrow range of sqft.