Evaluating the Claims of Energy Efficiency: The Interaction of Temperature Response, New Construction, and House Size

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This paper studies whether new buildings or old buildings in part of Southern California, USA, respond more (in terms of electricity use) to periods of high temperature. California has had extensive building energy efficiency policy development since the late 1970s. Newer buildings are subject to stricter building energy codes. However, program evaluation using micro-level field data has been very limited. This paper uses a large dataset of monthly household-level electricity panel data linked to census-block-group-level building and household characteristics to estimate the electricity-temperature response of different building vintages. Engineering models of building codes predict a lower temperature response for newer, more efficient buildings, ceteris paribus. Controlling for the number of bedrooms and income, new buildings (1980-2000) have a statistically significant higher temperature response than old buildings (pre-1979). To explain this finding, new buildings may be used differently (behavior), new buildings may have different equipment (appliance stock), or building codes may not be as effective in practice as they are designed (lax enforcement). In any case, these results advocate for a more careful interpretation of the past success and external validity of building energy efficiency programs.

1. Introduction

California has had extensive building energy efficiency policy development since the late 1970s. Newer buildings are subject to stricter building energy codes which should save energy. However, program evaluation using micro-level field data has been very limited. This paper uses a large dataset of monthly household-level electricity panel data linked to census-block-group-level building and household characteristics to estimate the electricity-temperature response of different building vintages. Engineering models of building codes predict a lower temperature response for newer, more efficient buildings, ceteris paribus. That is, the increase in electricity from 65°F to 85°F for a new home should be *less* than that for an older, less efficient home.

A comparison of the temperature response of new buildings versus old buildings is important for climate change and energy policy. In the US, residential buildings account for 21% of 2008 CO2 emissions (U.S. Envirnmental Protection Agency 2010) with about 50% of residential energy going to space heating and air conditioning (Energy Information Administration 2009). California since the 1970's, has implemented increasingly strict building and appliance codes and have claimed, via engineering calculations, energy/electricity decreases of 14-18% of total load. Because these standards must meet cost-effectiveness criteria, they are of positive net present value, akin to $20 bills left on the floor. If these results are real and can be duplicated elsewhere, they provide the potential for decreasing energy use with positive financial payback. For example, building insulation is the first element in McKinsey and Co.'s CO2 abatement curve (Per-Anders Enkvist and Rosander 2007) with a cost of -150€/CO2E.

There are two reasons to be cautious about these claims of energy efficiency and to look toward field evidence. First, actual savings may not achieve the level of claimed savings, potentially because engineering assumptions are too optimistic or because actual implementation does not meet the design specification. Second, other factors such as changes in occupant behavior, the choice of appliances, and the design of buildings may counteract the effects of energy efficiency. For example, the rebound effect predicts that utility maximizing consumers may increase the use of air conditioning (by setting their thermostats lower) in response to increased air conditioning energy efficiency.

This paper presents one of the first tests of the cumulative effect of building codes (including the above-mentioned confounding responses) using field data on electricity use linked to building vintage. Household billing 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 household characteristics at the census block group level identifies the temperature response by vintage. Due to data limitations, it is not possible to separate building codes from the other factors, though some auxiliary data is discussed.

The main findings are (1) that buildings built in the 1970s use much less electricity on hot days compared to buildings built prior to 1970, (2) that buildings built in the 1980s and 1990s use more electricity compared to buildings built prior to 1970 and in the 1970s, and (3) that these results hold after controlling for the number of bedrooms (a proxy for house size) and income and are robust to two common econometric specifications.

The organization of the paper is as follows. Section 2 presents a literature review. Section 3 presents an econometric model. Section 4 presents a description of the data. Section 5 estimates the model and discusses results. Section 6 concludes.

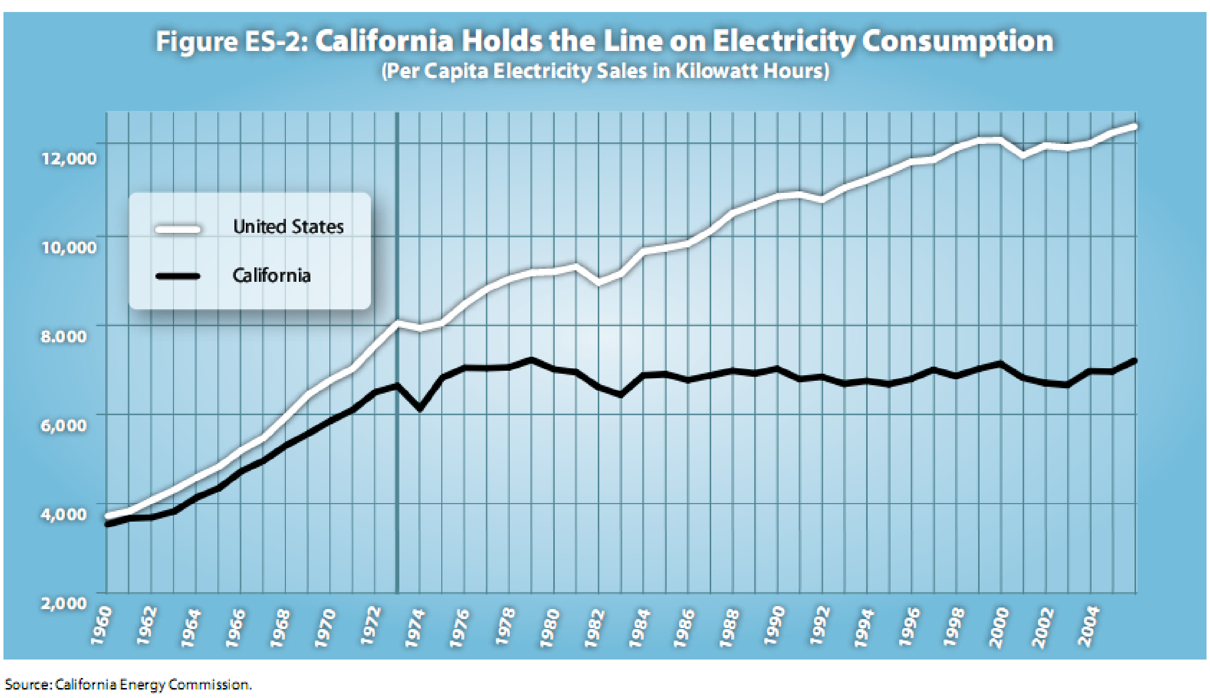
2. Existing Field Evidence on Energy Efficiency

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% (Fig 1). Explanations of this time series phenomenon, commonly referred to as the Rosenfeld Curve, vary widely and many point to California's policies, especially the establishment of building and appliance standards, as major contributors. However, correlation (Fig 1) is not causation.

Though this figure is widely cited as evidence, its strength 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 (Fig 2) presents a quick visual contrast to California's impressive performance relative to the United States (Fig 1). Three other Western states have flat residential electricity per capita since 1974 though they have had much more limited energy efficiency programs than California and have started them at different times (Aroonruengsawat, Auffhammer and Sanstad 2009). This comparison of Fig 2 with Fig 1 suggests that aggregate-level interpretations of California's success depend heavily on the choice of counterfactuals. To accurately look at the impact of California's energy efficiency policies, we must look at details beyond these aggregate statistics.

The link between energy efficiency policy and energy efficiency savings is controversial because of lack of reliable field evidence. Relying on field evidence, rather than engineering estimates, economists and practitioners caution that savings claims from engineering estimates overestimate real-world savings. Recent surveys such as Gillingham, Newell and Palmer (2006) and Gillingham, Newell and Palmer (2009) highlight the spectrum of evidence used to investigate energy efficiency. "Ex-post" studies use field data; electricity use data (at the household, utility, or state level) is of special interest to economists. In contrast, "ex

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



ante" articles, such as Meyers, McMahon, McNeil and Liu (2003), are primarily based on laboratory studies of energy use under simulated test conditions.

The California Energy Commission publishes their estimates of the savings due to these policies based on running scenarios through an engineering model; Marshall and Gorin (2007) find that energy use would be 18% higher in the absence of build. Rosenfeld (2008) argues that per capita electricity sales would have been 14% higher without California standards and programs.

Economists and policy evaluators, starting in the 1980s, have questioned whether claimed energy savings overstate actual savings. Joskow and Marron (1992) describe many factors

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

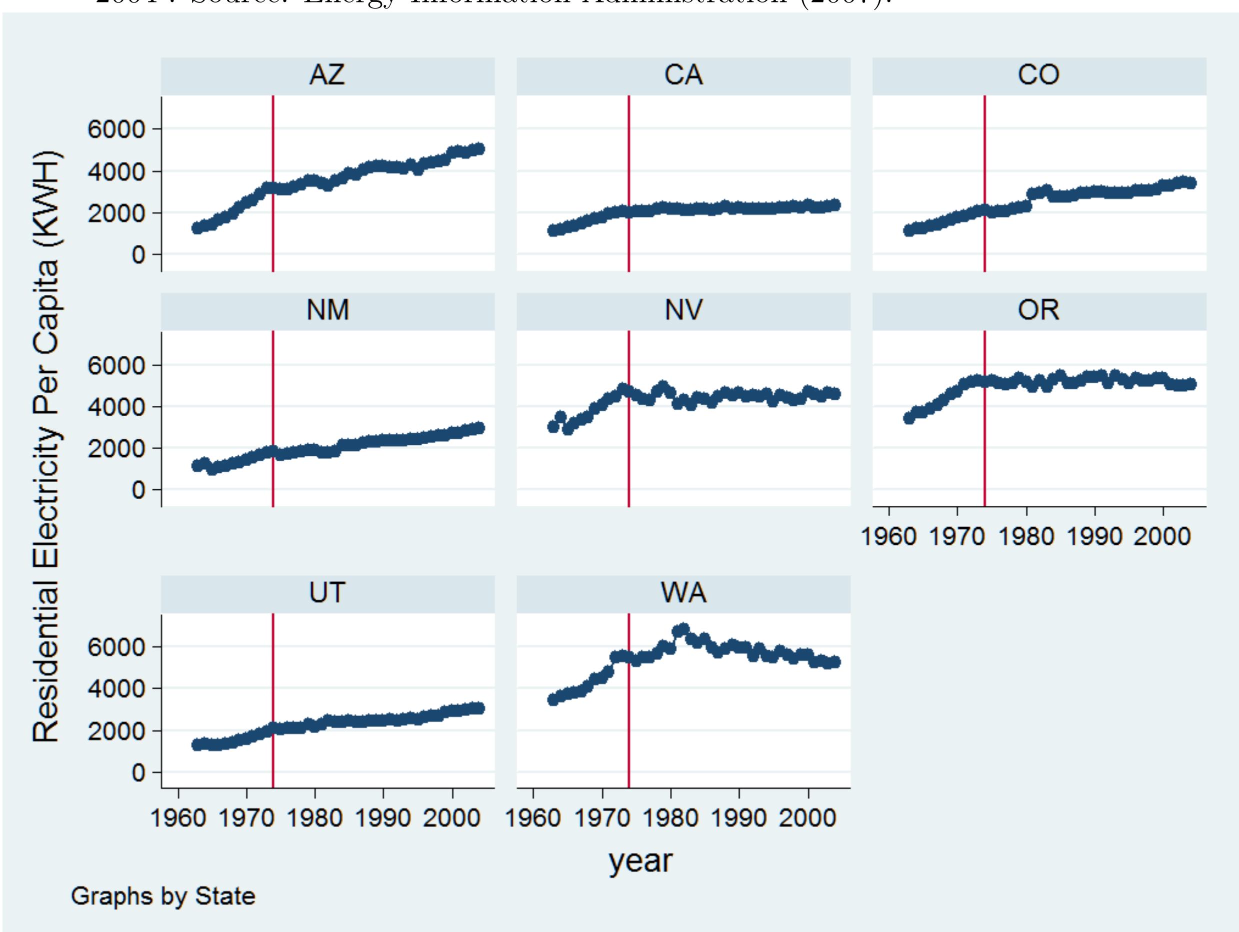


Table 1. Residential Energy Savings due to Building and Appliance Standards and Total Residential Load, by Utility for 2005 (in GWH). Source: Marshall and Gorin (2007) and author's calculations

	LADWP	PGE	SCE	SDGE	SMUD	Total
Savings from Building Standards	310	2533	1621	208	760	5431
Savings from Appliance Standards	919	3732	3256	807	599	9314
Total Residential	8000	34000	30000	7100	4500	83600
Percent Savings from Building and Appliance Standards	15%	18%	16%	14%	30%	18%

that contribute to overstatement of program cost-effectiveness. 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 reinterpret the results of Brown and White (1992), an evaluation of a weatherization program in the Pacific Northwest using billing data. They find that the ratio of measured to estimated savings to be 0.42 and 0.31 for 1988 and 1989 programs respectively. As more current evidence that ex post and ex ante measurements differ, Larsen and Nesbakken (2004) compare an econometric decomposition approach to the predictions of engineering models in Norway. They find that the two approaches decompose end uses quite differently. A number of public agency studies have evaluated weatherization programs using billing data in a treatment evaluation framework. Hirst (1990) surveys this work. In looking specifically at different efficiency interventions, Hewett et al (1986) finds the ratio of actual to predicted savings are under unity for several interventions. Point estimates of the ratios are 0.775 for high efficiency furnaces and boilers; 0.460 for wall insulation; and 0.784 for attic insulation.

The papers by Aroonruengsawat et al. (2009), Horowitz (2007), Sudarshan and Sweeney (2008), Loughran and Kulick (2004), and Auffhammer, Blumstein and Fowlie (2008) use annual data at the state or utility level to estimate the impact of energy efficiency programs. Research at the annual level cannot look at the intra-year variation in energy usage. Also, since they use other states or utilities as their counterfactuals, they are prone to potential bias due to (state, year)-specific differences. In general, they find evidence that energy efficiency programs reduce energy consumption.

Several recent papers address temperature response or building codes with monthly household data. Two very recent papers estimate the impact of building standards or building vintage using monthly billing data along with detailed building characteristics. Jacobsen and Kotchen (2009) analyze a code change in Florida using a sharp regression discontinuity. Though their identification strategy is very clean, their focus on one city in Florida between 1999 and 2005 may have limited external validity, for example, to California. Furthermore, their estimate of a 4-6% decrease in electricity and natural gas consumption is potentially explained by a 5% decrease in square footage for the "after code change" treatment group. Costa and Kahn (2010) estimate the differences in total electricity use by building vintage for buildings in Sacramento, California. This paper uses a different methodology of specifically focusing on temperature response. Aroonruengsawat and Auffhammer (2009) examine the variation in the non-linear relationship between temperature and electricity use by 16 climate zones in California. They build on earlier work on temperature response with annual-state level data by Deschênes and Greenstone (2008).

3. Econometric Model

Direct estimation of electricity consumption by vintage is complicated by the fact that a building's vintage, i.e. the year it was built, does not change over time. Hence, it is econometrically incompatible to include both a household fixed effect as well as the building vintage. Costa and Kahn (2010) elect to not use household fixed effects and instead include a large number of controls, as depicted in Eq. 1

$$ln(KWH\_useperday_{it}) = \sum_{v=1}^{VINTAGES} [\lambda_v V_{iv}] + \mathbf{bZ} + \varepsilon_{it} \quad (1)$$

The λ_v are the average differences in electricity consumption across vintages after controlling for $\mathbf{Z}$, a wide variety of demographic, house characteristic, block characteristics, and temperature variables. My approach differs in two ways. First, the building vintage effect of interest to me is via temperature response because the strongest effect is through building insulation and related temperature response effects. Second, focusing on building vintage interacted with temperature response enables me to use the flexibility of a household fixed effect without relying on parametric assumptions.

In an ideal experimental framework where the building code of each building vintage could be randomly assigned and observed on an individual basis, the following pooled regression from Eq. 2 could be run to uncover the average temperature response of each vintage's building code.

$$ln(KWH\_useperday_{it}) = \sum_{p=1}^{BINS} \Big(\sum_{v=1}^{VINTAGES} [\beta_{pv} V_{iv}] \Big) * D_{pit} + \alpha_i + \varepsilon_{it} \qquad (2)$$

where

- i, t index households, time (monthly billing period)
- $BINS$ represents the number of temperature bins (5°F wide), p indexes them.
- $VINTAGES$ represents the number of building vintage categories, v indexes them.
- V_{iv} is in [0,1] and represents membership in vintage v for household i
- 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

The mean temperature-invariant consumption is captured by the household fixed effect, α_i. Importantly, this will capture variation in appliance ownership, building size, and usage patterns that are not correlated with temperature rather than parametrically controlling for it. The parameters of interest, are the β_{pv}, which represent the temperature response for the pth temperature bin for the vth vintage[1]. 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. If new buildings are more efficient, then $\beta_{pv^*} < \beta_{pv'}$ when v^* is newer than v' for any p in the air conditioning range of temperatures.

[1] One of the temperature bins, 65°F − 70°F is left out as the reference temperature, otherwise the rank condition is violated.

The first complication relates to the non-random allocation of building vintage. New buildings tend to be larger, have more rooms, be inhabited by people with larger incomes, use more electricity, and are more likely to have central air conditioning but less likely to have room air conditioning (KEMA-XENERGY 2004). Importantly, insofar as these differences only affect temperature invariant use, these are controlled for by the household fixed effect. However, these differences may impact the electricity-temperature response. A larger house takes more energy to cool, higher income may increase the use of air conditioning, and more ownership of central air conditioning would all positively bias temperature response of new buildings relative to the idealized experiment (Eq 2). In contrast, higher incomes could be associated with more efficient appliance choice, which would introduce negative bias.

The second complication for empirical analysis is that vintages are observed at the census block group level, not at the household level. Hence, instead of a binary variable for membership in a vintage category, the proportion of households of each vintage in the group is assigned to each household in the group.

These considerations modify the estimating equation to include (1) control variables for income and bedrooms, and (2) modify census block group variables to use the group average for income, bedrooms, and vintage bins. The resulting equation is Eq. 3[2] .

$$
\begin{aligned}
ln(KWH\_useperday_{ijt}) = \; & \textstyle\sum_{p=1}^{BINS} \Bigg(\sum_{v=1}^{VINTAGES} [\beta_{pv} V_{jv}] + \\
& \gamma_p ln(AvIncome_j) + \\
& \delta_p ln(AvBedrooms_j) \Bigg) * D_{pit} + \\
& \alpha_i + \varepsilon_{it}
\end{aligned}
\tag{3}
$$

[2]This footnote explicitly explains describes the variables in Eq. 3

- i, j, t index households, 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 cyle t where the average temperature is in the pth bin
- $AvIncome_j$ is the average income per household in j
- $AvBedrooms_j$ is the average bedrooms per household j

4. Description of the Data

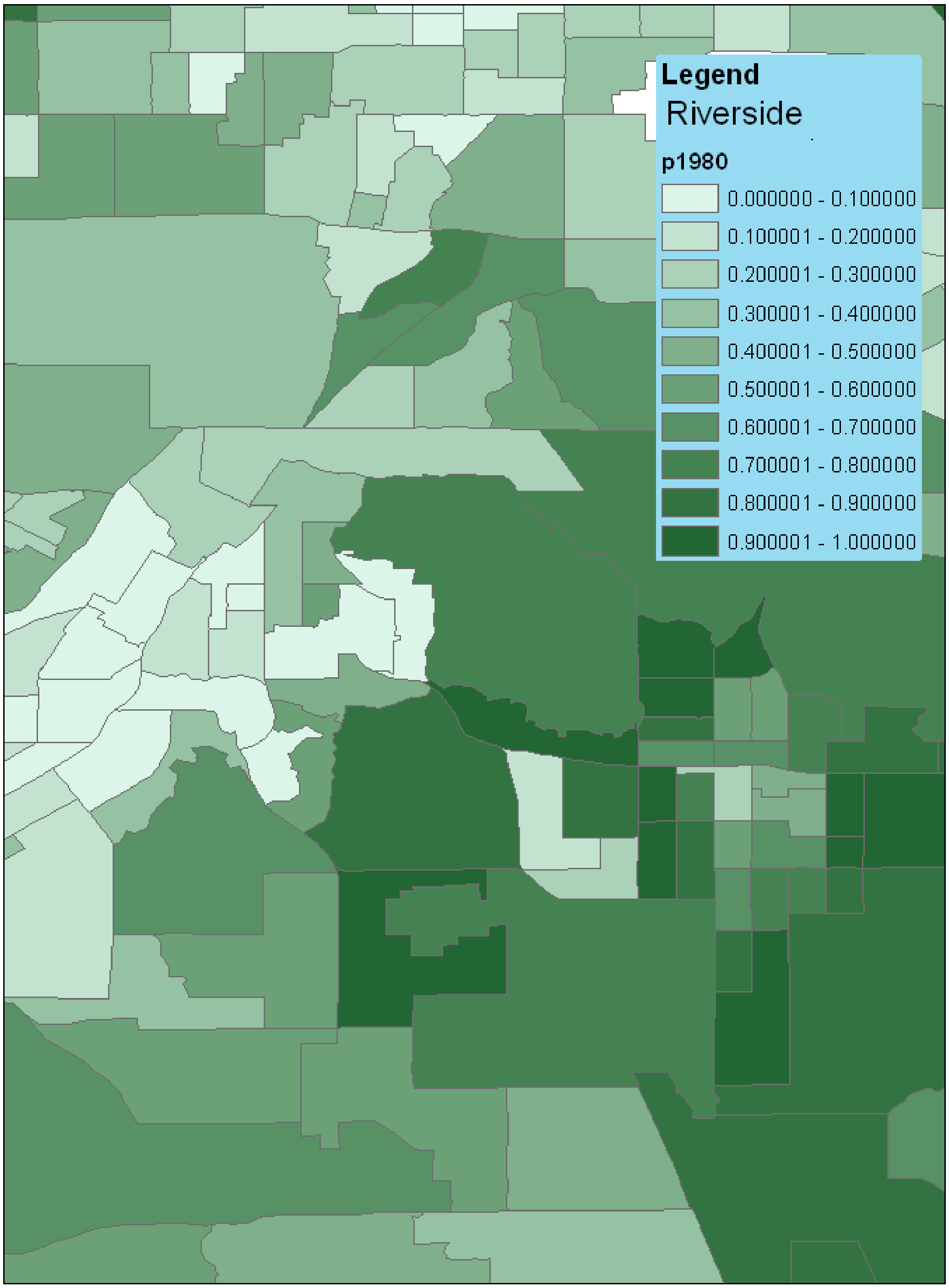
Three sources of information are combined to run this analysis at the (household, month) level for bills and the (census block group, month) level for socioeconomic and building characteristics. First, fine-scale daily weather data is computed from PRISM data (Daly 1996) and National Climatic Data Center (2009) data using the algorithm developed by Schlenker and Roberts (2009) for agricultural yield estimation. Second, under special arrangement with Southern California Edison (SCE) and San Diego Gas and Electric (SDGE), monthly billing data is used. Third, detailed census-block-group-level data is taken from the Summary File 3 reports of the US Census for 2000 (United States Census Bureau 2009).

The 2000 US Census provides housing age, income, and house size. Summary File 3 has, by census block group, proportions of the vintage of housing, proportions of housing type (apartment vs single family) and the number of rooms, and proportions within different income groups. 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; a census tract is roughly 3 census blocks. 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.

Weather data is generated according to the algorithm used by Schlenker and Roberts (2009), and 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 is then matched via Zip9 to the 4mile x 4mile grid of the weather data and to the census block group (polygon) for census data within which the Zip9's Lat, Lon is contained.

The current results are restricted to running on a 1 in 5 random sample of households within Riverside County for which SCE is the electric utility. The reason Riverside County was chosen was because it is an inland area with a wide range of temperatures, there is considerable variation in the building vintage built since building standards were implemented, and because Aroonruengsawat and Auffhammer (2009) found this region to have substantial

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



average temperature response. A 1 in 5 random sample was used to decrease the number of observations to a workable size of 3.9million observations of about 32000 households with an average of 121 bills per account, or about 10 years. Data is present from 1998-2009. Bills with 25 days or less or 35 days or more were dropped (about 5%). Customers noted as all-electric customers or as CARE customers (low-income rate program) were not dropped.

Summary statistics of the data are in Table 2. The top section reports information from the billing data. The average household use per day is 25.5KWH, or 9307KWH per year. This is about 50% higher than the 6189 KWH per year average for the SCE utility (KEMA-XENERGY 2004) but lower than the national average of 11,500 KWH per year (Energy Information Administration 2009).

The middle section of the summary statistics is weather data that has been binned in 5°F bins according to the mean temperature for the day and scaled by the days in the bill so that they represent the proportion of time in a billing cycle in each bin. The sum of the means of the bins sum up to 1. The mode of the average temperature is bin55-60°F and 15% of all days are in this bin.

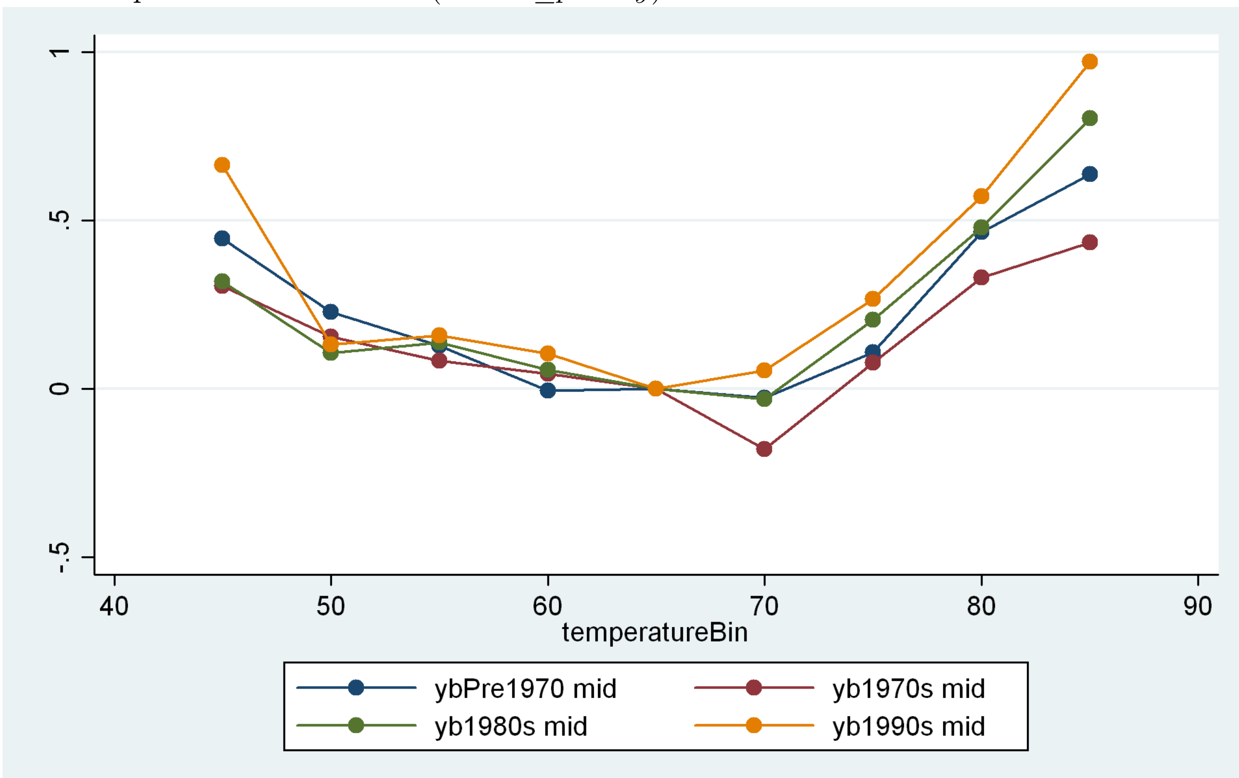
The last section of the summary statistics is building and household characteristics from the Census data at the level of the census block group. The average number of bedrooms is 2.7 and the average household income is about $52,000.[3] By the census block groups, 80% of buildings were built since 1970, 60% since 1980, and 26% since 1990. That some counties have had 0 percent built since 1970 and some have had 97% since 1990 means that there is substantial variation across census block group in building vintage.

[3]Census data gives counts of households in different bedrooms, rooms, and income bins. The average is approximate because a representative value is used for each bin.

Table 2: Summary Statistics.

Variable	Mean	Std. Dev.	Min	Max
BILLING DATA				
useperday	25.52	22.17	-341.2	1376
days	30.44	1.499	26	34
WEATHER DATA (Temperature Bins)				
bin20-25°F	0			
bin25-30°F	6.21E-08			
bin30-35°F	1.55E-05			
bin35-40°F	5.78E-04			
bin40-45°F	0.01			
bin45-50°F	0.05			
bin50-55°F	0.11			
bin55-60°F	0.15			
bin60-65°F	0.14			
bin65-70°F	0.12			
bin70-75°F	0.13			
bin75-80°F	0.12			
bin80-85°F	0.08			
bin85-90°F	0.04			
bin90-95°F	0.04			
bin95-100°F	0.01			
bin100-105°F	1.71E-3			
bin105-110°F	8.68E-5			
bin110-115°F	0			
CENSUS DATA				
approxAvBedrooms	2.700	0.5777	1.117	4.362
approxAvRooms	5.492	0.9386	2.780	7.938
percentsince1970	0.802	0.214	0	1
percentsince1980	0.596	0.292	0	1
percentsince1990	0.263	0.246	0	0.977
approxAvIncome	\$52253	\$17083	\$19291	\$108917
housingUnits	1176	1017	40	5539
Observations	3903836			

FIGURE 4. Temperature response by building vintage,
Dependent variable is $ln(KWH\_perday)$



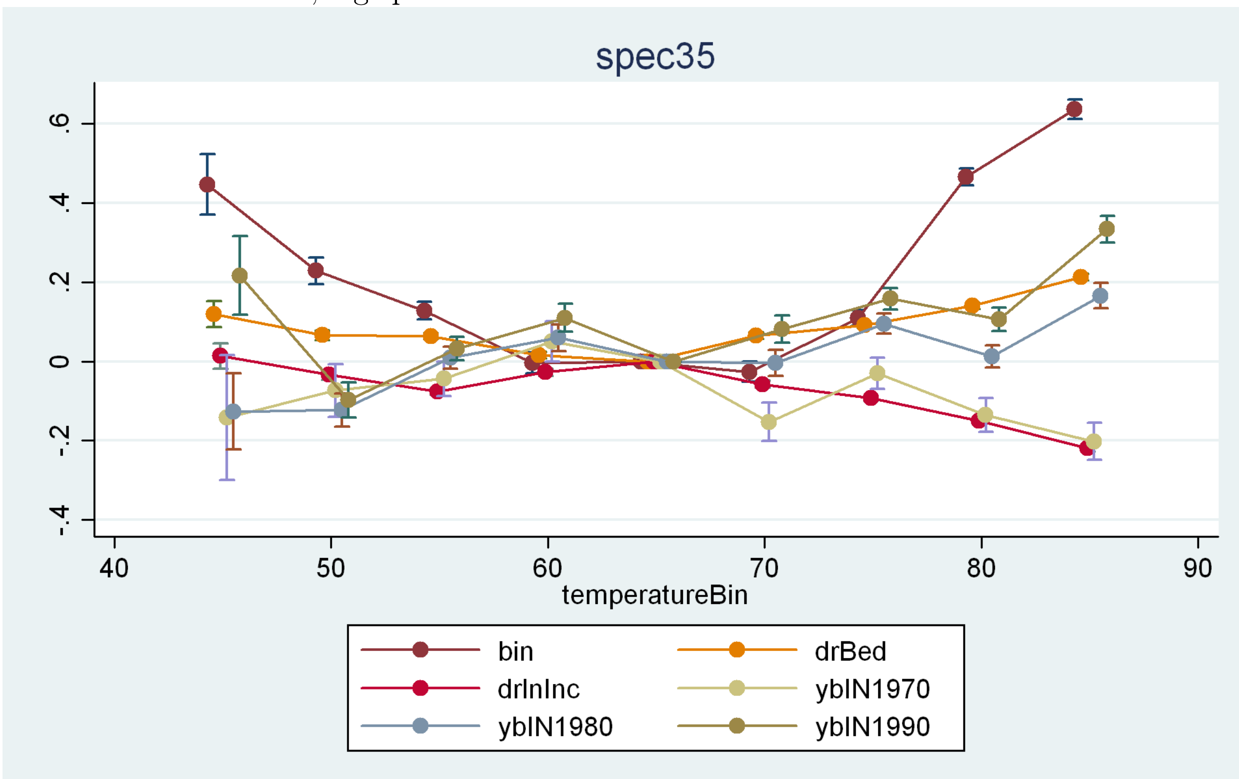
Estimated temperature response by building vintage at mean of ln(AverageIncome) and AverageBedrooms, log specification.

5. Results

5.1. **Main Results, log specifications.** First, I present a simpler to interpret graph in Figure 4. This shows the estimated temperature response varying by four categories of building vintage (Pre1970s, 1970s, 1980s, 1990s). Notice that the top curve is for the 1990s building vintage category; hence these buildings have point estimates representing the highest temperature response.

The detailed results of the main specification in Eq. 3 are presented in tabular form in Table 3 and presented graphically for 5 degree bins in Fig 5. These are results for one regression. In the table, each column is for temperature response interacted with different covariates.

FIGURE 5. Temperature response and interactions with building vintage and other covariates, log specification



To interpret the graph, data points are indicated by the upper bound of the bin; i.e. the data point at 70 refers to the bin from 65°F to 70°F. 65°F has been chosen as the zero point; hence all amounts are relative to the electricity use in the 65°F bin. Data points are jittered horizontally so that one can distinguish each data series separately. The error bars signify 95% confidence intervals. The y-axis is $ln(KWH\_useperday)$. Only the region from 45 to 85°F is displayed; there is much less data in the more extreme temperature ranges which results in very statistically imprecise estimates.

This graph differs from the earlier graph in that the ybIN1990 curve represents the *difference* between temperature response for 1990s buildings *relative to* pre1970s beuildings.

To explain each data series, the "bin" curve represents the electricity-temperature response at the mean of ln(AverageIncome) and the mean of AverageBedrooms for buildings built prior to 1970. For this cohort, the estimated temperature response decreases when one approaches 65°F and then increases past 65°F. To interpret a point estimate, if the temperature were increased from 60-65°F to 75-80°F, then the home is estimated to use about 40% more

TABLE 3. Estimation results, temperature response and interactions with vintage and other covariates
Dependent variable is $ln(KWH\_perday)$

Bin	base	in1970-base	in1980-base	in1990-base	ln(Inc)	Bedrooms
bin040	0.434	-1.037	0.616	-0.313	-0.225	0.0336
	0.177	0.399	0.242	0.238	0.0714	0.0775
bin045	0.447	-0.142	-0.127	0.217	0.0137	0.119
	0.0388	0.0806	0.0491	0.051	0.0164	0.0169
bin050	0.229	-0.0735	-0.123	-0.0977	-0.0342	0.0663
	0.0173	0.0337	0.0213	0.0224	0.00626	0.00613
bin055	0.128	-0.0439	0.00887	0.0318	-0.0766	0.0638
	0.0114	0.0222	0.0145	0.0152	0.00395	0.00381
bin060	-0.00431	0.05	0.06	0.11	-0.0276	0.0157
	0.0132	0.0258	0.0172	0.018	0.00454	0.00443
bin070	-0.0263	-0.153	-0.00441	0.0816	-0.0578	0.0652
	0.0127	0.025	0.0166	0.0174	0.00446	0.00426
bin075	0.109	-0.0303	0.0953	0.158	-0.0927	0.0918
	0.0101	0.0199	0.0132	0.0138	0.00369	0.00352
bin080	0.466	-0.135	0.0129	0.106	-0.15	0.14
	0.0112	0.0219	0.0144	0.0153	0.00386	0.0038
bin085	0.637	-0.202	0.166	0.334	-0.22	0.213
	0.0125	0.0243	0.0162	0.0173	0.00408	0.00417
bin090	1.083	-0.627	-0.31	-0.119	-0.2	0.289
	0.0165	0.0306	0.0225	0.0268	0.0046	0.00609

Includes household-level fixed effects. $r^2 = 0.266$. 3885761 observations over 32038 households. Results for temperature bins <40°F or >90°F have been omitted. Standard errors in second row.

electricity per day. drBed and drlnInc represent the additional impact for a one standard deviation difference in AverageBedrooms or ln(AverageIncome). These variables were demeaned and rescaled by the standard deviation to aid in interpretation. Increasing AverageBedrooms (drBed) has the expected sign of increasing the temperature response, and having greater effect at more extreme temperatures. Interestingly, increasing ln(AverageIncome) (drlnInc) has the opposite effect; coefficients are negative meaning richer homes are less temperature responsive. This may be because, holding all else constant, richer people in this area have better appliances or better quality homes in terms of thermal energy efficiency.

The results are mostly statistically significantly different from zero, especially far away from 65°F temperatures. For both cold weather (left of 65°F) and hot weather (right of 65°F), ybIN1970 is negative, meaning that buildings built in the 1970s use less electricity than pre-1970 buildings and thus have a lower temperature response, consistent in sign with the predictions of energy efficiency. In contrast, ybIN1980 is mixed, with negative coefficients left of 65°F and positive coefficients to the right of 65°F. Focusing on hot weather (right of 65°F), not only do these buildings have a higher temperature response than 1970s buildings, but they are worse than those built prior to 1970.

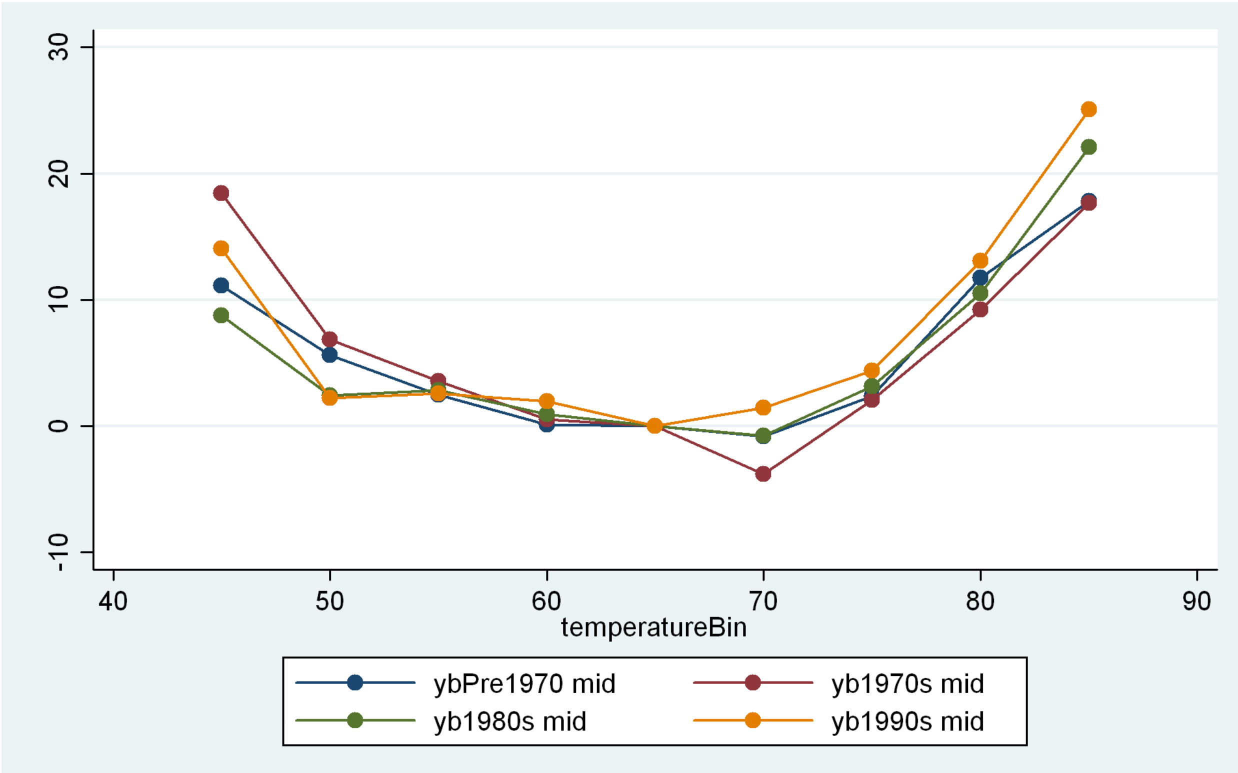
For buildings built since the 1990s, the results are even worse for hot weather. ybIN1990 is even more positive than ybIN1980, which means that buildings in the 1990s have a higher temperature response curve than buildings built in the 1980s, buildings built in the 1970s, and pre-1970 buildings.

5.2. **Secondary Results, level specifications.** Figures 6 and 7 shows the results of regression with identical covariates but with the regressor set as the level of KWH_perday rather than $ln(KWH\_perday)$. Results do change, with the 1980s building coefficients in hot weather hovering near zero from 70 to 80°F. However, the ordering of yb1970, yb1980, and yb1990 are the same.

5.3. **Additional robustness checks / Alternative identification strategies.** A total of 52 similar specifications were run, which included interactions of several combinations of building vintage, income, bedrooms. These interactions may be important, and some are suggested by engineering models. For example, insulation will have a different effect if there are more bedrooms in a non-additive way. Equivalent graphs for each were produced, and available upon request, but omitted here because of space constraints. The results for the 1970s, 1980s, and 1990s held under these alternative specifications.

Economists should note the omission of prices in the regressions, and secondly the inclusion of some data from the time period of the California Electricity Crisis of 2000-2001. To the first concern, there is price variation, but the price variation is assumed to be uncorrelated with temperature variation. Hence, by the property of weather exogeneity, omitting prices will not bias these results. An important caveat is if price elasticities vary with temperature, in which case changes on prices could bias results. In most specifications, price elasticities are not estimated as depending on temperature. In one important exception, (Reiss and

FIGURE 6. Temperature response by building vintage
Dependent variable is KWH_perday

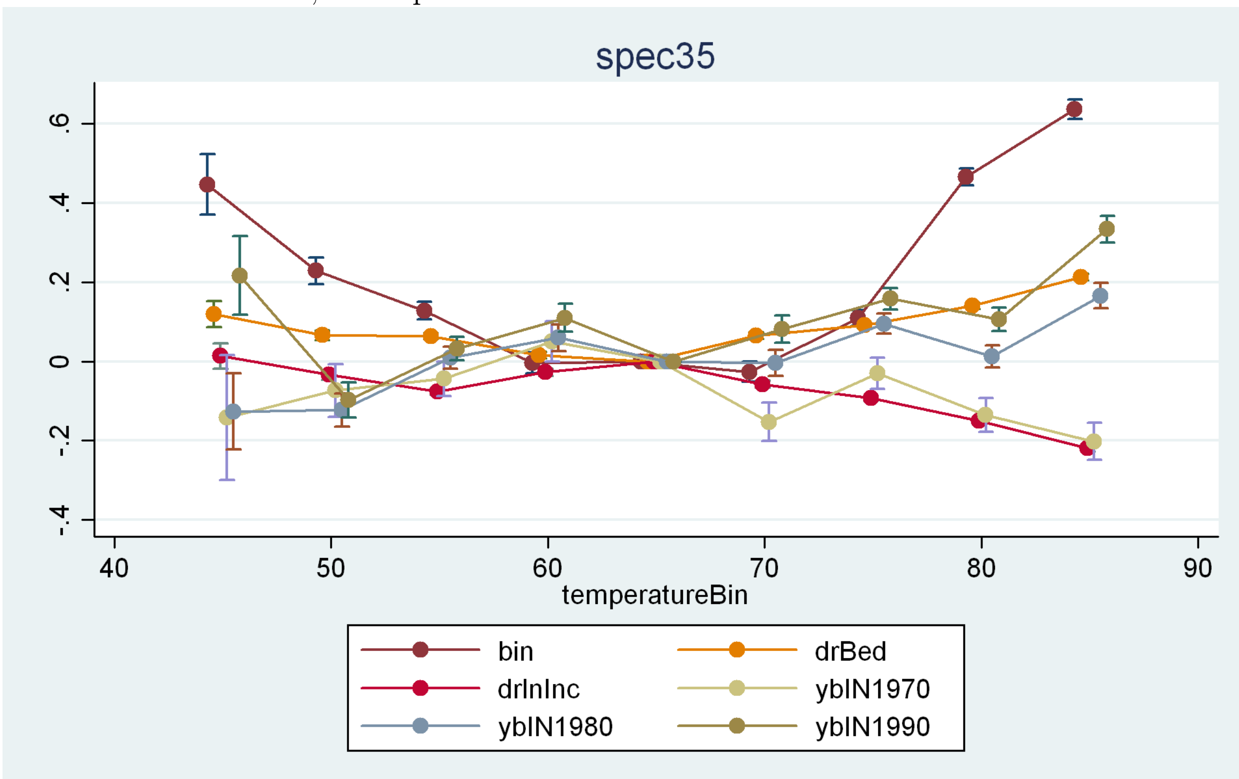


Estimated temperature response by building vintage at mean of ln(AverageIncome) and AverageBedrooms, log specification.

White 2005) separately estimate price elasticities for different end uses, but do not allow elasticity to also vary by temperature. To the second criticism, it is likely that rolling blackouts will mute the temperature response on very hot days subject to rolling blackouts, or that households of different vintages adapted their energy use differently. The direction of bias could go either way depending on whether blackouts and biases were more common for different building vintages.

As previously admitted, the coefficients are not exclusively linked to building codes, meaning that other factors may be driving the results. First, it may be that buildings in the 1980s or 1990s have different rates of air conditioning appliance ownership compared to those built earlier. Consequently, the increases in electricity use would not be "waste" in terms

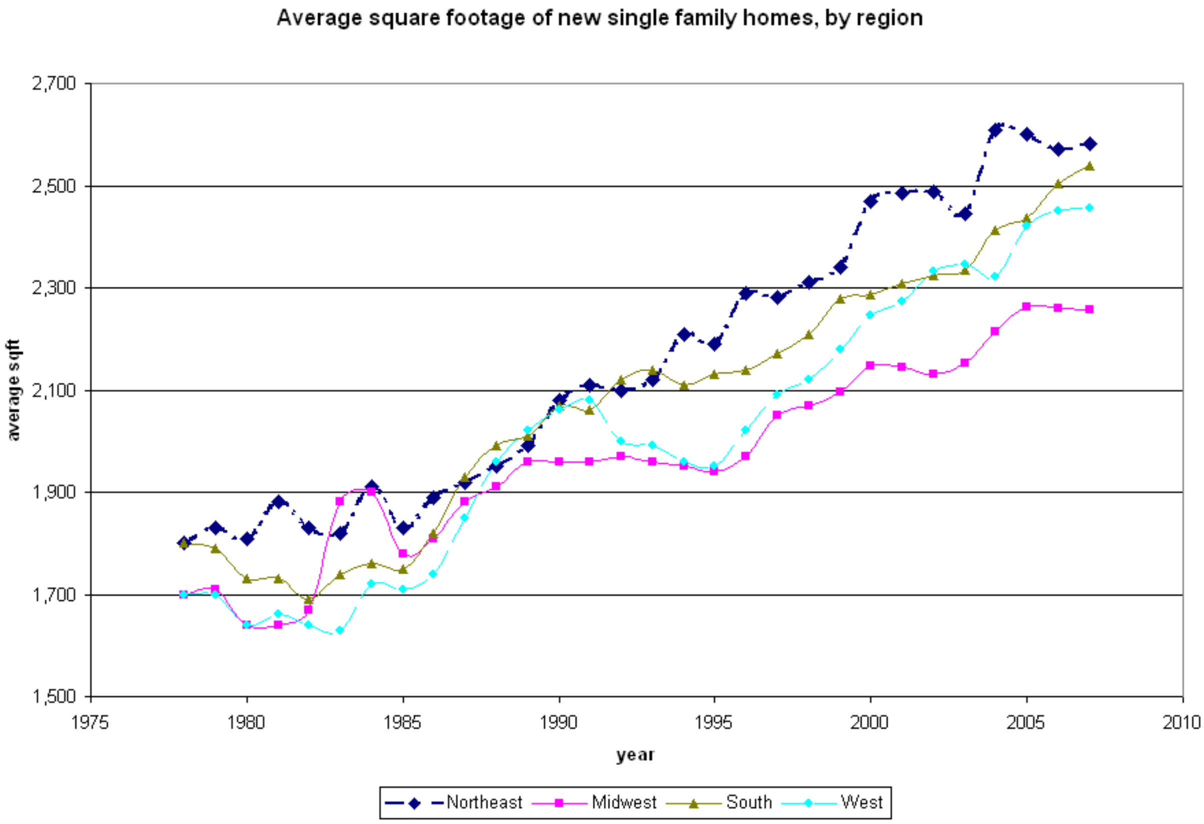
Figure 7. Temperature response and interactions with building vintage and other covariates, level specification



of lost energy, but would represent increases in comfort. However, auxiliary data (KEMA-XENERGY 2004)shows that air conditioning ownership is uniformly high (90-100%) across building vintages with central air conditioning more common than room air conditioners for newer buildings. However, the temperature response for 1990s buildings is about 30-36% higher at 90°F, which could not be explained even if adjusted down by to 10% difference in air conditioning ownership.

Secondly, although I control for the number of bedrooms; thus capturing size increases where bedrooms have increased, I do not control for the size of each bedroom. As depicted in the Fig 8 below, which comes from Census Data, the average size of buildings has increased. Thirdly, there may be a compositional difference between 1970s buildings and those constructed afterward. Apartments may bias the results. If more 1970s buildings are apartments and more 1990s buildings are single family homes, then the coefficient on ybIN1990 will pick up the (presumably higher) temperature response of single family homes. Lastly,

FIGURE 8. Homesizes for new single family homes by census region. Source: (US Census n.d.)



data on retrofits are unfortunately not available. Building retrofits (that change the building shell) are legally subject to building code requirements. Appliance standards may improve old buildings when appliances are replaced.

Addressing these potential confounds is the primary concern of future work on this paper. This means finding alternate ways of identification, i.e. constructing a better counterfactual. I will try to incorporate information on the proportion of apartments, incorporate the homogeneity of building vintage (e.g., tract home development) within a region, control for income and bedrooms nonlinearly, use rooms instead of bedrooms to potentially address shortcomings of bedrooms as a proxy for size, and conduct separate estimation for all-electric customers and subsidized low-income customers. Conducting this analysis for more counties may also allow us to see if this pattern of results also holds for the rest of California.

Despite these potential problems, the focus on temperature response both targets the part of energy use that building codes address, temperature response, while allowing for flexible control for household variation in appliances and behavior through the household fixed effect. The already completed robustness checks have resulted in a fairly stable result.

This paper finds (1) that buildings built in the 1970s use much less electricity on hot days compared to buildings built prior to 1970, (2) that buildings built in the 1980s and 1990s use more electricity compared to buildings built prior to 1970 and in the 1970s, and (3) that these results are statistically significant, hold after controlling for the number of bedrooms (a proxy for house size) and income, and are robust to two common econometric specifications.

6. Conclusion

The key contribution of this paper is to focus on the impact of building vintage on temperature response. The key finding is that temperature response for new buildings (or more precisely, in census block groups with more new buildings) varies by vintage, that 1970s buildings have a lower temperature response than pre-1970s buildings and that 1990s buildings have a higher temperature response. This evidence is against the predictions implied by building standards legislation, which predicts lower temperature response.

It is not safe to conclude from this paper that building codes in California have failed, but it should temper declarations that they are a success and especially temper the interpretation of the Rosenfeld Curve for California as "evidence" that California energy efficiency policies are the cause of California's impressive energy efficiency performance.

It's important to carefully interpret what the claims of building codes and energy efficiency have been. This can be facilitated by placing claims into two categories: relative-to-counterfactual changes and absolute changes. The numbers presented by the CEC exemplify relative-to-counterfactual changes. Using an engineering model, energy usage is 18% lower with building standards as designed as compared to a hypothetical world without any standard. The proper way to validate this claim in the field is to compare a building that implemented the standard with a building that doesn't meet the standard; unfortunately a building that doesn't meet the standard doesn't exist and so this claim cannot be validated.

In contrast, the Rosenfeld Curve offers an absolute comparison. Per capita residential electricity use in California has not increased since roughly 1974. This absolute comparison doesn't require us to look at a hypothetical counterfactual. If people in old buildings are the same as they were in 1974, this means that people in new buildings overall are doing the same. We know that these new buildings are larger. Hence, they must be using less energy in order to have the same overall performance. But this paper shows that they are doing *worse* in terms of temperature response; with temperature response being the primary mechanism of building standards. Hence, by this logic, something else must be going on.

If we accept that 1990s buildings have overall higher temperature response and that the statewide residential electricity use is flat, this leads us to explore alternatives, some of which may not be pleasant. As the buildings performance contractors point out, there is a difference between the standard as designed and the standard as implemented. If building standard implementation isn't tested, there are many reasons why builders will shirk in this category. If bad implementation is in fact rampant, the upside is that there is a large potential resource for energy savings (without reducing comfort) if implementation is improved. Another potential explanation is that flatness of electricity use is due to compositional changes. That is, if development from 1970-1990s was concentrated in electricity-non-intensive coastal areas, this would lead to an apparent decrease in electricity relative to uniform development. However, in recent years, development is expected to be more concentrated in the hotter inland areas of California. As discussed at length in Aroonruengsawat and Auffhammer (2009), population growth and where population growth occurs could be the most significant drivers of electricity growth, swamping energy efficiency. Cost effective energy efficiency is still an important policy, but verification that it delivers on its promise should not be overlooked.

Energy efficiency policies have been tapped as a large resource to address climate change. In California's current efforts (California Air Resources Board December 2008), approximately 20% of the reductions to meet 2020 goals come from energy efficiency. It is imperative to test results in the field and understand what the policies actually deliver, not just what they promise to deliver.

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