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Why Has California's Residential Electricity Consumption Been Rising So Slowly since the 1980s?: A Microeconometric Approach

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Abstract

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Why Has California's Residential Electricity Consumption Been Rising So Slowly Since the 1980s?: A Microeconometric Approach

Using unique microeconomic data we document the roles of household demographics, ideology and structure in electricity demand. Homes built after 1983 use less electricity than home built before 1960, coincident with stricter building codes. Homes built in the 1970s and early 1980s use more electricity despite building codes in part because the price of electricity at the time of construction was low. We construct an aggregate residential electricity consumption index. Building codes partially explain California's slowly rising consumption from 1980 to 2006 while other factors (such as rising incomes and increased new home sizes) go in the opposite direction.

California's electricity use per capita has been almost flat from 1973 to the present whereas that of the U.S. has increased by 50 percent. Explanations for this divergence, called the Rosenfeld curve (named after Arthur Rosenfeld of the California Energy Commission), have focused on California's energy policies, in particular its increasingly strict building and appliance codes, as well as its milder climate, household demographic trends, and its higher energy and land prices which have made its homes smaller and may have driven some energy intensive heavy industries out of the state (Charles 2009).

The residential sector consumes roughly 34% of California's electricity. Between 1970 and 2007 residential retail electricity sales per housing unit increased by 58 percent for the nation but by only 33 percent for California.[1] Underlying these macro trend averages are the individual purchase decisions of millions of heterogeneous households. At any point in time, there is large variation across households in electricity purchases, but this variation is stable over time. Residential monthly electricity sales data from a California county show that between 2001 and 2008 the ratio of the 90th to the 10th percentile is between 6 and 7 in any calendar year.

This paper uses several unique data sets to examine cross-sectional and temporal variation in household electricity consumption. Our study contributes to a growing literature on residential electricity demand (Aroonruengsawan and Auffhammer 2009; Borenstein 2009; Reiss and White 2005, 2008). Similar to recent studies, we work with a large residential panel data base that provides monthly electricity purchases for every home in a California county over the years 2000 to 2009. Unlike the recent literature we also have information on the home's physical characteristics, the demographic and socioeconomic characteristics of the household

[1] Total retail electricity sales are from the Energy State Data System (SEDS) of the Energy Information Administration http://www.eia.doe.gov/emeu/states/_seds.html . The number of housing units are from the 2006 American Community Survey and from US Department of Commerce (1993).

living in the home, measures of own and neighborhood ideology, and information about the attributes of the community the home is in. We use these data to investigate why households differ with respect to their electricity purchases at a point in time and over time.

Building codes were first instituted in 1978 and then subsequently strengthened. Coincident with the strengthening of building codes, homes built after 1983 consume less electricity than homes built before 1960. But homes built between 1978 and 1983 consumed more electricity than home built prior to 1960 despite the extant building codes. Building codes could be ineffective if there is a "rebound" effect leading consumers to increase electricity usage (e.g. cranking up the air conditioning) or if builders do not effectively implement the code (e.g. they install poor insulation). We may not observe an effect of building codes if there are countervailing trends such as the installation of energy-consuming features or the construction of shoddier dwellings. We argue that houses built in the 1970s and early 1980s were energy inefficient in part because the price of electricity was low. Although household electricity purchases are not very responsive to contemporaneous prices, the price of electricity at the time the house was built is negatively correlated with current energy expenditures. We also document how electricity purchases depend on liberal/environmentalist ideology, characteristics of the household such as income and number of persons, and characteristics of the residence such as its size.

We use our regression estimates to construct an aggregate residential electricity consumption time series index. This index enables us to decompose the residential sector's total change in electricity consumption into several key subcategories including changes over time in the vintages of the building stock, in household demographics, in the size of homes, and in the location of the population. [2] Employing data from 1980 to 2006, we use our

[2] Sudarshan and Sweeney (2008) explain the Rosenfeld curve by employing a macro shift share approach in which they ask how much of the overall difference between California and the rest

decomposition to document countervailing macro trends. We show that while the increase in household incomes and in the square footage of new homes both predict rising average electricity consumption, the phase in of building codes partially offsets these effects. The average home is becoming more energy efficient as new homes are built under more stringent codes and homes built during the 1970s and early 1980s begin to represent a smaller share of the overall housing stock.

Empirical Framework

Within a household production framework, a household values electricity as an input in producing comfort (e.g. indoor temperature) and leisure and household production activities . A household's electricity consumption depends on three choices: 1) the choice of a specific home that differs along dimensions such as size, vintage, and presence of a pool; 2) the choice of appliances and renovations made to the structure; and, 3) utilization of appliances for leisure and household activities, indoor temperature control and illumination.

A house is a long-lasting durable. At its birth, building codes and decisions made by the developer affect the home's energy efficiency. A developer's decisions depend on building codes, technology, and energy prices at the time of construction.[3] Houses built during years of low electricity prices may be less energy efficient because consumers demand less efficient houses.

When a household first moves into a home, it may make changes to the home such as updating durable appliances. If energy efficiency is not capitalized into the resale price of

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of the nation can be explained by the composition of California households, urbanization, industry composition, structure floor space, fuel type used, and climate.

[3] Treating energy as an input into the price of housing services, Quigley (1984) shows that an increase in energy prices leads to a decline in the demand for housing and a decline in the demand for energy inputs, including residential electricity demand.

homes, then home owners with the longest expected future tenure in the home have the greatest incentive to invest in new energy efficient durables. Once these durables are installed, the household faces temperature shocks and chooses durables depending on its demographics, relative prices, income, and time spent at home.

A household's total monthly electricity purchases depend in part on household demographics, time spent at home and how this time is used, and a whole collection of past actions (such as durables choices and decisions about the construction of the home) that are only partially observed by the econometrician. We therefore focus on estimating reduced form household/month electricity purchase regressions as a function of household income and demographic characteristics, electricity rates, year built, and proxies for household ideology. All else equal, we posit that environmentalist households will consume less electricity.[4] We focus on homeowners because we can observe neither landlord characteristics nor the contractual agreement between the landlord and tenant (Levinson and Niemann 2004).

We investigate the role of building codes and prices at the time the home was built in determining household monthly electricity purchases. We proxy for building codes using vintage year dummies. These dummies proxy not just for building codes, but also for the energy efficiency of major appliances, general construction standards and for aging effects (i.e. houses losing their energy efficiency as they age). As seen in Table 1, energy efficiency requirements for California homes have become stricter since the introduction of energy efficiency standards for residential buildings in 1978. Standards for appliances (not shown)

[4] Kotchen and Moore (2007), and Kahn (2007), Kahn and Morris (2009), Kahn and Vaughn (2009) have documented that environmentalists exhibit "greener" day to day consumption choices than the average person. Kotchen and Moore (2007) find that in Michigan environmentalists consume less electricity than observationally similar people. Kahn (2007) documents that environmentalists are more likely to have a smaller carbon footprint (based on driving, vehicles owned, and their home's physical attributes) than the average person. One possible explanation for these facts is that environmentalists gain pleasure from engaging in "voluntary restraint".

have also become stricter.[5] Rosenfeld (2008) argues that per capita electricity sales in California would have been 14% higher without California standards and programs. Table 1 also shows that there were countervailing trends. In a survey of households in the county served by the utility whose records we examine, those living in homes built in the 1970s have older heating and cooling systems than those living in older homes. An increased prevalence of heating and cooling systems with ducts also might reduce the energy efficiency of homes built in the 1970s relative to earlier years. Finally, because real electricity prices in California were falling in the 1960s and 1970s and only began to rise in the 1980s, we would expect that homes built in the 1970s would be less energy efficient than earlier and later homes.

Our data, described in detail in the next section, come from a California utility which serves an entire county and a small part of another. Compared to the nation as a whole, this county has the same proportion of college graduates (24% in the nation versus 25% in this county) and the same proportion of residents above age 64 (12% in the nation versus 11% in this county), but its population has a smaller share of whites (76% in the nation versus 66% in this county).

The utility did not institute large price increases in the years for which we have data (2000-2008). In 2001 the utility increased its pricing tiers from two to three (see Table 2 for 2008 tier pricing). There were rate changes in 2001 (coincident with a mass media campaign and therefore unidentifiable), 2005, and 2008, but electricity purchases were remarkably consistent across quantiles (see Table 3). We estimate a price elasticity using panel data, but our data do not provide much price variation. Our data are best suited for examining the effects

[5]Energy efficiency codes changed for refrigerators in 1977, 1979, 1987, 1992, 2001; for air-conditioners in 1978, 1979, 1981, 1984, 1988, 1991, 1992, 1993, 1995, and 2006; for clothes washers in 1994, 2004, and 2007; for electric furnaces and boilers in 2008 and for small water heaters in 2004 but also in earlier years (see Nadel 2002 and Residential Compliance Manuals from 1978 to the present). See http://www.energy.ca.gov/2007publications/CEC-400-2007-017/CEC-400-2007-017-45DAY.PDF

of household and home characteristics such as income, ideology, and year built on electricity purchases because they provide unusually rich detail on these characteristics.

Data

Our primary data set consists of household level billing data from September 2000 to December 2008. These data provide us with information on kilowatt hours purchased per billing cycle, billing cycle dates, whether the home generated power, whether the household uses electric heat (referred to as electric homes), and whether the household is enrolled in the utility's renewable energy program, their medical assistance program, or their energy assistance program. We link each billing cycle to the mean daytime and nighttime temperature in that billing cycle.

We merge 2008 credit bureau data with our residential billing data. These credit bureau data provide us with household income; demographic characteristics of the household such as ethnicity, age of the household head, and number of persons in the household; and, the year the house was built and other house characteristics such as square footage, whether the house has a pool, and the type of roof the house has. We also have access to the 2009 credit bureau data. These two cross-sections allow us to create a short panel data set.[6]

The 2008 credit bureau data contain information on 520,835 households and we restrict the sample to the 309,149 single family homeowners. These households are slightly older (a mean age of 55 for the household head) and include fewer household members (a mean of 2.2) compared to a random sample of single family homeowners in the metropolitan area of our utility in the American Community Survey (ACS) of 2005-2008 (where the mean age of the household head is 53 and the mean number of persons in the household is 2.8).

[6] We have monthly/household panel data for the dependent variable (electricity purchases) and data on household demographics from the 2008 and 2009 credit bureau cross-sectional data sets.

We merge individual voter registration and marketing data with our data set.[7] For registered voters we know party affiliation, level of education, and whether the individual donates to environmental organizations. We were able to link half of our sample to the voter registration data. (We do not limit our sample to the registered.) We linked either the person whose name was on the utility bill or the first person on the utility bill.[8] The individuals we could not link were living in smaller households and in block groups with a low proportion of the college-educated, were more likely to receive a subsidy for electricity because of their low income, and were more likely to have a household head above age 60.[9] We also merge with these data, by the block group, the share of registered voters who were liberal (Democrat, Green, or Peace and Freedom) in 2000 and the share of vehicles which were hybrids in June 2009.[10] We expect that environmentalists are more likely to live in liberal, educated communities.

We have access to two other revealed preference measures of a household's environmentalism. From the data base with voter registration information, we know whether a household has donated money to an environmental group and we know whether the household has signed up for the utility's renewable power program. Each household decides whether to opt in and pay a fixed cost of $3 a month to have 50% of its power generated by renewables or $6 a month to have 100% of its power generated by renewables.[11]

[7] We purchased the data from www.aristotle.com.
[8] Only 5% of households were "mixed" between conservatives and liberals.
[9] Relative to all homeowners in the same county these individuals were also more likely to be of Asian or other ancestry rather than of European ancestry, but were less likely to be Spanish speaking. They were also lower income.
[10] The political voter registration data are from http://swdb.berkeley.edu/. While we acknowledge that it would be better to merge 2008 hybrid registrations rather than future (June 2009) registrations, vehicles are a durable good and many of the vehicles were owned as of 2008. A block group's hybrid vehicle ownership is thus likely to be highly correlated between 2008 and 2009.
[11] The collected revenue is used by the electric utility to purchase and produce power from wind, water, and sun.

We use these data to examine the effects of income, demographics, ideology, and building vintage effects on 2008 daily household energy purchases. Because building year dummies will capture the effects of building codes, electricity prices at the time the house was built, and aging effects, we turn to additional data to understand the building year patterns we uncover. These data include a 2008 Home Energy Survey carried out by the utility which we linked to our cross-sectional 2008 data and which provides us with information on 495 single family homeowner households, panel data from the utility, and census data.

We use a sample of California owner-occupied, single family homes from the 2000 5% IPUMS (Integrated Public Use Sample) to examine the effect of electricity prices in the year the home was built on current energy expenditures. Respondents were asked their annual electricity expenditures. We restrict to households in which the head is ages 30-65. We know average electricity prices in the utility district at the time the home was constructed.[12] Because our price data are available from 1960 onward only, we restrict our sample to homes that are at most 40 years old in the year 2000. We use these data to examine whether homes built in years when electricity prices were low used more electricity in calendar year 2000.

Our panel data, which begin in September 2000, allow us to examine the extent to which home vintage reflects aging effects and whether renovations, which we know about from permit data for the major city served by the utility, affect a home's electricity purchases. The panel

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[12] We thank Tom Gorin at California Energy Commission for providing us with data on mean annual residential electricity rates by utility since 1960. The IPUMS data identifies geographical areas called PUMAs. We use the Mable Geocorr mapping file to map PUMAs to counties. Erin Mansur provided us with a bridge file that allowed us to assign each county to a utility. The IPUMS data reports a home's year built in roughly ten year categories. Using this information and the home's PUMA location allows us to merge to each record the time averaged real utility price data. When a county was served by more than one utility, we averaged across the two utility prices. We cluster the standard errors by county/built year interval since the average electricity price does not vary within this category.

data allow us to test the robustness of our cross-sectional 2008 estimates by controlling for house and for family fixed effects in a sample of households who moved into different homes within the electric utility service area between 2008 and 2009, the years for which we have information on income and demographic characteristics. We use the panel data from 2000 to 2008 to examine whether among movers within the electric utility district the residence or the family explains more of the variation in electricity purchases. We also use the full electric utility panel of approximately 50 million billing cycle observations, which includes owners, renters, and apartment dwellers, to examine how different households respond to climate and price changes. Our exploration of price effects employs both the variation provided by the modest rate increases and by differences in winter and summer prices. We know the billing cycle that each household is on. For example, some households may be on a July 15th to August 14th cycle while other households may be on a July 4th to August 3rd cycle. Thus two different households in the same calendar year and same month who are on different billing cycles will face *different* climate conditions and electricity prices. The utility's peak season is from May to October. Thus, between April and May prices rise and between October and November prices fall. We exploit these discontinuities to estimate price elasticities.[13]

Home and Demographic Characteristics, Ideology and Prices

Our first specification uses the 2008 billing data linked to the credit bureau data. We regress the logarithm of mean daily kilowatt hours purchased by a household in each billing cycle on household and house characteristics and neighborhood ideology, that is we run

1) $$\ln(kWh) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon$$

[13] We also investigated using the price schedule as an instrument for the average price. Although the average price was correlated with the number of days on the peak schedule, the R squared was low. Price increases both over time and across tiers have been more modest in this utility than in other California utilities.

where $X_1$is household income; $X_2$is a vector of demographic, ideological, and other characteristics including age, ethnicity, whether Spanish is spoken at home, the year the household moved into the house, the number of persons in the household, the party of registration, whether the household donates to environmental organizations, whether the household purchases energy from renewable resources, and the special utility rate of the household (medical assistance or energy assistance); X_3 is a vector of house characteristics (square footage, electric heat, roof type, and whether the house has a pool); X_4 is a vector of census block group characteristics, consisting of the fraction of registered voters who were "liberal" (Democrats, Green Party, or Peace and Freedom) in 2000 and the fraction of registered vehicles that were hybrids in June 2009; X_5 is the mean of daytime and nighttime temperature in the billing cycle (we also examine the interaction between liberal and mean temperature); $X_6$is a vector of building year dummies (single years with pre-1960 as the omitted category); and, ε is an error term. The dummies enable us to determine if stronger building codes coincide with improved electricity efficiency. Standard errors are clustered on the household and the block level.

As we discussed in the empirical framework section, we recognize that we are collapsing both discrete choices (over home type and appliances) and continuous choice (utilization) into one outcome measure; monthly electricity consumption. The cost of this approach is that we cannot claim to recover how our explanatory variables affect each of these three choices. Instead, we recover a "total effect".[14]

[14] Leading structural papers such as Dubin and McFadden (1984) , Goldberg (1998), and Mansur, Mendelsohn, and Morrison (2008) have jointly modeled the decision of durable purchase and utilization. In the case of cars, a household simultaneously chooses what car to buy and how much to drive it. The price per mile of driving depends on the car chosen, so in a regression of utilization (miles driven) on demographics and price per mile, this last variable is endogenous. It is important to note that we are not following this empirical strategy. Our dependent variable is not "utilization" it is total electricity consumption. We are assuming that the error term in equation (1) is uncorrelated with the unobserved determinants of housing type.

We estimate Equation 1 using OLS to investigate the association between house and family characteristics and electricity purchases. We realize that people who live in big homes with swimming pools may be "different on unobservables". If those with an unobserved taste for electricity intensive goods self select to live in large homes that have energy consuming attributes (such as swimming pools), then our OLS estimates will not recover the true causal effects of home size and swimming pools on a random household's electricity consumption. To investigate further the role of housing features on electricity purchases, we turn to panel data to control for the family fixed effect. Using a sample of movers, we observe the same family living in two different homes. We also can control for a residence fixed effect in the panel data and study how the family attributes are associated with electricity consumption based on observing different families in the same house.[15]

The marginal and average price that households face for electricity is a choice variable because of the utility's rising block tier pricing system. Households consuming more electricity face a higher marginal price. Recent research (see Borenstein 2009 and Reiss and White 2005) examines whether households are responsive to average or marginal prices. In this paper, we pursue two different strategies for examining how robust are our results once we control for electricity prices.

We control for electricity prices by modifying Equation 1 to include electricity price as an independent variable. Because prices are potentially endogenous and we do not have a credible instrument, we use Reiss and White's (2005) price elasticity estimate of -0.39. We assume that this price elasticity is the same for all households in our sample, thus ruling out differential price responses by demographic group. We then rewrite Equation 1 as

[15] These results are based on a short (2008 to 2009) panel for the subset of within electric utility service area movers.

$$ln(kWh) = \beta_0 - 0.39 \times ln(P) + \beta X + \varepsilon$$

where P is the price of electricity and X is a vector of other control variables. We calculate each household's average price per kilowatt-hour of electricity by month (P^*), redefine our dependent variable as $ln(kWh) + 0.39ln(P^*)$, and rerun Equation 1.[16] Although economic theory predicts that households should respond to the marginal price they are paying, Ito (2010) finds that households are more likely to respond to their average price of non-linear electricity rates. Borenstein (2009) also finds that customers do not respond to the marginal price. Our transformation thus permits us to study the robustness of our results once we control for price.

Table 4 reports estimates of equation 1. We estimate a small income elasticity of 0.05 and an elasticity for the square footage of the home of 0.42, holding all factors constant. Our estimated income elasticity is small because we control for most manifestations of income, such as a larger house and the presence of a pool. When we restrict our sample to households that received no income or medical needs subsidies and control only for age, when the household moved into the house, the number of persons in the household, temperature, electric heat, and year built dummies, we obtained an income elasticity of 0.173 ($\hat{\sigma} =$ 0.006).

Table 4 also shows that Asians, other non-European ethnics, and Spanish language speakers purchase fewer kilowatt hours, perhaps because of unobserved wealth effects. The later a household moved into a house (measured by the year of the move), the less electricity it purchases. For every additional ten years lived in the home, household electricity purchases increase by 1%. We view this variable as proxying for the average age of the durable stock. We also investigated using the number of heating and cooling degree days rather than average temperature. We found coefficients of 0.001 and 0.002 on the number of heating and cooling degree days, respectively, both of which were statistically significant at less than the 1% level.

[16] Monte Carlo simulations show that this is equivalent to constraining the coefficient on price to be equal to -0.39. We also perform robustness tests using different values of the elasticity.

However, controlling for heating and cooling degree days rather than average temperature did not change the coefficients on our other variables. Note that despite being able to control for a large number of household, structure, and neighborhood attributes, we can explain relatively little of the variance in electricity consumption -- the R^2 in these regressions averages around 0.26.

Our results highlight the role that ideology plays in explaining cross-sectional variation in electricity purchases. Controlling for structure and census block group characteristics and household income and demographics, registered Democrats, Greens, and Peace and Freedom purchase less electricity than registered Republicans, American Party, or Libertarians. A Green purchases 0.096 and a Democrat 0.039 fewer mean daily kWh (in logs) than Republicans. Those enrolled in the utility's renewable energy program purchase 0.011 fewer mean daily kWh (in logs). The greater the fraction of liberals in a block group and the greater the fraction of hybrids among registered vehicles in the block group the lower are electricity purchases.[17] A one percentage point increase in the block's liberal share is associated with a decline of 0.36 in the logarithm of electricity purchases, a decline of 30% relative to mean daily kWh purchased. The second column of Table 4 shows that when we restrict ourselves to billing cycles when the average temperature was greater than 74°F, we find that voluntary restraint is greater in the summer. Greens consume 0.111 less than Republicans and the coefficient on liberal community jumps from -0.36 to -0.60. We cannot pin down why electricity consumption is lower in more liberal communities. Either liberals who choose to live in liberal communities are more liberal and practice greater voluntary restraint or social pressure in liberal communities encourages individuals to conserve on electricity consumption.

[17] Our demographic results such as household income, age, and household size are in line with previous estimates discussed in studies such as Lutzenhiser (1993), Schipper, Bartlett, Hawk and Vine (1989), Wilson and Dowlatabadi (2007).

We probed the robustness of our results by dropping incomplete observations. Year built, square footage, age of household head, income, and number of household members are unknown for 1, 10, 32, 2, and 3% of the sample, respectively. With the exception of age of household head, little explains whether one of these observations is missing. In the case of age of household head, having the income based subsidy increased the probability of a missing age for the household head by 0.11. Running the first specification on the sample of complete observations did not materially change the results (results not shown). For example, the coefficients on square footage and income were 0.443 ($\hat{\sigma} = 0.008$) and 0.065 ($\hat{\sigma} =$0.005), respectively.

We further probed the robustness of our results by clustering the standard errors at the household rather than on the billing cycle and census block. Our standard errors were slightly smaller when we clustered at the household level. For example, using the first specification, we obtained standard errors on square footage, income, registered Democrat, and presence of a pool of 0.004, 0.002, 0.003, and 0.003, respectively, compared to respective standard errors of 0.007, 0.003, 0.003, and 0.004 in Table 4.

When we control for price effects by modifying our dependent variable to equal $ln(kWh) + 0.39ln(P^*)$ and re-run our regressions, our results show a slightly greater reduction in daily kilowatt hours among liberals, customers living in neighborhoods with a high fraction of hybrid vehicles, users of renewable energy and customers living in houses built after 1983 (see Table 4). Accounting for price effects leads to an even greater increase in daily kilowatt hours among customers with a pool and customers living in bigger homes (compare the right column to the left column of Table 4). Electric home customers enjoy a lower average and marginal price (because their steps in the tier system are longer and they face lower winter rates). The positive effect of having an electric home falls slightly once we account for price in our dependent variable. Our results are robust to different price elasticities. For example, for price elasticities between -0.59 and -0.19, the coefficients on income vary between -0.058 and -0.056 and those on square footage vary between 0.438 and 0.466.

We further investigate the role of electricity prices on consumption by using the full 50 million panel observations. We calculate for each year/month in our sample the mean price per kilowatt hour that households faced. This mean price is exogenously determined for any household. Prices vary because of rate changes in 2001, 2005, and 2008 and, more importantly, because of rate increases in the summer. We estimate

$$\ln(kwh) = \beta_0 + \beta_1 T + \beta_2 T^2 + \beta_3 \ln(P) + \beta_4 H + \varepsilon \tag{2}$$

where T is temperature in the billing cycle, P is the price, and H is a vector of household fixed effects. Standard errors are clustered on the billing cycle. We obtain a statistically insignificant coefficient of -0.126 ($\hat{\sigma}$=.081) on the logarithm of the price of electricity (full results not shown). This is smaller than Reiss and White's (2005) price elasticity estimate of -0.28 from OLS estimation and of -0.39 based on GMM estimation. Our estimate is also smaller than Borenstein's (2009) median average price elasticity of -0.217 but well within his estimated range. In addition, in the panel registered liberals and households living in block groups with a high proportion of liberals reduce their consumption during the summer months.[18]

We test the robustness of our cross-sectional estimates by examining movers between 2008 and 2009 linked to the 2008 and 2009 credit bureau data. This second "short" panel allows us to examine households who moved into different homes within the electric utility service area and residences whose owners changed. In looking at households who moved into different homes, we include a household fixed effect and test how the home's attributes (size

[18] Full results are not shown. The coefficient on the interaction between average temperature and liberal block group was -0.016 and the coefficient on the interaction between average temperature and being a member of the Green Party or the Peace and Freedom party was -0.001. Both coefficients are statistically significant at the 0.1 percent level.

and year built) affect electricity consumption. In looking at homes with different owners, we include a home fixed effect to study how changes in the demographics of the family (income and age) correlate with electricity consumption. Specifically, we estimate

3) $$\ln(kwh) = \delta_{home} + \beta_0 + \beta_1(Household\ Characteristics) + \varepsilon$$

and

4) $$\ln(kwh) = \delta_{household} + \beta_0 + \beta_2(Home\ Characteristics) + \varepsilon$$

where δ is the home or household fixed effect.

Cross-sectional regressions (such as equation 1) are subject to the criticism that there may be unobserved features of the home or the household that are correlated with the observables. We use our short panel from 2008 to 2009 and focus on households who moved between electric utility service area homes over this period and on the same house in the electric utility service area with two different owners. Unfortunately, there are only 3,000 such movers. We use these data and estimate Equations 3 and 4. The panel specification that includes a home fixed effect allows us to estimate the role of household size and household income and the panel specification that includes a household fixed effect allows us to estimate the role of housing attributes such as square feet and year built on electricity consumption. The panel results with fixed effects yield "within" estimates that are generally similar to the OLS results estimated on the same sample (see Appendix Table A and see the next section for results on year built dummies in our cross-sectional regression). This robustness test raises our confidence in our cross-sectional estimates.

Building Codes and Year Dummies

California introduced its energy efficiency standards for new construction in 1978. Figure 1, which plots year dummies from the first specification given in Table 4 for every year after 1960 (pre-1960 is the omitted category), demonstrates that electricity purchases for households living in houses built when those codes were implemented are not lower than homes built before these new codes were enacted. Controlling for our host of demographic, structure and ideology variables, we find a distinctive non-monotonic relationship between a home's year built and electricity consumption in 2008. Relative to homes built before 1960, homes built between 1960 and 1983 consume roughly 5% more electricity. Homes built in the 1990s consume 15% less electricity than homes built in the 1978 to 1983 period. Starting from 1984 to the present, we observe a monotonic negative relationship between year built and electricity consumption. Relative to homes built before 1960, those living in houses built in 2006 or later consume 16% fewer kilowatt hours. When we restrict to billing cycles when the average temperature was greater than 74°F (results not shown), households' increase in daily kilowatt hours is greater for houses built between 1960-1983 relative to houses built before 1960 and the decline in daily kilowatt hours for post 1992 structures is smaller compared to our results for all billing cycles.

We turn to various data sets to determine why families living houses built in 1960-1983 purchase more electricity than families living in houses built prior to 1960 and why starting in the mid-1980s we observe a negative relationship between year built and electricity purchases. Potential explanations include include building codes (which could explain the negative relationship between year built and electricity purchases since the mid-1980s), the age of major appliances, electricity prices when the house was built (a potential explanation for the higher electricity purchases of household living in 1960-1983 houses relative to those living in pre-1960 housing), and aging effects (which could explain why households living in more recently constructed homes use less electricity).

The age of major appliances and the presence of insulation cannot explain why electricity usage is less for more recent building vintages. When we used a 2008 Home Energy

Survey for 495 single family homeowner households, we found that houses built after 1992 were more energy efficient than houses built before 1960 regardless of whether we controlled for the age and type of appliances. Controlling for variables such as the age of the furnace, the age of the HVAC, the type of windows, the presence of insulation, the number of refrigerators, the age of the refrigerator, and the number of LCD and plasma TVs, we found that that coefficient on built in 1992 or later relative to built before 1960 was -0.191 ($\hat{\sigma} = 0.073$). Without these controls, the coefficient was -0.199 ($\hat{\sigma}$ =0.080). The sample is too small to draw any conclusions about the role of old heating and cooling systems in explaining why houses built in 1960-1983 consume more electricity than houses built before 1960. When we control for age and type of appliances, the coefficient on built between1960-1983 falls from 0.068 ($\hat{\sigma} = 0.062$) to 0.041 ($\hat{\sigma}$ =0.058). Although the point estimate implies that older appliances explain roughly 40% of the difference in electricity consumption between pre-1960 and 1960-1983 buildings, the coefficient on built between 1960-1983 is statistically insignificant.

We investigate why houses built in 1960-1983 consume more electricity than homes built prior to 1960 by examining whether households living in houses built in years when energy prices were low purchase more energy. Between 1960 and 1983 our electric utility's real price of kilowatt hours in 1977 dollars fell from 3.2 cents per kilowatt hour to 2.6 cents per kilowatt hour, reaching a low in the late 1970s. Real prices then rose, reaching a high in the late 1980s and then fluctuating in a narrow band. In other California utility districts the 1970s were a period of low energy rates as well.

Using the 2000 IPUMS we compare houses built in different years in the same neighborhood at the same point in time. We specify the log of annual household electricity expenditure, E, as a function of the logarithm of the mean price of electricity in the electric utility district in the building vintage year (P), a vector of house year built dummies (Y), a vector of house characteristics (H), including electric heat and number of rooms, a vector of socioeconomic and demographic statistics (X), geographical fixed effects (F) called "PUMAs" in the Census data, and an error term (ε):

5) $$ln(E) = \beta_0 + \beta_1 ln(P) + \beta_2 Y + \beta_3 H + \beta_4 X + \beta_5 F + \varepsilon.$$

Because of data availability our year built dummies are less than 2 years old (the omitted category), 2-5 years ago, 6-10 years ago, 11-20 years ago, 21-30 years ago, and 31-40 years ago. Our socioeconomic and demographic variables include the logarithm of household income, the Duncan Socioeconomic Index, race, the number of persons in the household, and the age of the household. We cluster the standard errors on electric utility district/year built dummies.[19]

The 2000 census data show that in California as a whole households living in houses built before 1998 have higher annual electricity bills controlling for electric heat, the number of rooms, household income and demographic characteristics, and PUMA fixed effects (results not shown). Houses built 1960-1989, and particularly those built in the 1970s, have higher electricity bills than houses built prior to 1960. Compared to houses built after 1998, the coefficients on year built pre-1960, 1960-69, 1970-79, 1980-89, 1990-94, and 1995-98 are 0.092 ($\hat{\sigma}$=.011), 0.132 ($\hat{\sigma}$=.012), 0.151 ($\hat{\sigma}$=.011), 0.124 ($\hat{\sigma}$=.011), 0.080 ($\hat{\sigma}$=.012), and 0.029 ($\hat{\sigma}$=.012), respectively.

Table 5, which looks at houses built after 1959 because our price data begin only in 1960, shows that houses built in periods of low electricity prices have a higher electricity bill.

[19] We recognize that pricing is non-linear and that we only have information on total expenditures not on total consumption. However, the two are correlated. In our utility data the correlation is 0.97. When we use our 2008 utility data to run cross-sectional regressions on total expenditures rather than on electricity consumption without controls for rate subsidies, our building year dummies still show that houses built in the 1970s and early 1980s consume more electricity than houses built prior to 1960 and that beginning in the mid-1980s houses that were built more recently consume less electricity.

This table also shows that past prices partially explain why houses built in the 1970s have such high electricity bills. Controlling for price in the local utility district and vintage year category, the magnitude of the coefficient on the year built 1970-79 dummy falls from 0.154 to 0.090. Past prices thus explain 42% of the difference in electricity expenditures between 1970-1979 and 1998-2000 homes. The price elasticity of annual electricity expenditures with respect to price at the time the house was built is -0.22.

Low electricity prices also encouraged the building of electric homes. When we estimated a probit model of whether the home was an electric home on the logarithm of the electricity price in the year and utility district when and where the house was built (and controlling for PUMA fixed effects), we obtained a coefficient of -0.058 ($\hat{\sigma}$=.019) on price (this is a derivative of the coefficient on price). However, because we include an electric heat dummy in all of our cross-sectional specifications the pattern that we observe in the year built dummies cannot be explained by whether a home is an electric home.

We use our panel data to estimate aging effects between 2000 and 2008, enabling us to understand the extent to which our year built dummies reflect aging. That is, we estimate

6) $$ln(kWh) = \beta_0 + \beta_1 T + \beta_2 A + \beta_3 F + \varepsilon$$

where T is mean temperature, A is current year minus year built, and F is a household fixed effect. We conclude that while there are aging effects, these effects are small (results not shown). We find that as a house ages, each additional year increases mean daily kWh by 0.1%. (When the dependent variable is the logarithm of mean daily kWh and control variables are temperature, a dummy for summer months, and house fixed effects, the coefficient on house age is 0.0011, $\widehat{\sigma}$=0.0005.)

How much is a house's energy efficiency determined by its year of birth, or can a home renovation change the energy efficiency of the dwelling? Table 1 showed that the pre-1960 housing stock was more likely to have been renovated than housing built between 1960 and 1983. But as discussed in the Appendix, most renovations increase energy consumption. Renovations therefore cannot explain why households living in homes built before 1960 purchase less electricity than households living in homes built in 1960-1983.

Although electricity prices at the time the house was built partially explain why houses built in 1960-1983 consume more electricity than houses built earlier, we cannot explain all of these vintages' higher consumption. Potential explanations include older heating and cooling systems and the increased prevalence of heating and cooling systems with ducts.

Explaining the Variance in Electricity Purchases

Our cross-sectional estimates imply that year built, and therefore the residence, is an important determinant of electricity purchases. Using our first regression in Table 4, we predict that if all households were living in a house built in 2007, monthly electricity purchases would fall by 12%. In contrast, if all households were members of the Green or Peace and Freedom party (in actuality less than 1% of all registered voters), donors to environmental causes, and purchasers of electricity from renewable sources monthly electricity purchases would fall by 6%. House characteristics explain mean electricity purchases, but, as Table 3 showed, the standard deviation of electricity purchases is as large as the mean. Our examination of movers and stayers in Appendix Table A showed that with residence fixed effects we can explain 98% of the variance in electricity purchases and that with family fixed effects we can explain 81% of the variance. But what are the relative contributions of residence and family to variance in electricity purchases?

We investigate how much of the variance in electricity purchases is explained by the characteristics of the residence and of the household by performing an analysis of variance among a random sample of movers within the electric utility service area. We examine movers between 2000-2008. For every single month, we perform a two-way ANOVA, in which we estimate the partial sum of squares for the residence and for the household among non-apartment dwellers. A comparison of the partial sum of squares for the residence and for the household reveals whether the structure or the family explains a greater proportion of the variance in electricity consumption. Because of computational limitations, we estimate two-way ANOVAs for random subsamples of the data within each month. We assign each home a number drawn randomly from an uniform distribution and restrict our monthly samples to observations that were randomly assigned a number less than or equal to 0.1. Our reported results drop apartment dwellers. The number of observations thus varies from month to month. We recognize that movers into a more electricity efficient structure may have different preferences or their household composition may have changed. The former will lead us to overestimate the contribution of residence to the variance in electricity purchases while the latter could lead us either to over- or under-estimate this contribution.

Table 6, which gives the partial sum of squares, the mean sum of squares, the degrees of freedom, and the F statistic for the model, the residence, and the family in every month, shows that both residence and household are statistically significant predictors of the variability in electricity purchases. The p values (not shown) for the F statistic for both residence and family are 0.00001 or less in every month.

Table 6 shows that the house itself accounts for a larger share of the variance in total electricity purchases than the household. For example, in January the residence accounts for roughly 84% (=(482/572)100) of the variability in purchases while the family accounts for only 3% (=(19/572)100) of this variability. The remaining 13% of the variability is accounted for by the residual. The partial sum of squares for the residence is more than three times larger than the partial sum of squares for the family in July, the hottest month of the year, and the partial sum of squares for the residence is more than two times larger than the partial sum of squares for the family in December, the coldest month of the year. When we included apartment dwellers, the partial sum of squares for residence was even larger than the partial sum of squares for the family.

Understanding Aggregate Time Series Trends

Between 1980 and 2006 residential electricity consumption per capita rose by 16% in California compared to 43% in the nation as a whole. Per housing unit, the respective increases were 21 and 32%.[20] What accounts for the "slow" California trend? Rising incomes, bigger home sizes, an increase in the share of electric homes from 10% in 1980 to 15% in 2006, and the move to warmer inland areas should increase electricity consumption. But the declining share of energy inefficient homes built in the 1970s (see Table 7) should decrease electricity consumption.

We examine how average household electricity consumption changes as the attributes of California households and structures, the temperature where most people live, and Californians' party registration have changed over time. We begin by estimating a modified version of our 2008 cross-sectional regression (Equation 1) for all electric utility homeowners using in the regression only attributes that are available in the 1980-2000 Censuses and the 2006 American Community Survey, in aggregate voter registration data, and in our cross-sectional data.[21] That is, we estimate

$$7)\qquad \text{kWh} = \beta_H(Household) + \beta_S(Structure) + \beta_T(Temperature) + \beta_D(Democrat) + \beta_Y(Year\ Built\ Dummies) + u$$

[20] Total retail electricity sales are from the Energy State (1993). Data System of the Energy Information Administration http://www.eia.doe.gov/emeu/states/_seds.html . The number of housing units and population estimates are from the 2006 American Community Survey and from US Department of Commerce (1993).

[21] Because we do not know square footage from census data we proxy for state-wide square footage using information on square footage by year built.

where the dependent variable is mean daily kWh per billing cycle in July 2008, our household variables are the age of the household head, the number of persons living in the household, and income; the home characteristics are square feet and whether the home has electric heat; Temperature is the mean of daytime and night-time temperature within the billing cycle; Democrat indicates that the utility customer is a registered Democrat; and the eight year dummies are indicators for built prior to 1940, built in 1940-1949, 1950-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, and built 2000 or later. We restrict our sample to registered Democrats and Republicans. The regression results are given in Appendix Table C.

We then calculate average electricity consumption per decade for the average California household who lives in single family housing. We calculate this by using our estimated coefficients, $\hat{\beta}_H, \hat{\beta}_S, \hat{\beta}_T, \hat{\beta}_D, \hat{\beta}_Y$, and sample means for household demographics and politics and structure attributes from the 1980, 1990, and 2000 Census, 2006 American Community Survey and voter registration data. We use county level July average temperature data and calculate a state level mean by calculating the population weighted July temperature exposure in each year. We use aggregate state political voter registration data to calculate the share Democrat in each year. To calculate our electricity consumption index, we combine these data sources along with our index weight estimates from the linear regression (see equation 7) and we estimate for each year t (1980,1990, 2000, and 2006):

8) $$kWh_t = \hat{\beta}_H\left(\overline{Household_t}\right) + \hat{\beta}_S(\overline{Structure_t}) + \hat{\beta}_T(\overline{Temperature_t}) + \hat{\beta}_D(\overline{Democrat_t}) + \hat{\beta}_Y(\overline{Year\ Dummies_t})$$

Our resulting index resembles a Paasche Index because we use our regression estimates of Equation 7 from 2008 as index weights to collapse the characteristics at each point in time into a single energy index. [22]

Table 8 reports our decomposition results. The units are kWh per day in July. We present the total average consumption by decade and disaggregate this total into the contributions from housing structure, household demographics, climate migration, and politics. Predicted average electricity consumption is rising over time by 8%.[23] The sub-indices show that different subcomponents are moving in opposite directions. Rising household income and increasingly larger home size have increased electricity consumption but partially offsetting this is the shrinking share of the housing stock built in the “brown vintages” from 1960 to 1980. Changes in household characteristics (income, household size, and age of the household head) predict greater consumption over time. Population growth in higher temperature areas has relatively little effect as do changes in the share of registered Democrats.[24]

Although we do not explicitly account for price changes, we acknowledge that prices may have played a role in the overall California trend. Real prices rose by 13% between 1980

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[22] We are assuming that index weights from the utility service area can be applied to all of California. The county served by the utility resembles the rest of California in the fraction of the age 25+ population with a bachelor’s degree and in household median income, but it has a smaller foreign-born population. Although trends in the fraction of the population with a bachelor’s degree and in household median income resemble those in the rest of the state, the county served by the utility has experienced a larger percentage increase in the foreign-born population.

[23] This is less than the observed increase in retail sales per housing unit of 21% in this time period. Because our regressions do not account for new appliances such as widescreen TVs, we should be under-predicting electricity usage.

[24] The share of Democrats, however, may be a poor predictor of environmentalism if Democrats have become greener over time.

and 2006, but in 1990 they were at their 2006 level and in 2000 they were at their 1980 level.[25] However, we do not observe changes in electricity consumption that coincide with changes in average prices.

Our index enables us to predict the effects of new construction on mean July daily kWh purchased. By 2025, California's population is projected to grow by 7 to 11 million people (Johnson 2010). This implies an additional 1.4 to 2.2 million single family owner occupied households given the current ratio of population to owner occupied homes. Assuming no demolition of homes built before 2006, 17 to 24% of households in 2025 will be living in a home built in 2006 or later. If these homes use the same amount of electricity as homes built in 2000 or later did in 2006, then average mean daily kWh purchased by each household will fall by 1 to 2 kWh.

Conclusion

Using several unique datasets we examined cross-sectional and longitudinal variation in homeowner electricity purchases and provided insights into why California's residential electricity consumption per household has been rising so slowly since the 1980s. Our cross-sectional estimates permitted us to account for the role of housing structure, household demographics, and ideology in residential electricity consumption and we found that the year a residence was built was an important determinant of current electricity purchases. California homes built between 1960 and 1983 currently consume more electricity than homes built prior to 1960 even though building codes were introduced in 1978. Low electricity prices at the time of construction partially explain the higher consumption of these homes. Old heating and cooling system and the introduction of systems with ducts in the 1970s may also play a role. Homes built after 1983 increasingly consume less electricity because of higher electricity prices

[25] See the Energy State Data System of the Energy Information Administration http://www.eia.doe.gov/emeu/states/_seds.html .

and strengthened building codes. Using longitudinal data and a sample of movers we also found that the residence explains more of the variance in electricity purchases than the household.

We used our cross-sectional estimates in an aggregation exercise where we averaged over housing and household types using the census counts. This aggregation allowed us to study how the average home evolves over time as demolition and new construction takes place and as the housing, socioeconomic, and demographic characteristics of diverse California households evolve. As homes built in 1960-1983 become a smaller share of the housing stock and new homes are built under existing or even more stringent codes, then, all else equal, average household electricity purchases will fall.

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Appendix

We examine how a house renovation affects electricity consumption using our panel data. For 2004 to 2008 we have permit data from the Development Services Department of the major city in our utility district. These data indicate the type of renovation (e.g. kitchen, HVAC, electrical, etc), when it was done, and the value of the renovation. We link these data to the single family homeowners in the credit bureau data and to their 2000-2008 billing data and analyze the subsample of renovators, comparing each household's electricity consumption before and after a major renovation.

We regress the logarithm of a household's mean daily kilowatt hours purchased in a billing cycle (kWh) on the mean temperature in the billing cycle (T) and the interaction between mean temperature and the percent of liberals in the block group and between mean temperature and political party of registration (L), a vector of dummy variables (R) indicating whether the household added square footage, a new roof, new windows, a new kitchen, a new HVAC, and a new water heater by the billing cycle date, a vector of dummy variables (W) indicating that work was in progress on a specific renovation, R, and household fixed effects (F):

$$A1) \qquad ln(kWh) = \beta_0 + \beta_1 T + \beta_2 (TxL) + \beta_3 R + \beta_4 W + \beta_5 F + \varepsilon$$

We also examine interactions between mean temperature and the dummy variables indicating specific renovations. Equation (A1) enables us simultaneously to examine the role of renovations in determining electricity consumption and, through testing for whether β_2 is negative, to test the voluntary restraint hypothesis that liberal/environmentalists consume less electricity on hotter days. As a comparison, we present results (without the renovation variables) for the entire electric utility panel of all customers (renters and owners) from 2000 to 2008. Standard errors are clustered on the billing cycle.

Appendix Table B shows that a new HVAC decreases electricity purchases for mean temperatures below 58.3°F or 14.6°C (roughly the 35th bottom mean temperature decile). At a temperature of 75°F (23.9°C) a new HVAC increases electricity purchases by 5%. This finding is consistent with past work documenting a rebound effect associated with new residential durables purchases (see Dubin, Miedema and Chandran 1986, and Davis 2008). Additions of square footage and new kitchens increase daily kilowatt hours purchased by 1.4 and 1.7%, respectively. A new roof decreases electricity purchases by 1.6%.