

Energy Demand and Energy Efficiency:  
What are the Policy Levers? or  
In Search of the Elusive Residential  
Demand Function

Michael Hanemann

Arizona State University & UC Berkeley

# The question being posed

The question being posed is not: what is an efficient way of pricing energy?

Instead, the questions are:

If you want to reduce residential energy use, how can you do this?

More generally, what is the residential demand curve for energy?

# The elusive demand function for energy

- To be sure, there is a huge literature in which economists have estimated residential demand curves for energy.
  - I myself have participated in such exercises.
- The question is: Are the estimated demand curves meaningful?
  - Do they reliably tell us what future demand will be a month from now, a year from now, or five years from now, either with or without some policy intervention?
  - I am not sure that they do.
  - I have the same doubt about commercial demand functions for energy
  - And I have the same doubt about residential demand functions for water.

# Why do I think the demand curve is problematic?

(1) For most residential users, their consumption of energy is invisible to them.

They have no way of knowing what quantity they are consuming at the time of consumption.

They have no idea what the price is, either, at the time of consumption.

(2) Their consumption of energy is mediated through the physical structure of the building they live in and the hardware in it.

Some of those things may not be under their control.

Even when they are controllable, those things won't be changed often or instantaneously.

# Compare to other users

- Household transportation
  - Rate of fuel consumption is visible – how often do you fill the car
- Industrial/commercial
  - Depending on the industry, decision makers may be highly aware of energy use.
    - E.g., fuel managers for trucking companies or airlines pay attention to achieving savings of 1-2% in fuel use – savings that are invisible to home owners

# Lack of data

- Before I go on to describe what I think is a better approach to modeling the residential demand for energy, I should acknowledge that whatever we do is constrained by the availability of data.
- The data needed for the approach that I advocate are not generally available.
- The implication: we need to push to gain access to better data

# The question of policy levers

- A key question underlying policy:
  - Do we want to reduce energy use by moving along a given demand curve?
  - Or, do we want to reduce it by *shifting* the demand curve inwards?
- The conventional approach to policy focuses on the former – getting the price right (raising the price appropriately) so as to reduce demand.
- The strategy in California over the past 40 years has aimed more at shifting the demand curve inwards by non-price initiatives.
- The recent interest in “nudges” – for example, messaging electricity users on their use relative to that of others – aims at shifting the demand curve inwards.

# The two issues converge

- How to shift the demand curve inwards
- How to conceptualize the demand curve and approach modeling it.

# Breaking down the data

- The key to making sense of residential energy demand is to decompose it. There are several ways to do this:
  - By end use
  - Conditional on housing type
    - Newly built home versus existing home or by home vintage
    - Conditional on housing characteristics
    - Conditional on types of appliances installed
  - Conditional on user type
    - Household characteristics (size, income, etc) for occupant
    - Household characteristics for neighborhood (sorting model, peer effects)
  - Conditional on timing of an event
    - Change of ownership, new owner vs existing owner
    - Conditional on policy intervention – price change, rationing, etc
    - Conditional on receipt of a nudge

# The target of the model

- Conventional economics models the demand for a commodity as though the consumer is constantly re-optimizing his consumption to match current circumstances.
- An alternative approach would focus on modeling when and how demand changes.
  - The assumption is that most of the time, the consumer just repeats what he normally does. He has some existing pattern of demand – “habitual demand”
  - However, sometimes circumstances change sufficiently to attract his attention. He then considers whether to make a change.
  - In the latter case, there are two things to model:
    - When does a change occur?
    - If a change occurs, what change will be selected?

# An analysis framed around changes

- How many households confront change (participate in experiment, etc)?
  - What percent of total users?
- What is the possible nature of the response
  - Change in appliances (refrigerator, dishwasher, etc)
  - Retrofit part of house – air conditioning, heating, lighting, kitchen
  - Change in behavior – use appliances less
- What percent of their usage might be changed
- The idea is to put an upper bound on how much change in usage could occur, over what time period.

# Analyses framed around changes

- Literature identifying different price elasticities for small price changes versus large price changes.
  - Suggests the importance of salience. Small price changes not salient, hardly likely to be noticed, therefore evoke little or no response. Large price charges likely to be salience.
- Literature on messaging
  - Comparing your use to that of others like you
    - Shown to induce reductions on the order of 3-4% in electricity use
    - Messaging with electricity bill
- Field experiments with conservation measures

# Returns to residential energy efficiency and conservation measures: A field experiment

Jordan F. Suter<sup>a,\*</sup>, Md Rumi Shammin<sup>b</sup>

<sup>a</sup> Oberlin College, Department of Economics, Oberlin, OH 44074, United States

<sup>b</sup> Oberlin College, Environmental Studies Program, Oberlin, OH 44074, United States

---

Residential energy conservation is a key component of contemporary energy and climate change policy in the US and elsewhere. Comparisons of the relative effectiveness of measures aimed at reducing residential energy consumption are made challenging, however, by the endogeneity of technology and energy use decisions. In this paper we describe a novel small-scale field experiment that uses randomized treatments to estimate the returns to three types of energy conservation measures in institutionally owned homes. The results from the experiment indicate considerable reductions in natural gas consumption associated with the installation of attic insulation and the provision of incentives for conservation. The results are supported by observations of ambient indoor temperature data, which show that households receiving incentives significantly reduce their temperature settings—especially when coupled with access to a programmable thermostat. The study will ideally provide guidance for institutions and communities considering energy efficiency measures and for future researchers designing randomized experiments to study residential energy use.

# A frontier approach to estimation

- Standard statistical modeling aims to estimate an average  $E\{y|x\}$ 
  - $y = X\beta + \varepsilon$ , where  $\varepsilon$  ranges from negative to positive
- An alternative focuses on estimating the best-practice frontier
  - $y = X\beta + \varepsilon$ , where  $\varepsilon \geq 0$ .
  - In some formulations  $\varepsilon$  may be a function of variables, such as price (the higher the price, the closer actual practice is to best practice?)
  - Requires individual level data.

- To illustrate the potential of improved data for investigating policy approaches, I turn to a debate about the determinants of energy efficiency in California.

# The California Issue

- In early 1970's, California was one of 5 or 6 states in which activists were pushing for reform of electric utility regulation. It was the only state in which those aspirations were fully realized.
- In 1974-5, California created
  - an institutional framework for statewide regulation of energy efficiency.
  - an infrastructure for research on energy efficiency.
- By 1980, it had also created a *culture* of energy efficiency.

# Two Energy Agencies in California

- The California Public Utilities Commission (CPUC) was formed in 1890 to regulate natural monopolies, like railroads, and later electric and gas utilities.
- The California Energy Commission (CEC) was formed in 1974 to regulate the environmental side of energy production and use.
- Now the two agencies work very closely, particularly to delay climate change.
- The Investor-Owned Utilities, under the guidance of the CPUC, spend “Public Goods Charge” money (rate-payer money) to do everything they can that is cost effective to beat existing standards.
- The Publicly-Owned utilities (20% of the power), under loose supervision by the CEC, do the same.

# CEC Responsibilities

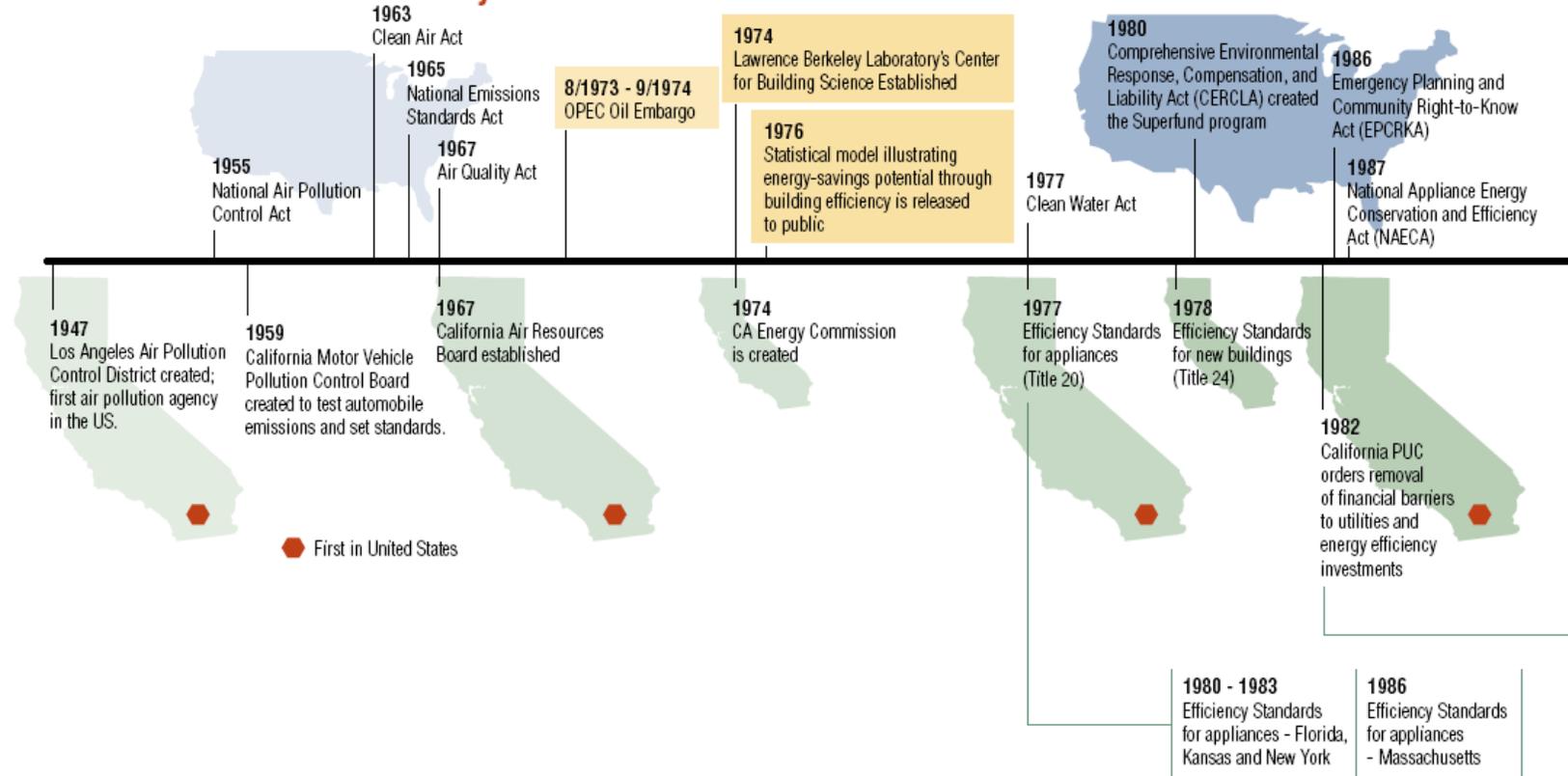
## Both Regulation and R&D

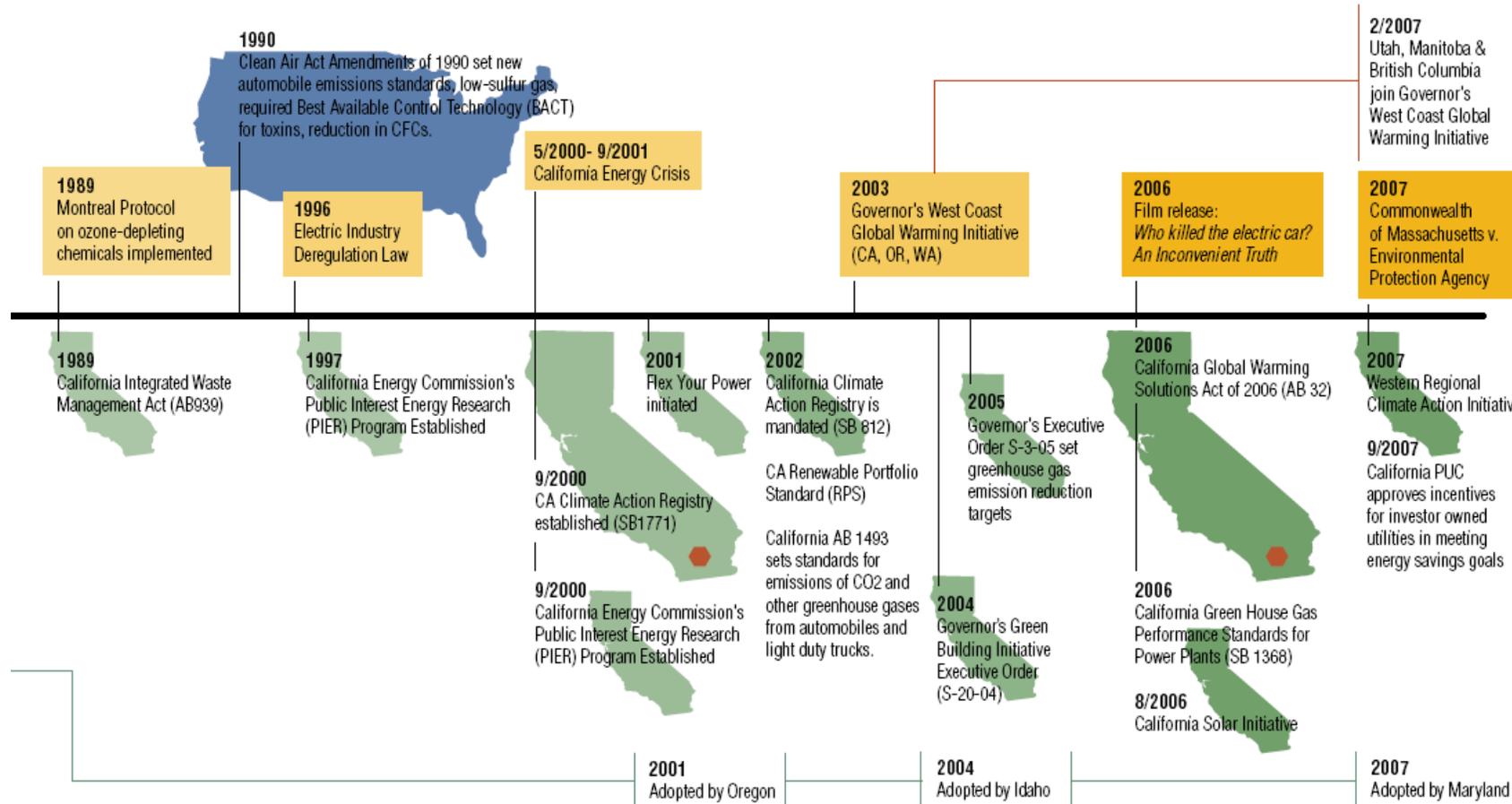
- California Building and Appliance Standards
  - Started 1977
  - Updated every few years
- Siting Thermal Power Plants Larger than 50 MW
- Forecasting Supply and Demand (electricity and fuels)
- Research and Development
  - ~ \$80 million per year
- CPUC & CEC are collaborating to introduce communicating electric meters and thermostats that are programmable to respond to time-dependent electric tariffs.

# Regulatory history: CA (lower panel) vs US (upper panel)

Source: Next10

## California Policy Innovations Over Time (Regulatory, Investment, Incentives) Set in Context with U.S. Policy Innovations and Other Historical Events





# Components of California Program

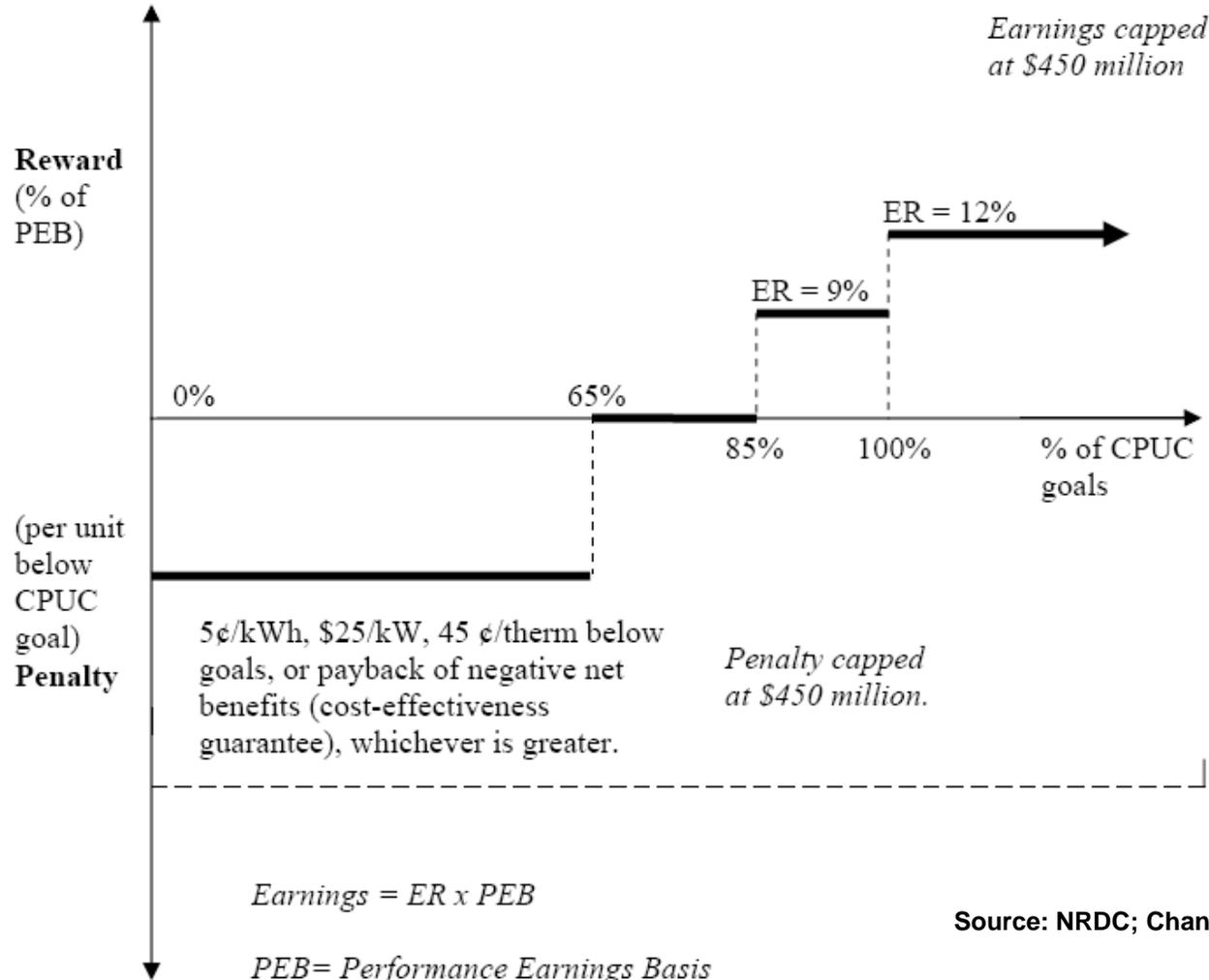
- Appliance standards & building energy codes
- Utility energy efficiency programs
- Rate decoupling
- Public goods charge
- Energy conservation incorporated in Integrated Resource Plan
- State energy conservation goal
- Renewable resource mandate
- Time of use pricing & advanced metering
- Carbon adder imposed by CPUC
- AB 32 sets cap on utility emissions
- Authorization of municipal energy finance districts

# Rate Decoupling

- Introduced in 1978 for natural gas, and 1982 for electricity.
- Utilities submit their revenue requirements and estimated sales to CPUC. CPUC sets rates.
- Any shortfall recovered later from customers. Any excess revenue credited back to customers.
- In 2007, “Decoupling Plus.” New system of and penalties to drive utilities beyond state’s 10-year energy savings targets.
- Result:
  - Higher electricity prices in California
  - Lower electricity consumption.
  - Due not just to movement along demand curve, but also to an inward shift in the demand curve.

# Energy Efficiency Incentive Mechanism Earnings/Penalty Curve

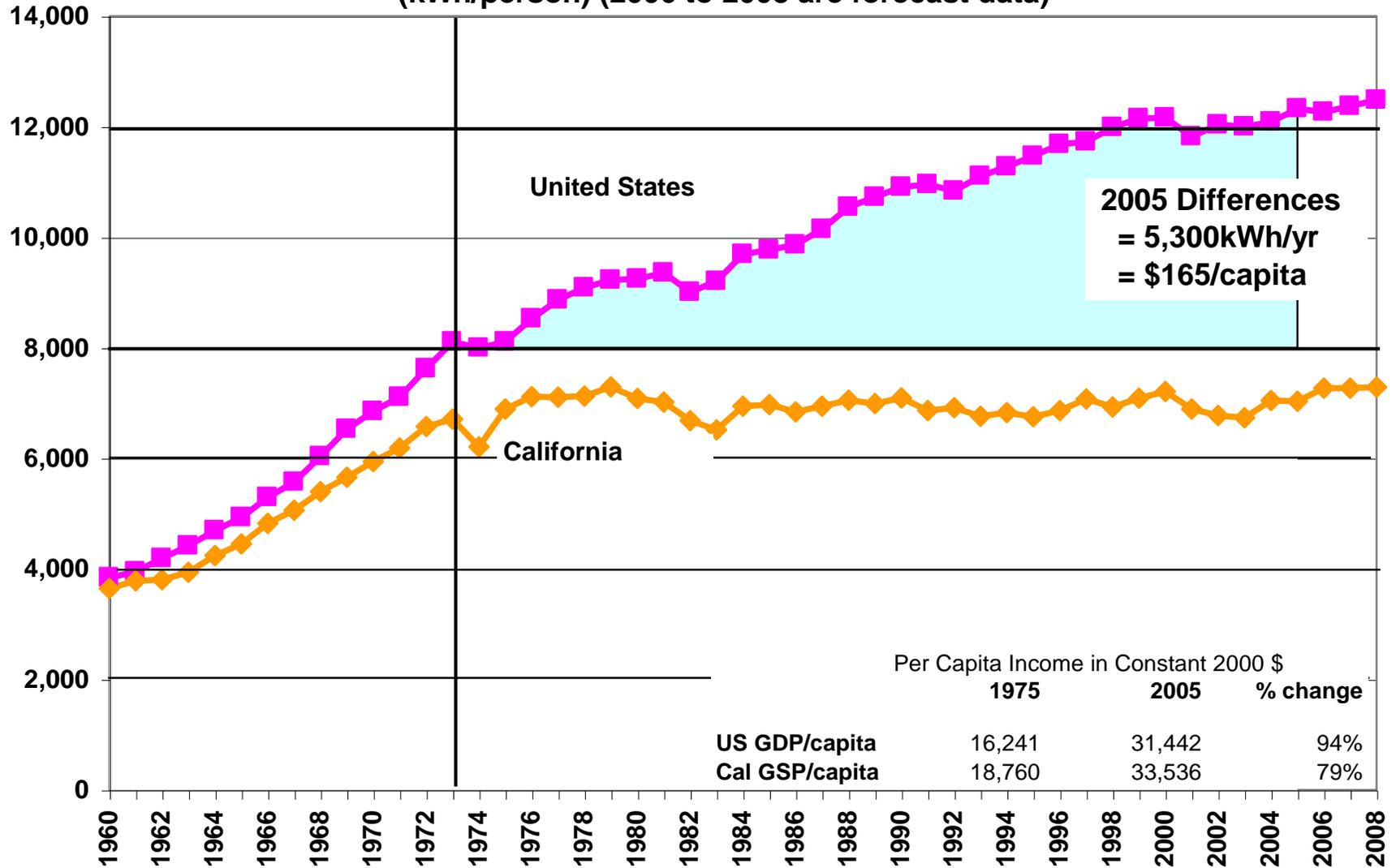
(D.07-09-043, p. 8)



Source: NRDC; Chang and Wang, 9/26/2007

PEB= Performance Earnings Basis  
ER= Earnings Rate (or Shared- Savings Rate)

**Per Capita Electricity Sales (not including self-generation)  
(kWh/person) (2006 to 2008 are forecast data)**



# This is known as the Rosenfeld Curve

- Dr. Art Rosenfeld became Governor Brown's energy adviser in 1974, and subsequently has served as the intellectual mentor to energy policymakers in California. Under Governor Schwarzenegger he served for 8 years as a California Energy Commissioner.
- This curve has attracted a growing attention from mainstream energy economists. There have been several attempts to deconstruct it.
- The most convincing, so far, is by Anant Sudarshan for a Stanford PhD thesis (2010).

# Deconstructing the 'Rosenfeld Curve': Why is Per Capita Residential Energy Consumption in California so Low?

Anant Sudarshan, Stanford University

USAEE-IAEE WP 10-063

December 2010

- Sudarshan estimates a set of (log) demand functions for households in California and other states using the RECS household level data for 2001 and 2005

The expressions for  $x_{e,t}$  and  $x_{h,t}$  in can be written as follows (following the expression derived in 3). Note that here  $Z_t$  has been separated into  $[Z_t' CA_t]$  where the first block is a matrix of demand modifiers (see Table 1) and the second is a vector of dummy variables ( $CA_t$ ) which is 1 when the household is located in California and 0 otherwise.

$$y_{e,t} = \ln(x_e) = \beta'_{e,t} Z_t' + \delta_{e,t}(CA) - \theta_{e,t} P_{e,t} + \epsilon_{e,t}$$

$$y_{h,t} = \ln(x_h) = \beta'_{h,t} Z_t' + \delta_{h,t}(CA) - \theta_{h,t} P_{h,t} + \epsilon_{h,t}$$

# The conditioning variables for household types

Demand Equation	$G_e$ : Type Characteristics (Electricity)	$G_h$ : Type Characteristics (Secondary Fuel)
Intercept	Intercept	Intercept
Cooling and Heating Degree Days	Electric Air-Conditioning	Electric Water Heating
Price (Electricity)	Electric Water Heating	Electric Heating
Price (Secondary Fuel)	Electric Heating	Home Ownership
Housing Unit Floorspace	Durables Ownership	Very Low Income
Household Size	Home Ownership	Time (Absent in $\tilde{G}$ )
Housing Unit Age	Very Low Income	
Occupancy Dummy	Time (Absent in $\tilde{G}$ )	
Urban/Rural Location		
California Dummy		

Table 1: Model covariates in demand function (left column) and heterogeneity segmentation for the two fuels (right columns). Number of types estimated from the data: 97 (electricity demand model), 31 (secondary heating fuel model).

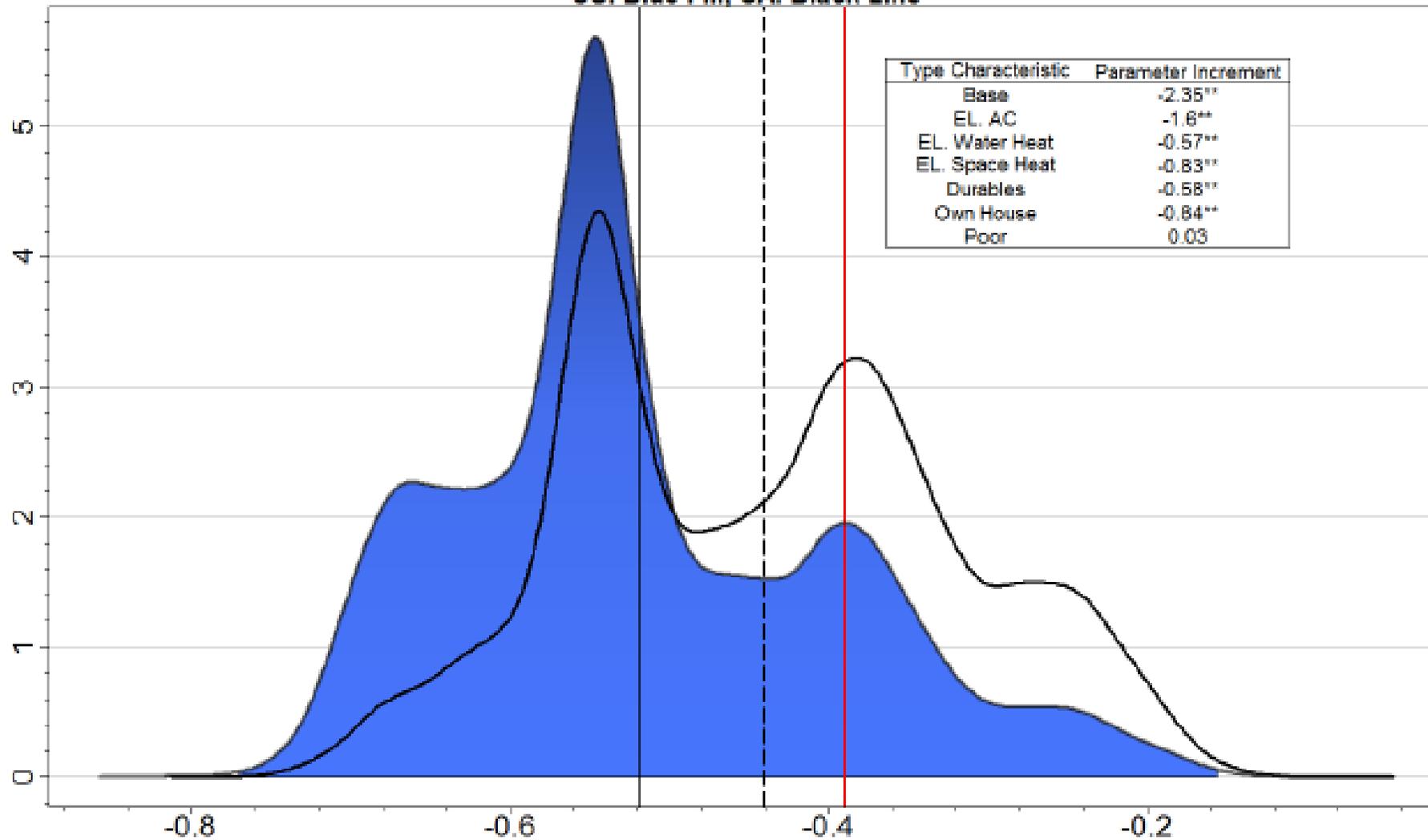
# Coefficient estimates by type

Parameter Variation with Type Characteristics in Electricity Demand Equation

	Intercept	HDD	CDD	HomeArea	HHMembers	OldHouse	NewHouse	AtHome	HHAge	Rural	Urban	CA ( $\delta$ )	PriceCoeff
Intercept	7.94**	0.09	0.40**	0.23**	1.05**	-0.06**	-0.16**	0.03	0.03	0.10**	-0.04	-0.13**	-2.35**
Electric Air-Conditioning	0.50**	-0.35**	0.25**	0.02	-0.10**	0.02	0.06*	0.02	-0.03	-0.03	-0.02	-0.09**	-1.60**
Electric Water Heating	0.46**	0.20**	-0.33**	-0.02	0.17**	-0.02	0.01	-0.01	-0.01	-0.04	-0.02	-0.01	-0.57**
Electric Heating	0.35**	0.03	-0.19**	0.05*	-0.11*	0.02	-0.06*	-0.05*	0.01	-0.02	-0.01	-0.05	-0.83**
Durables	0.39**	-0.04	0.08	-0.10**	0.06	0.02	0.05	-0.01	0.01	0.04	-0.02	0.08**	-0.58**
Home Ownership	0.43**	-0.21**	-0.24**	-0.08**	-0.01	-0.04	-0.06	-0.01	0.01	-0.04	0.02	0.01	-0.84**
Low Income	-0.03	-0.04	-0.11*	0.01	0.08	0.06**	0.05*	0.00	-0.07**	0.02	0.05*	-0.06*	0.03
Time	-0.01	0.05	0.13**	-0.04*	0.06	0.00	0.08**	0.02	-0.07**	0.01	-0.01	-0.07**	NA
Units	1	10000 DD	5000 DD	1000 sq.ft	10 persons	1	1	1	50yrs	1	1	1	1 cent/KWh

### Simulated Population Distribution of Electricity Price Elasticity

US: Blue Fill, CA: Black Line



Black line: Average PE, Black dash: Average California PE, Red line: Average California PE from Reiss and White 2005

Figure 6: Variation in price elasticity across household types. Elasticities are computed from price coefficient estimates assuming an average price of 10 cents per KWh. Average elasticity for California and the US population differs due to differences in type distribution.

# Sudarshan's result

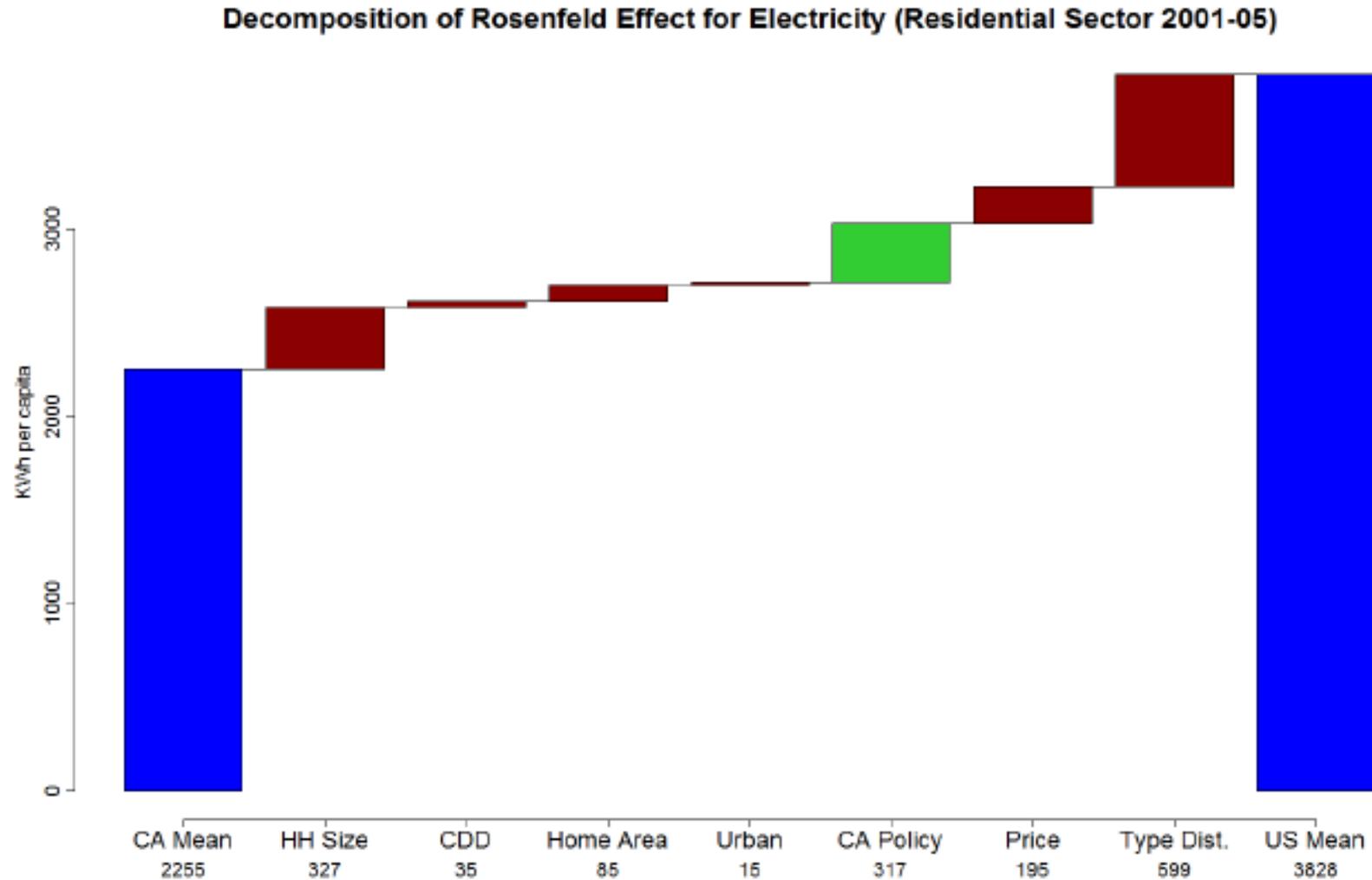
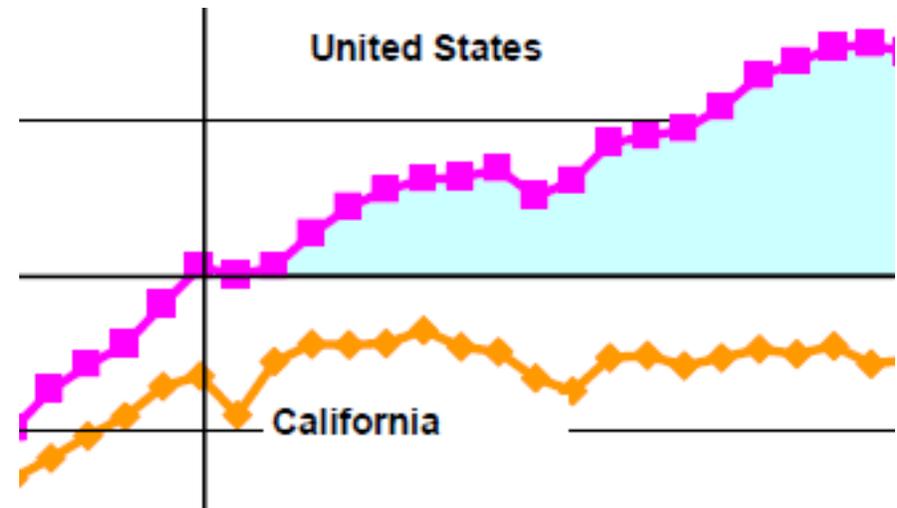


Figure 8: A decomposition of the difference between California and the rest of the country in per capita electricity consumption. Numbers at the bottom are block heights in annual KWh per capita. The green block is the bound on California program effects (the  $\delta$  dummy).

- This shows that, with regard to the difference in per capita electricity use between California and the rest of the US in 2001-2005, the differences in households types account for more than the policy initiatives in place in California at that time.
- But, this is the wrong question.
- The real question is why did demand level off in California in the mid-1970s?



WHY HAS CALIFORNIA'S RESIDENTIAL ELECTRICITY CONSUMPTION BEEN SO FLAT SINCE THE 1980S?:  
A MICROECONOMETRIC APPROACH

Dora L. Costa  
Matthew E. Kahn

Working Paper 15978  
<http://www.nber.org/papers/w15978>

NATIONAL BUREAU OF ECONOMIC RESEARCH  
1050 Massachusetts Avenue  
Cambridge, MA 02138  
May 2010

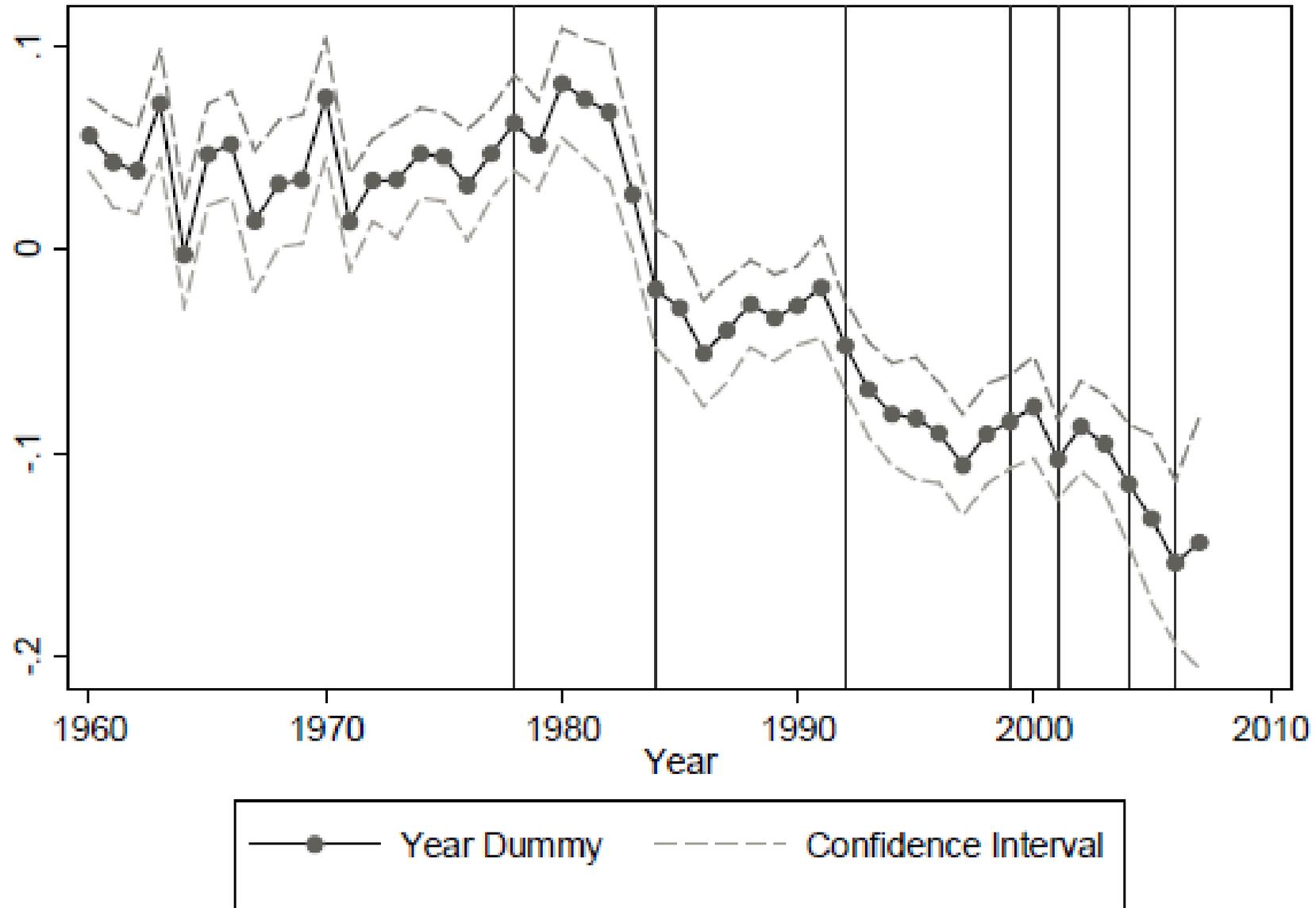
# Distinctive features of study

- Household level billing data for every home in county, 2000-2009.
  - Kwh purchased per billing cycle, whether house uses electric heat, whether enrolled in renewable energy program
- Combine with weather data
- Merge with 2008 & 2009 credit bureau data
  - Household income, ethnicity, age of head of household, number of people, year house built, size of house, whether has a pool.
- Merge with voter registration data
- Merge with marketing data

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

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,  $\varepsilon$  is

Figure 1: Effect of Year Built on Mean Daily Kilowatt Hours Purchased by Households in Calendar Year 2008



# Movers 2008-2009

- Costa & Kahn did a separate analysis of houses where the occupant moved during 2008 or 2009.
- They know the energy used by the family in its old home and its new home.
- They know the energy used in the home with the old occupant and the new occupant.
- They exploit this information to identify the influence of the house versus the people on energy use

Our panel data show that while a house is energy inefficient both because of its structure and the people living within it, the house itself accounts for a larger share of the variance in total electricity purchases (see Table 6). Our analysis of variance shows that in a random sample of movers moving to different homes within the utility district between 2000 and 2008, 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.

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 8 shows that most renovations increase energy consumption. 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 percent. 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 percent, respectively. A new roof decreases electricity purchases by 1.6 percent.

# Conclusion

- We need much more disaggregated data.
- With such data we can understand what is going with regard to energy use.
- With that understanding we can target policy interventions – price and non-price – in a manner more likely to produce effective results.
- Without such data, we have a hollow understanding and are severely limited in the effectiveness of our interventions.