Empirical Methods for the Analysis of the Energy Transition: Day 4

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Today's outline

1) Demand side policies evaluation

   - Experiments
   - ML

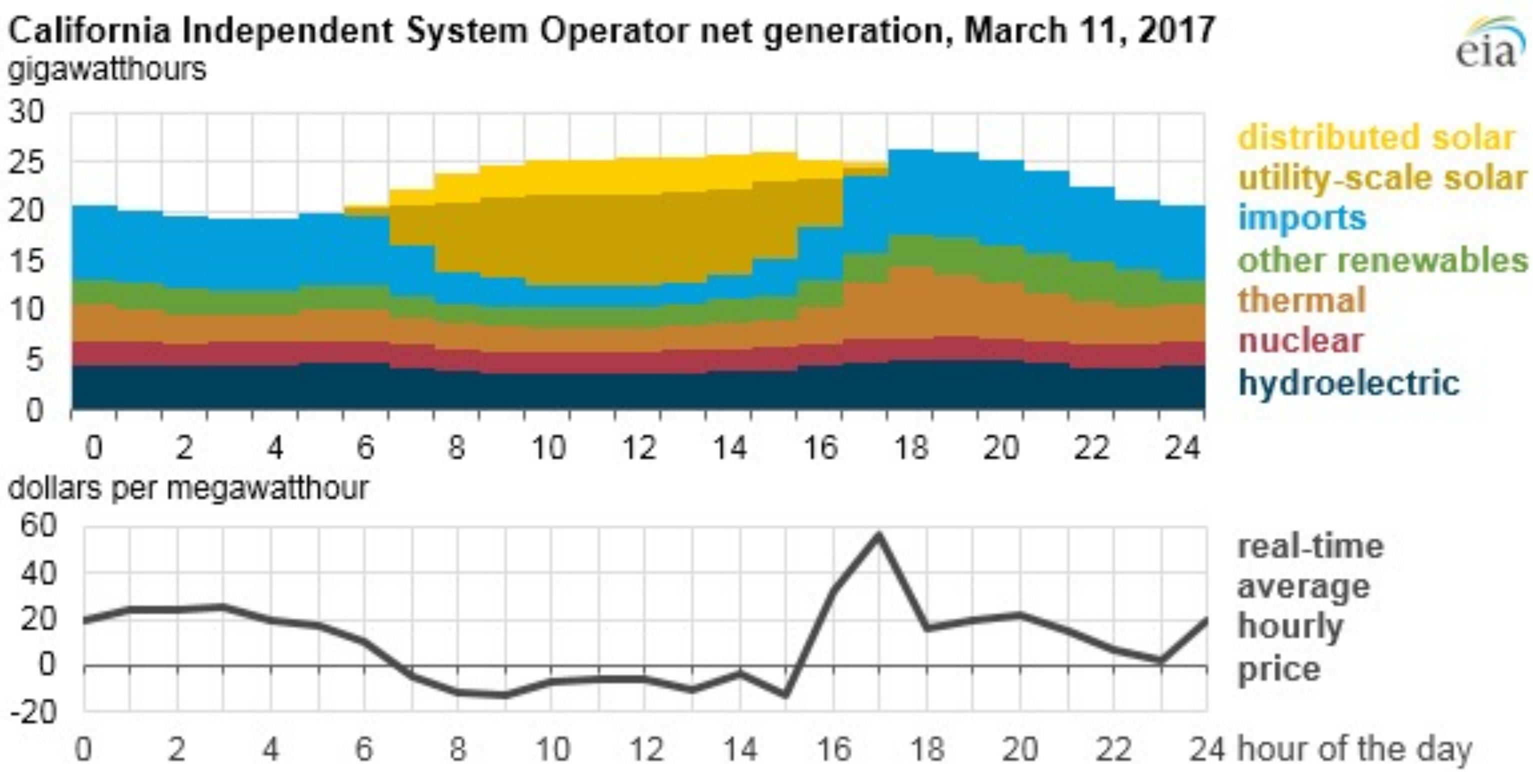
2) Case study: Real-time pricing in Spain

Electricity Demand – why do we care?

- Electricity demand has been plateauing due to energy efficiency improvements.
- But it is expected to grow considerably as we electrify more areas of the economy (e.g., cars).
- Electricity demand is generally very unresponsive, but that does not go well with renewables…

Electricity Demand – why do we care?

- Response even more important when there is a lot of renewable energy!



Electricity Demand – why do we care?

- In the US, 34% of GHG emissions come from electricity (EPA 2007).
  - Big focus on shifting to cleaner technologies.
  - Shifting demand to when cleaner technologies are available can also be equally effective and make the transition cheaper.

- If we reduce demand, it is important to think about which consumption we should try to lower.
  - GHG depends on the source of electricity
    - The location of end-use consumption
    - The day and time of end-use consumption

Energy demand: several response margins

- We will separate between two strategies:

  - **Energy efficiency**: becoming better at consuming the same goods, e.g., LEDs, building retrofit, better appliances, etc.

  - **Demand response**: reducing our consumption if prices are high

- I will discuss papers from both, as they can be very related in methods and type of data.

Energy efficiency

- We do not consume energy directly
  - We consume "energy services" produced with energy inputs
- Energy efficiency refers to the productivity of energy inputs:

  Energy efficiency = energy services / energy input

- Examples
  - *Example 1*: keep room at 65F for an hour
  - *Example 2*: run a washing machine at 4pm
  - *Example 3*?

The energy efficiency gap

- The energy efficiency gap refers to potential underinvestment in energy efficient technologies (typically by the part of consumers) – second channel of inefficiency.
- Defined as “a wedge between the cost-minimizing level of energy efficiency and the level actually realized.”
- Suggests there are other market failures at play.

The energy efficiency gap – Debate

"Energy efficiency offers a vast, low-cost energy resource for the U.S. economy—but only if the nation can craft a comprehensive and innovative approach to unlock it."

–McKinsey & Co. (2009), *Unlocking Energy Efficiency in the U.S. Economy*

"When one tallies up the available empirical evidence from different contexts, it is difficult to substantiate claims of a pervasive energy-efficiency gap… the empirical magnitudes of the investment inefficiencies appear to be smaller, indeed substantially smaller, than the massive potential savings calculated in engineering analyses such as McKinsey & Co. (2009).

- Alcott and Greenstone (2012), *Journal of Economic Perspectives*

The energy efficiency gap – Evidence

- There is somewhat of a debate on how much of an “energy efficiency puzzle” there is.
  - Engineering view: typically more “optimistic”
  - Economists view: typically more “pessimistic”
- Studies find a wide range of estimates of costs of energy efficiency.

Evidence – Empirical difficulties I

- Studies of energy efficiency gap are difficult:
  - Typically in non-randomized settings
  - Randomized experiments can be very expensive
- Ideal world:
  - Have two parallel universes with the same consumers
  - Offer energy-efficient appliance rebate in one and compare
- In practice from observational data:
  - Consumers might be changing other things at the same time
  - Inframarginal consumers: they would have bought the better appliance anyway (should not count)
  - Often only include "program" costs

Evidence – Empirical difficulties II

- Engineering measurement to go around some of these difficulties:
  - Tries to get at the savings by formulating a model of energy consumption.
  - Circumvents the problem of households changing other consumption aspects at the same time
  - Does not deal with infra-marginal types

- In practice from observational data:
  - Consumers might change their behavior also with respect to the new appliance (e.g., better AC, use it more)
  - Known as “rebound affect”

Example – "Cash for Coolers"

- Since 2009 over 1.5 million refrigerators and air-conditioners have been replaced through Mexico's "Cash for Coolers" Program.

C4C program details

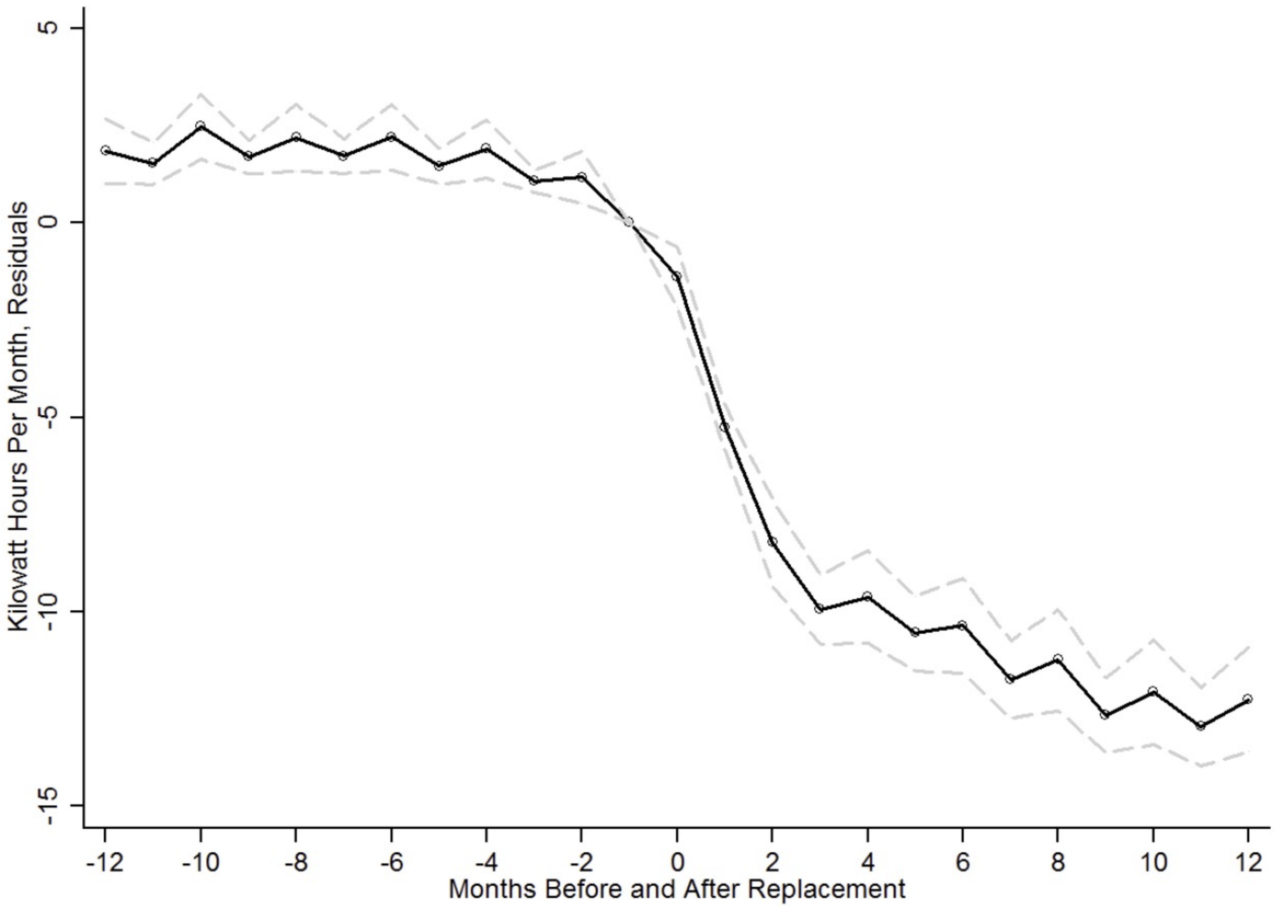
- Includes both refrigerators and room air-conditioners
  - To date 90% refrigerators, 10% air-conditioners
  - Direct cash subsidies of up to $185
  - Also low-interest credit against future electric bills
- Old appliance must be 10+ years old
  - Verified by the retailer to be working at time of replacement
  - Then permanently disassembled in recycling centers
- New appliance must meet exceed 2002 standard by 5%.

C4C assessment

- *Lucas Davis, Alan Fuchs, and Paul Gertler, "Cash for Coolers".*
- What is the effect of *C4C* on electricity consumption?
  - What is the implied cost per "negawatt"?
  - What is the implied cost per ton of carbon dioxide abated?
  - How does this compare to *ex ante* predictions?
- What broader lessons can be learned from *C4C* for the design of energy efficiency programs?

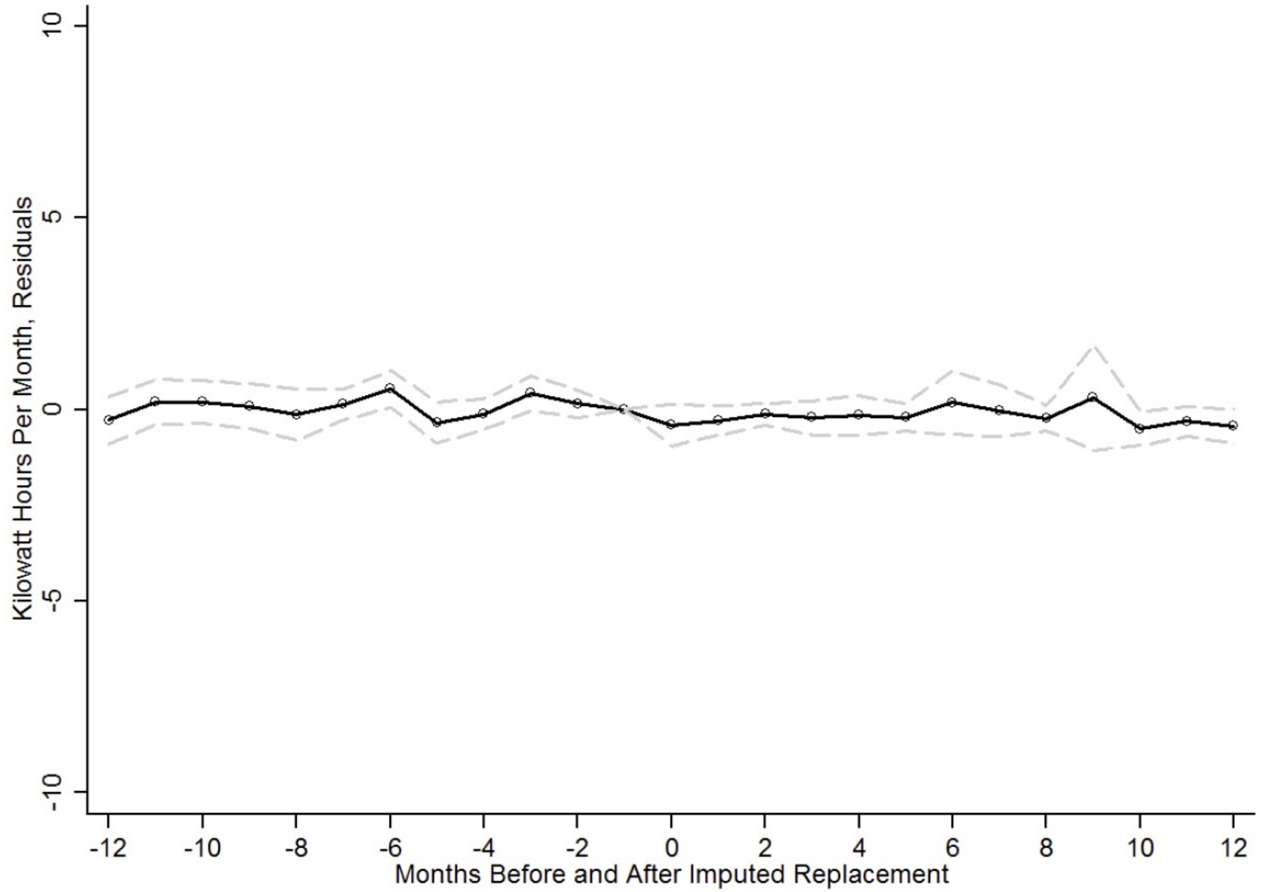
C4C impacts

FIGURE 2
The Effect of Refrigerator Replacement on Household Electricity Consumption



C4C impacts

FIGURE 3
Assessing the Validity of the Control Group



C4C and rebound

TABLE 2
The Effect of Appliance Replacement on Household Electricity Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
$1[\text{New Refrigerator}]_{it}$	-11.2**	-11.0**	-11.0**	-11.5**	-11.5**	-11.4**
	(0.5)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)
$1[\text{New Air Conditioner}]_{it}$	8.5*	6.6**	-0.2	-0.7	1.2	1.2
	(3.6)	(2.2)	(0.8)	(0.8)	(0.8)	(0.9)
$1[\text{New Air Conditioner}]_{it} \times 1[\text{Summer Months}]_{it}$			16.5**	16.6**	12.6**	14.5**
			(4.2)	(4.2)	(3.9)	(4.1)
Household By Calendar Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Sample By County Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Including Linear Time Trend for Participants	No	No	No	Yes	No	No
Including Treatment Households Only	No	No	No	No	Yes	Yes
Dropping Month of Replacement	No	No	No	No	No	Yes
Number of Households	1,914,160	1,914,160	1,914,160	1,914,160	957,080	957,080

C4C and rebound – Potential causes

1. The new appliances tended to be larger and have more features.
   - These features are valued by households, but use more electricity
   - For example, through-the-door ice adds 80 kWh per year
2. The old appliances tended to be close to the minimum age threshold.
   - Refrigerators average age 13.2 years
   - Air-conditioner average age 10.9 years
3. Households likely increased utilization of air-conditioners.
   - Valued by households, but increased electricity consumption.
   - This may have been amplified by the increasing block rates
4. Some of the old appliances were probably not working.

C4C cost effectiveness

TABLE 4
Electricity Consumption, Carbon Dioxide Emissions, and Cost-Effectiveness

	Refrigerators (1)	Air Conditioners (2)	Both Appliances Combined (3)
C. Cost-Effectiveness			
Total Direct Program Cost (U.S. 2010 dollars, millions)	\$129.9	\$13.3	\$143.2
Program Cost Per Kilowatt Hour (U.S. 2010 dollars)	\$0.25	--	\$0.30
Program Cost Per Ton of Carbon Dioxide (U.S. 2010 dollars)	\$427	--	\$506

Machine learning and policy evaluation

- Several papers now highlight the usefulness of machine learning in the context of panel regressions (e.g., see work by Athey).
- Electricity consumption data at high frequency lends itself very well to the use of ML.
- See Christensen, P., Francisco, P., Myers, E., & Souza, M. (2021) for another example of this.

- *Can it really help? How?*

Burlig Knittel Rapson Reguant Wolfram (2020)

Slides

Demand response

- Demand response programs are intended to **increase the elasticity of demand**.
  - Reduce or shift in periods of congestion
- This response should help balance supply and demand.
  - “Demand follows supply” vs.
  - ”Supply follows demand”
- It can be achieved with incentives (pecuniary or not) or via smart devices and artificial intelligence.

Electricity Demand – how responsive?

- As we explained, demand for electricity tends to be highly inelastic.
- Many consumers are unaware of their costs of electricity, especially their *marginal* cost of electricity.
- Even for businesses and industrial producers, electricity might be a small share of total inputs.
  - With some important exceptions!
  - And increasingly more aware of the opportunities.

Electricity Demand – how responsive?

- Estimates of residential demand electricity typically in the range of -0.3 to -0.1.
- Even long-run estimates appear to be in inelastic range, -0.8 to -0.4.

- Elasticities might be difficult to interpret, as most consumers do not face the mg. cost of electricity.
- Some studies examine how they respond to their average price of electricity, and it is still limited.

Energy efficiency vs demand response

- **Demand response**:
  - Getting consumers to change their behavior (when to consume and how much) as a response to a "signal".
  - Smart appliances/thermostats crucial to enable demand response.
- Demand response might induce consumers to engage in direct energy efficiency as well!
  - *Example*: someone consumes a lot of electricity at peak times because of washing machine consumption.
  - If shifted to real-time prices, decide to shift demand, or decide to buy a more efficient appliance (or automatic).

Electricity metering pre-XXI

- Electricity was (and still is in many places) metered only once a month, as water and gas.
- Difficult to imagine how consumers should respond to prices, if we do not even know how much they consume!

- Some utilities experimented with time-varying prices of electricity.
  - However, it had to be based on “representative” load curve for the neighborhood or for that kind of consumer

Smart meters

- Nowadays, there is a substantial push and rollout of smart meters.
- These meters enable collection of real-time electricity consumption data (typically every 15 minutes).

- The "economics" of smart meters
  - In some areas, they pay for themselves due to the savings in metering "by-hand"
  - Biggest trade-off is when to adopt, as technologies are getting better

Smart meters and their popularity

- Smart meters have received some criticisms:
  - Confidentiality issues, data storage
  - Consumers will face erratic prices
    - Note that one could always offer a flat-rate contract for a premium
  - Competition concerns, obfuscation
  - Health concerns (?)

- Efforts are put in place to preserve the data collected in a safe manner.
- Overall, it seems that the benefits could outweigh the costs.

“Smart” pricing

- Smart meters unable a more tailored approach to electricity pricing.
- Different pricing formulas:
  – Flat tariff (most common, traditional)
  – Time-of-use pricing
  – Critical peak pricing
  – Real-time pricing
  – Non-price interventions (not necessarily smart)

TOU pricing

- This type of pricing model is similar to time-based telephone or internet plans.
- Depending on the hour of the day, the day of the week or the season, there is a schedule of pre-arranged prices.
- These prices tend to be fixed by hour, so the prices are far from being in “real-time”.
- Yet, it can get consumers to engage in time-shifting behavior.
  - E.g., put washing machine at night

Critical peak pricing

- This type of intervention is implemented to get consumers to respond during extreme events.
  - Typically, extremely hot days in which air conditioning brings up electricity consumptions to very high levels
- Consumers agree to get really high prices on at most 10 critical peak events per summer.
- In compensation, they get a discount.
- Limitations: gets larger responses in critical days, but it only harvests responses in few events.

Real-time pricing

- In its most extreme form, consumers pay the wholesale price of electricity (plus the additional surcharges for distribution, taxes).
- Consumers fully internalize the conditions in the market (at least in theory).
- It implies that they can be made aware of:
  - Demand conditions
  - Renewable and other supply availability
  - Carbon/NOx/SO2 costs if pollution prices in the market

Behavioral interventions

- Real-time pricing or time-of-use not always available, and often limited consumer engagement.
- Behavioral interventions attempt to engage residential consumers in a non-price manner.
  – Convince them that their effort is important to the system (e.g., post-Fukushima in Japan)
  – Show them how other neighbors are doing
  – Create competitions (e.g., in dorms where students don’t see their electricity bill at the individual level)

Implications of real-time pricing

- Real-time pricing has short run effects:
  - Shifts demand from high price times
- In the long run, it also has implications for the generation mix.
  - The long run implications between TOU and real-time can be quite different (Borenstein, 2005)
- In the peak-load pricing model:
  - Avoid investments for extreme outcomes.
  - Reduces need for batteries in transition.

Demand response effectiveness

- A big challenge emerges.
- One criticism of real-time pricing initiatives is that consumers are not attentive enough to their electricity costs.
- Even if consumers face real-time prices, they might not have the willingness to respond, or they might not even be at home.

So… do consumers respond? And how much?

Real-time pricing and experiments

- There is a large literature of experiments examining the effects of real-time pricing.
- Studies are performed in conjunction with the utilities, who have an interest in understanding the implications of these policies.
- Typical design:
  - Identify a target population
  - Encourage switching to real-time to treatment group
  - Compare encouraged group to the rest

Difficulties with experiments

- Encouragement of real-time pricing can have limited adoption in a baseline population.
- Alternative design:
  - Identify a target population that wants to adopt real-time pricing
  - Randomize who actually gets real-time pricing
  - Compare treatment group to control

- Limited external validity: *How applicable is it for people who do not want real-time pricing?*

Two examples

- Jessoe and Rapson (2015)
  - Look at the importance of information provision to achieve demand response
- Allcott and (2014)
  - Look at the importance of social comparisons to achieve demand response
  - Examine long-run persistence of the effects

Jessoe and Rapson (2015)

- What does the paper do?
  - Estimate demand responses when consumers see simple information
  - Based on a randomized control trial under different informational treatments
- What does the paper find?
  - Informed households are three standard deviations more responsive to temporary price increases
  - Conservation extends beyond pricing events

Research Design

- RCT with utility in Connecticut during July and August of 2011 (peak electricity demand).
- Encouragement across all costumers, intervention focused on those who decide to participate.
- Treatments:
  - Control. 207 households.
  - Price only. 130 households. Notification day prior to high price event ($0.50) and thirty minutes prior ($1.25).
  - Price + IHD. 100 households. Same as price plus real-time information about electricity use and price.

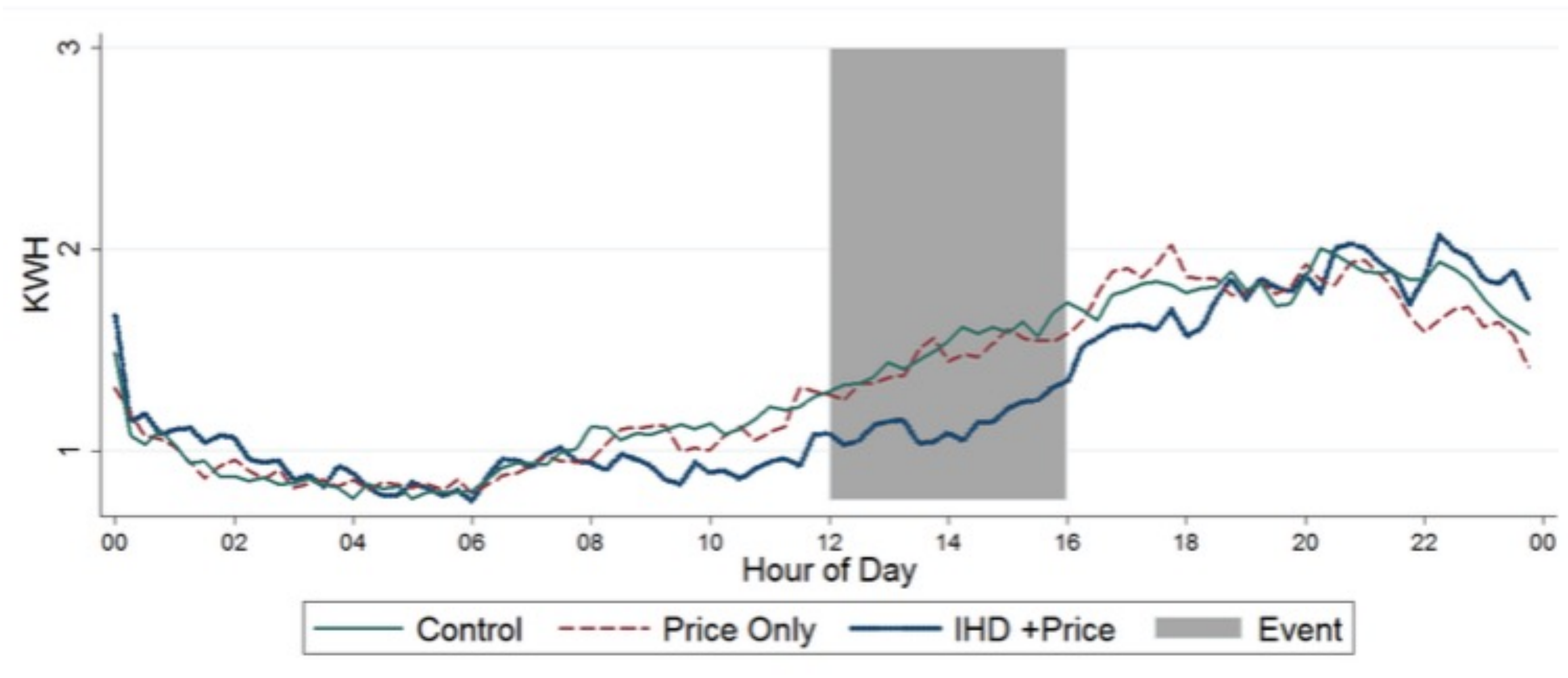
Main Results

Table 5—Treatment Effects (*Unbalanced Panel*)

Event type:	All (1)	All (2)	All (3)	All (4)	Day ahead (DA) (5)	30min (TM) (6)
Panel A. ITT unbalanced panel						
Price-only	−0.031	−0.054	−0.027	−0.038	−0.071*	0.006
	(0.036)	(0.036)	(0.036)	(0.036)	(0.042)	(0.044)
Price + IHD	−0.116**	−0.137***	−0.123***	−0.137***	−0.171***	−0.084
	(0.048)	(0.048)	(0.047)	(0.046)	(0.051)	(0.057)
Prob($P = P + I$)	0.096*	0.098*	0.051*	0.044**	0.066*	0.130
R^2	0.001	0.054	0.536	0.583	0.583	0.583
Panel B. ToT unbalanced panel						
Price-only	−0.032	−0.056	−0.028	−0.040	−0.074*	0.007
	(0.037)	(0.037)	(0.037)	(0.037)	(0.044)	(0.046)
Price + IHD	−0.143**	−0.170***	−0.153***	−0.170***	−0.217***	−0.100
	(0.058)	(0.058)	(0.057)	(0.057)	(0.064)	(0.067)
Prob($P = P + I$)	0.061*	0.052*	0.030**	0.023**	0.025**	0.115
R^2	0.001	0.054	0.536	0.583	0.583	0.583
HH FEs	No	No	Yes	Yes	Yes	Yes
Hour-by-day FEs	No	Yes	No	Yes	Yes	Yes
Number of events	6	6	6	6	3	3
Number of HHs	437	437	437	437	437	401

Main Results

Figure 6: August 26, 2011: 4hr $0.50 increase, day-ahead notice



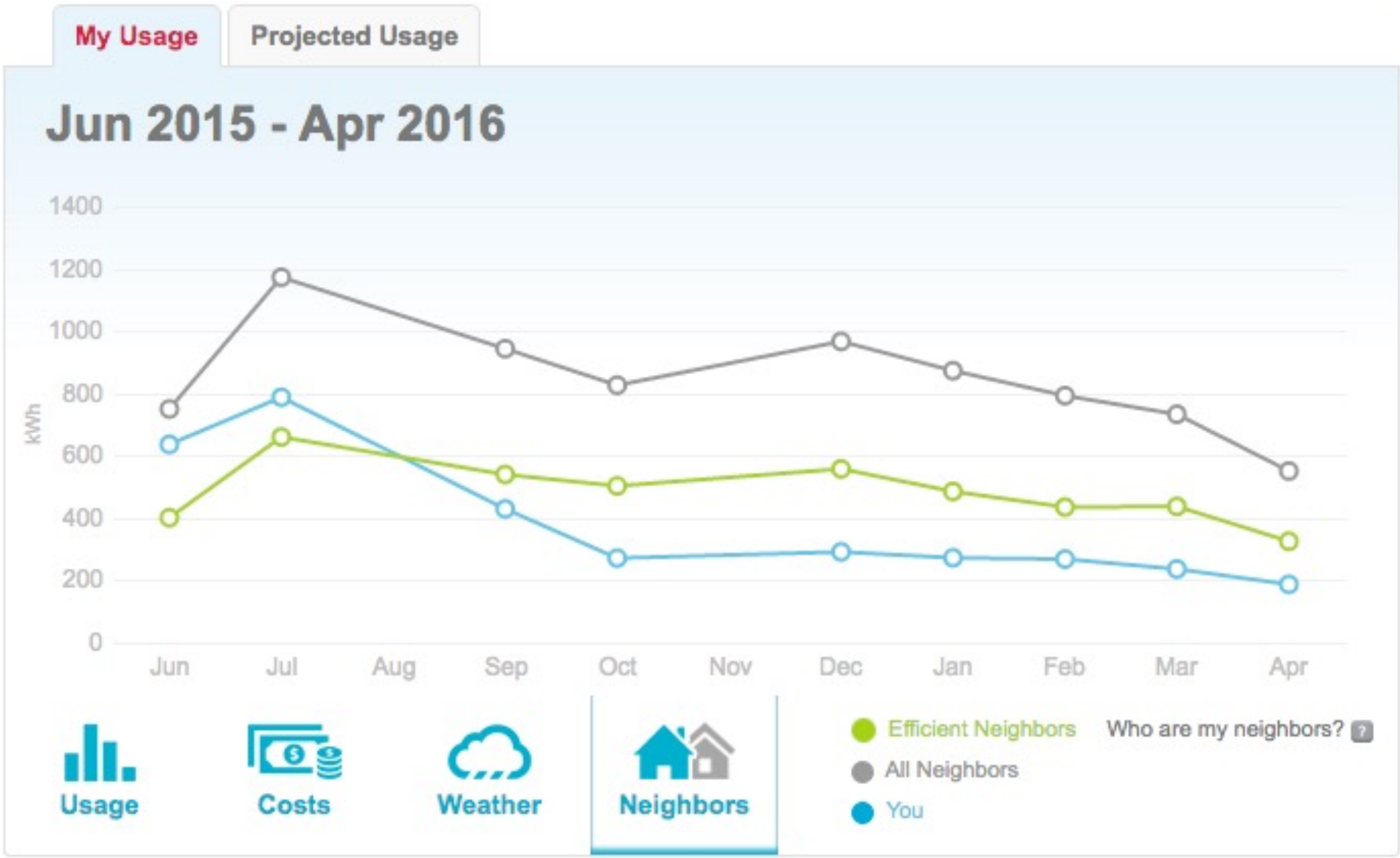
Additional Results

- Effect of price and price + IHD most pronounced if consumers confirmed receipt.
- Otherwise, insignificant although still negative for IHD.
- Learning and experience seem to play a role, habit formation implies savings in other hours.
- Consumers who experience more with IHD appear to be most responsive.
  - Potential for unobserved heterogeneity

Allcott and Rogers (2014)

- What does the paper do?
  - Look at responses of consumers to a behavioral intervention (comparison to neighbors)
  - Look at three different climatic areas
  - Analyze data over an extended period of time
- What does the paper find?
  - Initial effects are large given limited intervention
  - ”Action and backsliding”, but persistent effects
  - Consumers respond even after two years

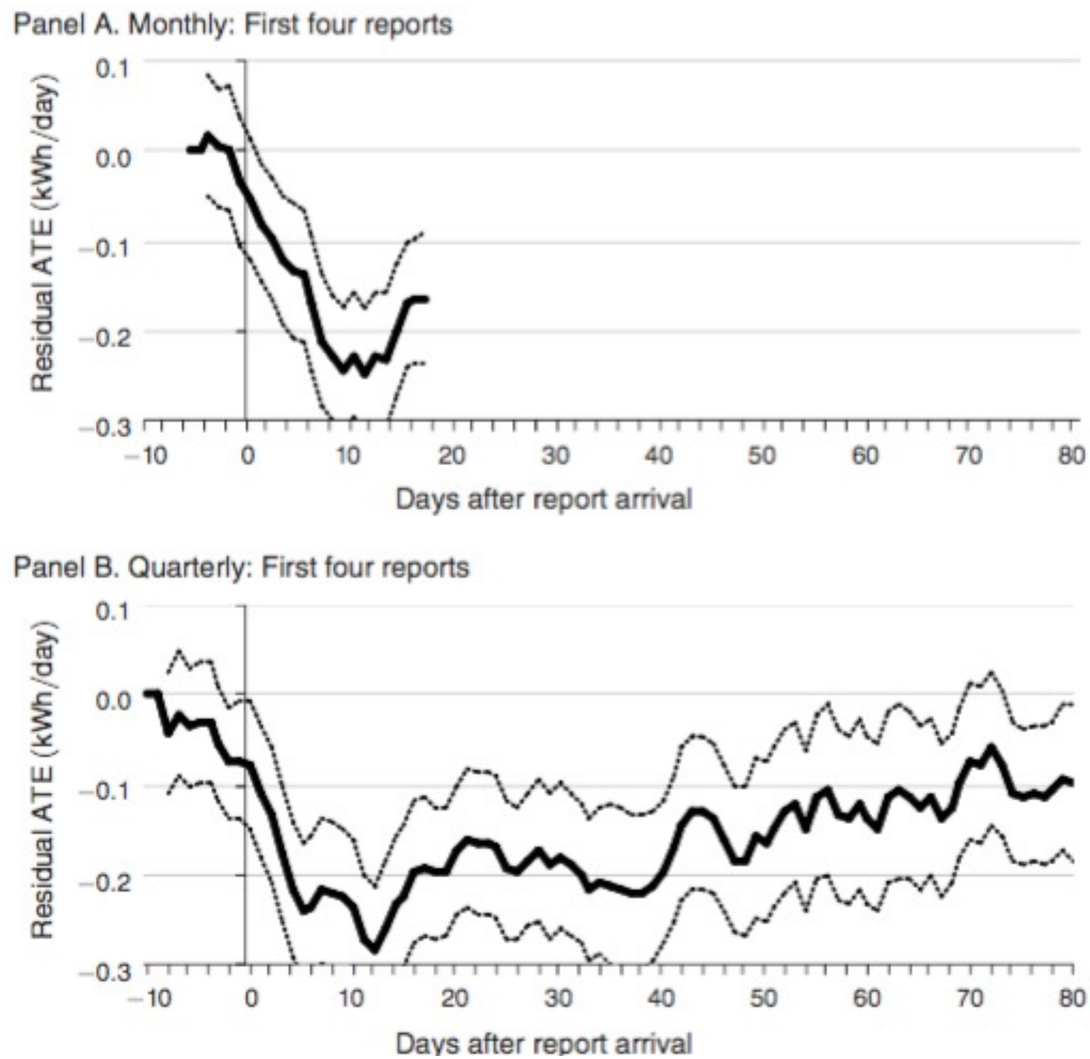
Smart meters and social comparisons



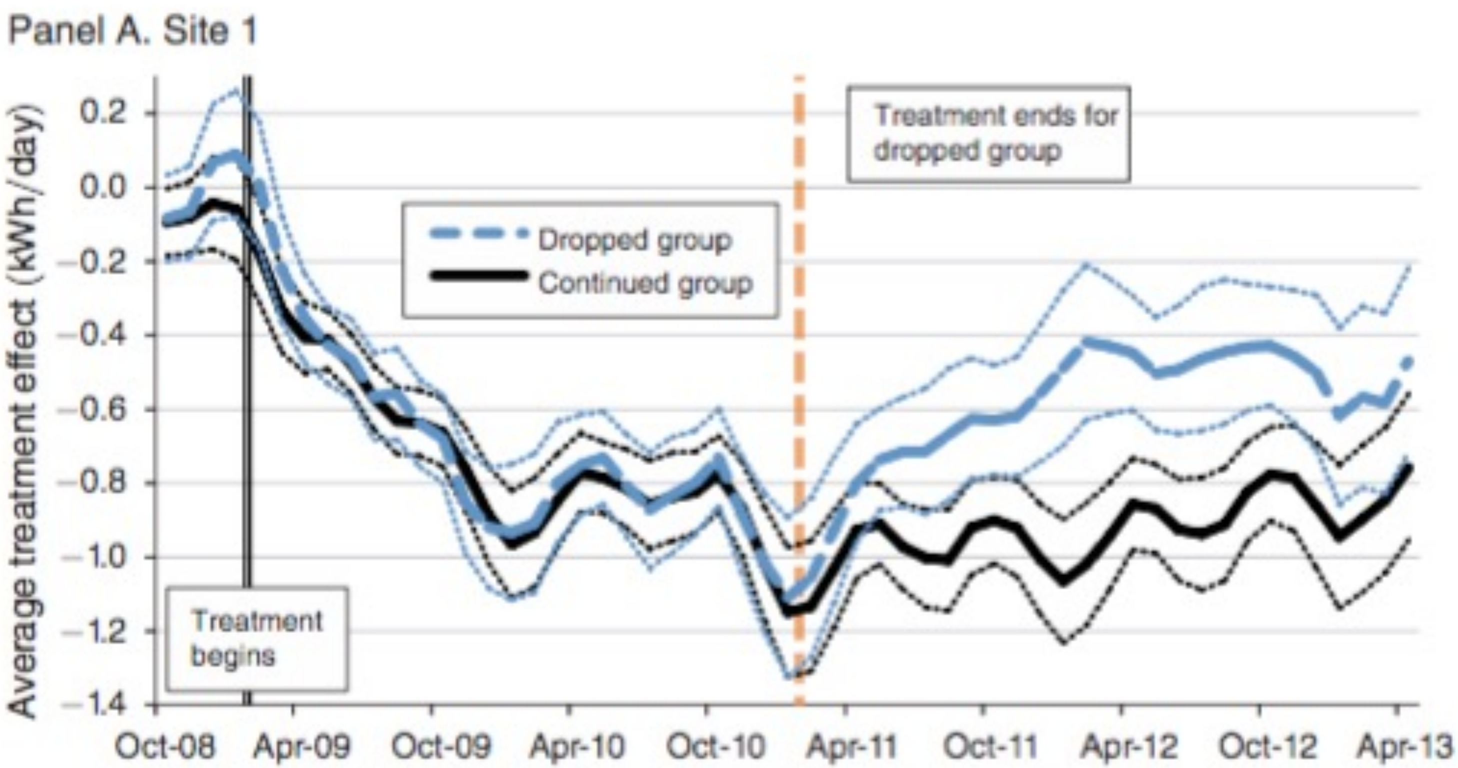
Research design

Site:	(1)	(2)	(3)
Region	Upper midwest	Northwest	Southwest
Average January heating degrees	46.9	25.4	19.3
Average July cooling degrees	5.6	2.2	8.9
Narrative			
Baseline period begins	October 2007	January 2007	April 2006
First reports generated	January and February 2009	October 2008	March to May 2008
Last report generated for dropped group	January 2011	September 2010	June 2010
End of sample	April 2013	March 2013	March 2013
Frequency			
	60 percent monthly 40 percent quarterly (Randomly assigned) Continued group changed to Biannual in 2011	72 percent monthly 28 percent quarterly (Randomly assigned)	71 percent monthly (heavier users) 29 percent quarterly (lighter users)
Number of households			
Treatment: Continued	26,262	23,399	21,630
Treatment: Dropped	12,368	11,543	12,117
Control	33,524	43,945	49,290
Total	72,154	78,887	83,037

Main results



Main results



Today's outline

1) Demand side policies evaluation
    - Experiments
    - ML
2) Case study: Real-time pricing in Spain

Fabra Rapson Reguant Wang (2021)

Slides

Next class

- Demand II.
  - What are the distributional impacts of the energy transition?
  - How can we get at the heterogeneous impacts of the transition?

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