# Empirical Methods for the Analysis of the Energy Transition

## Slide Set 7

Prof. Mar Reguant

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# Demand side policies evaluation

# Electricity demand

- 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 quite **inelastic and unresponsive**, but that does not go well with renewables or the current energy crisis. . .

Electricity is an essential input and difficult to substitute

# Demand and the energy transition

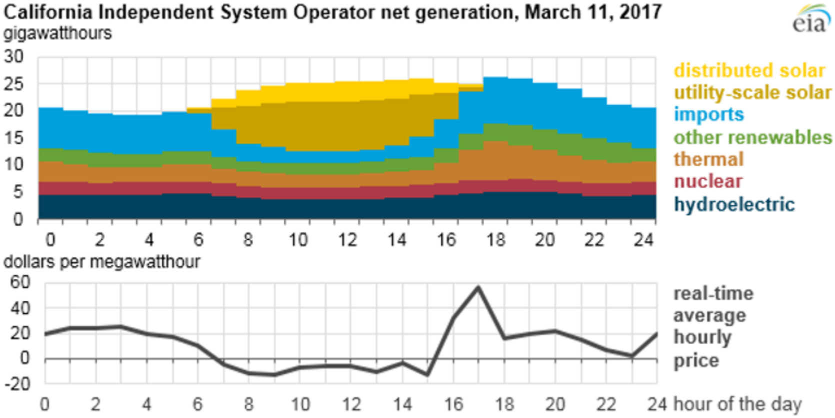
- We have been focusing so far on the supply side of the energy transition:
  - Wind and solar power integration
  - Climate policies to tax emissions
  - Transmission expansion
- Demand also needs to play a crucial role in our **need to reduce emissions** in a path to net zero.
  - Reduction of demand
  - Flexibility of demand
  - Participation of demand

# How can demand policies help?

- Reducing demand directly contributes to lowering our emissions.
- Making demand more flexible can also be extremely valuable.
  - Shifting demand to when cleaner technologies are available.
  - It also makes energy cheaper (e.g., shift to solar).
- Even more important in moments of extreme conditions (e.g., high system pressure, risk of blackouts) (e.g., see Ito, Ida, Tanaka (2018)).

# Electricity demand and renewables

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



# 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.

Today we will discuss demand response via pricing. All of these interact with technology adoption, electrification, and distributed energy adoption.

# 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.
- *Important!* Demand response might induce consumers to engage in 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).

# Demand response

- Demand response programs are intended to **increase the elasticity of demand**.
- This response should help balance supply and demand.
  - "Demand follows supply" vs.
  - "Supply follows demand"
- Well known properties of **dynamic pricing** (e.g., Borenstein and Holland, 2005):
  - Energy conservation in high-priced hours.
  - Load-shifting from high-priced to low-priced hours.
    $\rightarrow$ Greater investment and productive efficiency.
    $\rightarrow$ Reduced market power.

# 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”
  - In addition, they can provide added services like individualized pricing as well as technical services (voltage control)

# “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)

# Demand response: Theory and Empirics

# Demand response: a large and growing literature

- Large **theoretical literature**: Borenstein (2005), Joskow and Tirole (2006, 2007), Borenstein and Holland (2005)...
- **Field experiments** on electricity demand response
  - Jessoe and Rapson (2014); Allcott (2011), Faruqui and Sergici (2010); Wolak (2010); Ito *et al.* (2018); Bolinger and Hartman (2018)...
  - Limited evidence of true real-time pricing (hourly price changes, instead of critical events or time-of-use).
  - Limited external validity (subjects participating in the experiments did so voluntarily).
- **Simulation** studies on the role of demand response in enabling zero-carbon generation
  - Imelda, Fripp and Roberts, 2018; Coffman et al., 2018.

# 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.
  - Disciplines market power.

# Borenstein and Holland (2005)

- Consider a market with a share of sensitive consumers (pay wholesale RTP price) and a share of insensitive consumers (pay constant price).

$$\tilde{D}_t(p_t, \overline{p}) = \alpha D_t(p_t) + (1-\alpha) D_t(\overline{p})$$

- Insensitive demand can be “too high”’ or “too low”.
- Theory + “toy” simulations
- *What are the long-run inefficiencies from mispricing? What is the second best policy?*

**On the efficiency of competitive electricity markets with time-invariant retail prices**

**Severin Borenstein***

**and**

**Stephen Holland****

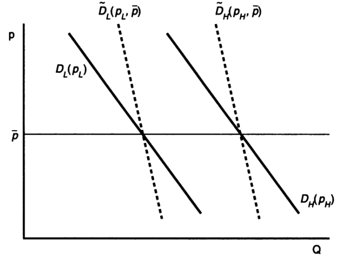
*Most customers in electricity markets do not face prices that change frequently to reflect changes in wholesale costs, known as real-time pricing (RTP). We show that not only does time-invariant pricing in competitive markets lead to prices and investment that are not first best, it even fails to achieve the constrained second-best optimum. Increasing the share of customers on RTP is likely to improve efficiency, though surprisingly it does not necessarily reduce capacity investment, and it is likely to harm customers that are already on RTP. Simulations demonstrate that the efficiency gains from RTP are potentially quite significant.*

# Borenstein and Holland (2005) – Main Results

- Thm 1. Pricing insensitive at weighted average price only optimal with constant elasticity. Second-best rate can be higher or lower.
- Thm 2. A subsidy or a tax can bridge the second-best gap.
- Thm 3. More consumers on RTP decreases long-run average prices.
- Thm 4. Capacity can go either way (but will tend to decrease with more RTP).

FIGURE 1

WHOLESALE DEMAND CURVES WITH AND WITHOUT SOME CUSTOMERS ON FLAT RATES



# Borenstein (2005)

- Very similar to previous paper (some parts the same) but adding time-of-use to comparisons
- *Is TOU good enough?*

**The Long-Run Efficiency of Real-Time Electricity Pricing**

*Severin Borenstein**

*Retail real-time pricing (RTP) of electricity – retail pricing that changes hourly to reflect the changing supply/demand balance – is very appealing to economists because it "sends the right price signals." Economic efficiency gains from RTP, however, are often confused with the short-term wealth transfers from producers to consumers that RTP can create. Abstracting from transfers, I focus on the long-run efficiency gains from adopting RTP in a competitive electricity market. Using simple simulations with realistic parameters, I demonstrate that the magnitude of efficiency gains from RTP is likely to be significant even if demand shows very little elasticity. I also show that "time-of-use" pricing, a simple peak and off-peak pricing system, is likely to capture a very small share of the efficiency gains that RTP offers.*

# Borenstein (2005) – Main Results

- RTP welfare gains >> TOU.
- Note: Some of the TOU rates are very high and the model breaks down if consumers elastic enough.

**Table 6: Welfare Effects of RTP versus TOU Pricing**

| A | B | C | D | E | F |
|---|---|---|---|---|---|
| Elasticity | Share on RTP/TOU | ANNUAL TOTAL SURPLUS CHANGE VS FLAT RATE RTP | "Quasi-wholesale" TOU | Actual TOU price ratios | "Cost-share" TOU |
| -0.025 | 0.333 | 112,060,365 | 16,269,127 | 10,657,394 | 6,928,165 |
| -0.025 | 0.666 | 205,800,109 | 32,538,254 | 21,314,789 | 13,856,330 |
| -0.025 | 0.999 | 271,333,946 | 48,807,381 | 31,972,183 | 20,784,495 |
| -0.050 | 0.333 | 196,836,537 | 32,226,253 | 21,322,177 | 13,683,652 |
| -0.050 | 0.666 | 314,219,558 | 64,452,506 | 42,644,355 | 27,367,305 |
| -0.050 | 0.999 | 388,316,857 | 96,678,759 | 63,966,532 | 41,050,957 |
| -0.100 | 0.333 | 302,262,176 | N/A | 42,006,103 | 26,159,344 |
| -0.100 | 0.666 | 439,987,363 | N/A | 84,012,206 | 52,318,689 |
| -0.100 | 0.999 | 537,284,137 | N/A | 126,018,309 | 78,478,033 |
| -0.150 | 0.333 | 370,238,483 | N/A | 61,775,434 | 37,387,646 |
| -0.150 | 0.666 | 530,960,593 | N/A | 123,550,868 | 74,775,291 |
| -0.150 | 0.999 | 647,620,518 | N/A | 185,326,302 | 112,162,937 |
| -0.300 | 0.333 | 509,388,631 | N/A | N/A | 65,167,555 |
| -0.300 | 0.666 | 730,577,275 | N/A | N/A | 130,335,110 |
| -0.300 | 0.999 | 888,877,347 | N/A | N/A | 195,502,666 |
| -0.500 | 0.333 | 641,472,723 | N/A | N/A | 92,710,676 |
| -0.500 | 0.666 | 922,328,312 | N/A | N/A | 185,421,352 |
| -0.500 | 0.999 | 1,098,811,460 | N/A | N/A | 278,132,028 |

# Demand response as a solution?

- Questions on the **real possibilities**:
  - Electricity demand quite inelastic (0.1-0.3).
  - Even long-run estimates appear to be in inelastic range, -0.8 to -0.4.
  - Consumers typically exposed to constant electricity prices.
  - Even if consumers face real-time prices, they might not have the willingness to respond, or they might not even be at home.
  - If exposed to **dynamic pricing**, will consumers respond?
- Several studies examine how they respond to their average price of electricity, but response typically still limited.

# Real-time pricing and experiments

A large part of the literature implements experiments of dynamic 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?
- Some researchers have managed to default everyone on a dynamic tariff, much more effective (Fowlie et al., 2021).

# 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)*andthirtyminutesprior*(1.25).
  - Price + IHD. 100 households. Same as price plus real-time information about electricity use and price.

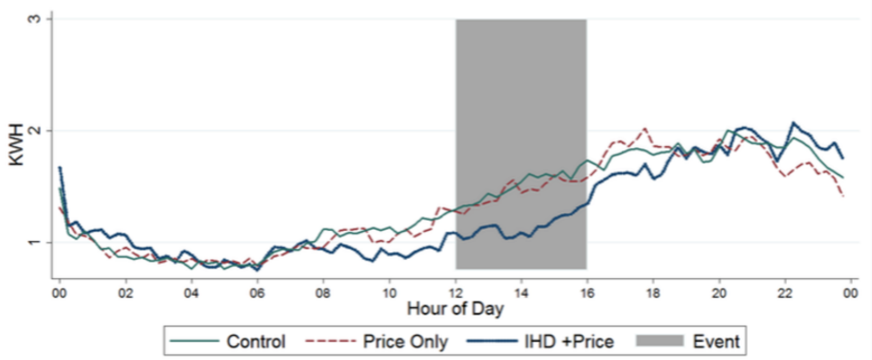
# Main Results

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



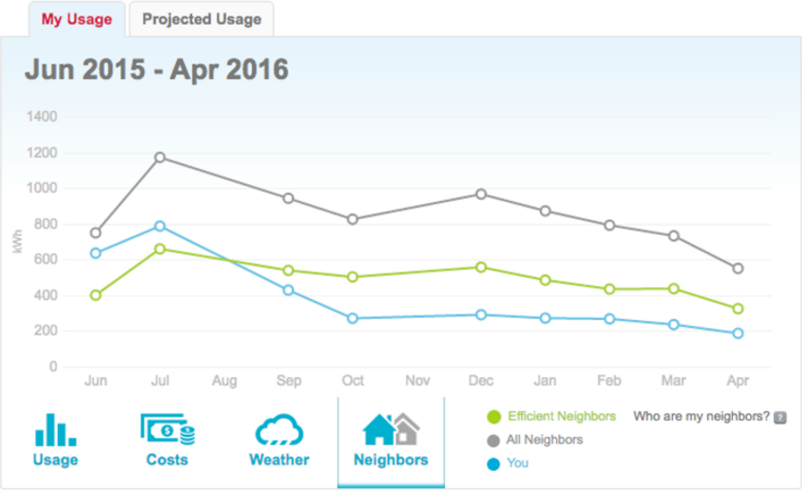
# Additional Results

- 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
- Important follow-up work shows that response is "medium-rum" (not immediate). One needs technology for truly rapid response (Bollinger and Hartman, 2021).

# 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

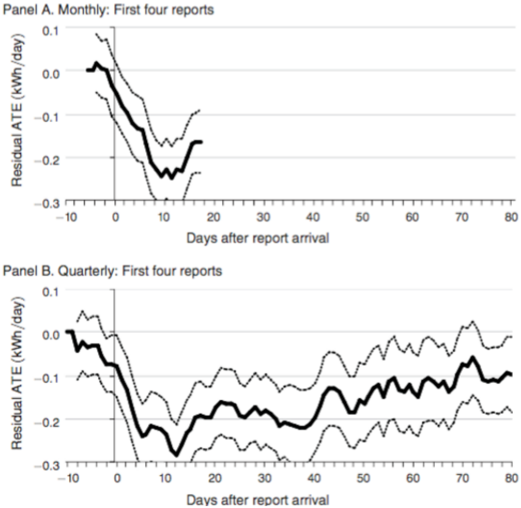
# Smart meters and social comparisons



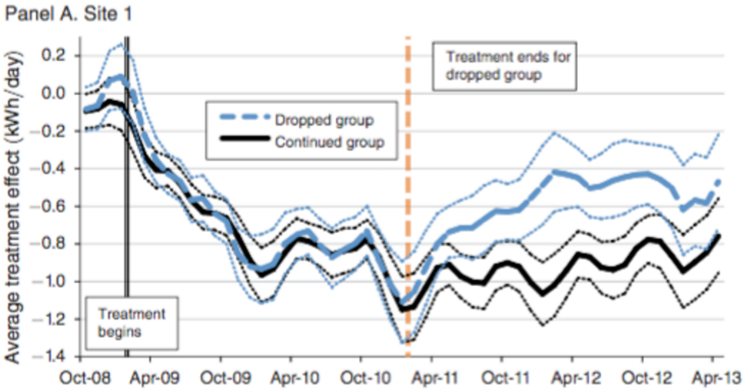
# Research Design

| 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



# Real-time Pricing (RTP) and Time-of-Use (TOU): Evidence from Spain

# Non-experimental evidence

- It is sometimes not feasible to run experiments at scale.
- One can exploit policy changes to examine the response of households, even if the environment is not perfectly controlled.
- Need to ensure that there are no "confounders" that could flaw the conclusions.

# Non-experimental tools

- Event study: before and after
- Difference-in-difference: before and after with a control
- Instrumental variables: exogenous factors to pick up "unconfounded" variation

These tools can be enhanced with machine learning. The papers today use machine learning in their implementation (lasso + forests). Today, we will practice with a simpler version.

# Today's examples

We will examine data from two research projects looking at the response of households to actual policies:

- Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market,
- Measuring the Impact of Time-of-Use Pricing on Electricity Consumption: Evidence from Spain

**Preview:** Even if RTP is in theory better, TOU shifts consumption much more.

# RTP: Fabra, Rapson, Reguant, and Wang (2021)

- April 2014: In Spain, RTP becomes the **default option for all households** (below 10 kW).
- Electricity **marginal price** composed of two parts:
  - **Energy component**: passthrough of hourly wholesale electricity market price (**RTP**), or time-invariant (non-RTP).
  - **Network component**: regulated costs charged at the margin; peak/off-peak prices (**TOU**) or time-invariant (non-TOU).

Unique opportunity to **measure demand response** to hourly price changes of the general population

# Data

- Smart-meter data for 4M Spanish households (January 2016- July 2017).
  - Over 4 Million households
  - For each household: hourly electricity consumption during 2016; plan characteristics and zip code.
  - Households on RTP are spread over approx 1.500 zip codes; those on non-RTP in approx 5000 zip codes.
  - We link the zipcode with detailed Census demographic data and temperature data.

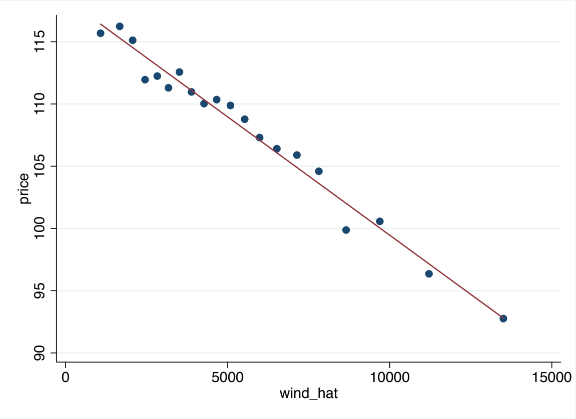
# Empirical strategy for RTP response

- We estimate the **short-run price elasticity** of consumers.
- Main regression (individual by individual or zip-code level):

$$\ln q_{ith} = \beta_i \ln p_{ith} + \phi X_{ith} + \gamma_{th} + \epsilon_{ith}.$$

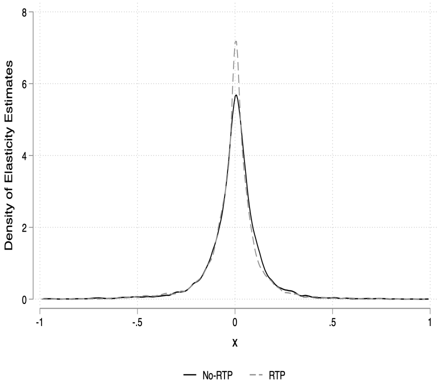
- In baseline specifications, we control for:
  - Temperature bins by hour.
  - Fixed effects: hour x month, year x month, day of week.
- Prices high when demand is high $\rightarrow$ Need to find an IV
  - Day-ahead wind forecast: reduces RTP prices

# IV strategy




- Instrument shows strong first stage, also after conditioning.
- Plausibly exogenous after controlling for local weather conditions.

# We find similar distributions of price elasticities




- Distribution centered around zero, median of no response.

# Average elasticities by group are close to zero

| | (1) p_iv11 | (2) p_iv21 | (3) p_iv31 | (4) p_lasso |
|---|---|---|---|---|
| rtp | -0.00513 | -0.00430 | -0.00374 | -0.00468 |
| | (0.00238) | (0.00237) | (0.00220) | (0.00217) |
| Constant | -0.00473 | -0.00883 | -0.0117 | -0.0237 |
| | (0.00244) | (0.00252) | (0.00182) | (0.00274) |
| Observations | 14598 | 14598 | 14598 | 14598 |

Standard errors in parentheses

- Not much of an effect from RTP.

# TOU: Enrich, Li, Mizrahi, and Reguant (2023)

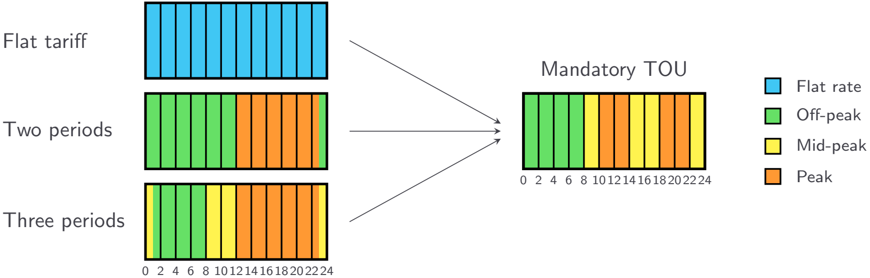
1. Energy cost (30%)
2. Taxes (20%)
3. System and Network charges (50%)

# TOU: Enrich, Li, Mizrahi, and Reguant (2023)

1. Energy cost (30%) $\Rightarrow$ on RTP since 2015
2. Taxes (20%)
3. System and Network charges (50%)

# TOU: Enrich, Li, Mizrahi, and Reguant (2023)

1. Energy cost (30%) ⇒ on RTP since 2015
2. Taxes (20%)
3. **System and Network charges (50%)⇒ changed June 2021**



# Data

- **Electricity Demand** (hourly data):
  - Spain: Spanish System Operator (**REE**) - at the programming unit level
  - Portugal: Iberian Market Operator (**OMIE**)
- **Consumers** (monthly data):
  - Spain: Spanish National Markets and Competition Commission (**CNMC**)
  - Portugal: Bulletins of the Liberalized Electricity Market
- **Temperature** (hourly data): NASA MERRA-2 - 50X50km grid

$\Rightarrow$ **Period:** Jan 2018 - Sep 14th 2021, excluding 2020.

# Machine Learning: Estimation

1. Estimate the following firm-hour specific regression using LASSO

$$Y_t = \gamma X_t + \epsilon_t$$

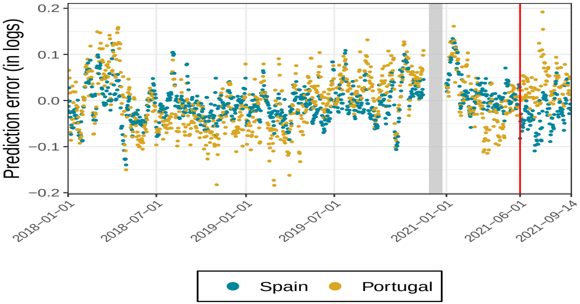
where

- $Y_t$ is the consumption per capita of each regulated utility and Portugal
- $X_t$ contains the following control variables: Month, weekend and national holiday dummies, Temperature (average, daily min and max) and all possible interactions
- Pre-treatment period: Jan 2018 - June 2021

# Panel Fixed effects: Differences-in-Differences

2. Create In- and Out-of-sample predictions ($\hat{Y}$) and estimate the following fixed-effects regression

$$Y_{fht} - \hat{Y}_{fht} = \beta D_{fht} + \lambda P_{fht} + \delta_f \delta_h \delta_m + \delta_f \delta_y + \tau_{ms} + \epsilon_{fht}$$



# Results: ML

| Outcome Variable: Prediction error (in logs) | | | |
|---|---|---|---|
| | Baseline | Weekends | Weekday |
| Off-Peak | -0.016*** | 0.015* | 0.017*** |
| | (0.006) | (0.009) | (0.004) |
| Mid-Peak | -0.078*** | -0.063** | -0.077*** |
| | (0.017) | (0.023) | (0.015) |
| Peak | -0.126*** | -0.079*** | -0.124*** |
| | (0.018) | (0.021) | (0.023) |
| Firm-Hour-Month | X | X | X |
| Firm-Year | X | X | X |
| Month of sample | X | X | X |

# Policy implications: RTP vs TOU

- RTP does not appear to engage customers in an effective manner, at least in the short-run.
  - Efficient pricing is necessary, but not sufficient.
  - Information provision and cost/benefits of responding.
- TOU potentially **more effective** (habituation, salience?), but theoretical literature emphasizes the **limits of TOU** to delivering all benefits from demand response.

# Policy implications: RTP vs TOU

- **Key challenge**: intermittency really not addressed with TOU; at the very least it requires general patterns with seasonal adjustments (e.g., solar); it doesn't work for wind.
  - Combine RTP+TOU+information provision at critical peaks.
  - Role of technology (smart thermostats), EVs, batteries.
- Need to analyze from a customer behavior point of view what the **"sweet spot"** could be.

# Next class

Demand II.

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

# References


- Blonz, J. A. (2021). Making the Best of the Second-Best: Welfare Consequences of Time-Varying Electricity Prices. Working paper.
- Burlig, F., Knittel, C., Rapson, D., Reguant, M., & Wolfram, C. (2020). Machine Learning from Schools about Energy Efficiency. Journal of the Association of Environmental and Resource Economists, 7(6), 1181–1217. https://doi.org/10.1086/710606
- Christensen, P., Francisco, P., Myers, E., & Souza, M. (2021). Decomposing the Wedge between Projected and Realized Returns in Energy Efficiency Programs. The Review of Economics and Statistics, 1–46. https://doi.org/10.1162/resta01087
- Jessoe, K., & Rapson, D. (2014). Knowledge is (Less) power: Experimental evidence from residential energy use. American Economic Review. https://doi.org/10.1257/aer.104.4.1417
- Jessoe, K., & Rapson, D. (2015). Commercial and Industrial Demand Response Under Mandatory Time-of-Use Electricity Pricing. Journal of Industrial Economics, 63(3), 397–421. https://doi.org/10.1111/joie.12082
- Fabra, N., Rapson, D., Reguant, M., & Wang, J. (2021). Estimating the Elasticity to Real-Time Pricing: Evidence from the Spanish Electricity Market. AEA Papers and Proceedings, 111, 425–429. https://doi.org/10.1257/pandp.20211007
- Fowlie et al. (2021). Default Effects And Follow-On Behaviour: Evidence From An Electricity Pricing Program, The Review of Economic Studies, Volume 88, Issue 6, November 2021, Pages 2886–2934, https://doi.org/10.1093/restud/rdab018
- Enrich, Li, Mizrahi, Reguant (2023). Measuring the Impact of Time-of-Use Pricing on Electricity Consumption: Evidence from Spain.