Efficiency and Distributional Impacts of Real-Time Pricing for Electricity

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Based on joint research with
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Decarbonizing power

- Need to drastically reduce Green House Gas emissions.
- The power sector has the greatest potential for carbon abatement.
- **Carbon-free (or net zero) electricity** by 2035-2050.
  - Massive deployment of renewable energies.

A challenge to decarbonizing power:

- **Renewables' intermittency** might lead to a potential mismatch between supply and demand.
- Changing the **supply-demand paradigm** in electricity:
  - Before: Supply follows demand
  - Now: Can demand follow supply?

A necessary condition for efficient demand response

Real Time Pricing (RTP):

- Charge consumers prices that reflect changes in the marginal costs of serving demand, in order to shift demand from high-cost hours to low-cost hours.

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Potential benefits:

- Provide flexibility to facilitate the integration of renewables.
- Mitigate the need to invest in back-up/storage capacity.
- Reduce production costs.
- Mitigate market power.

A rich literature on the benefits of dynamic pricing

- Jessoe and Rapson (2014), Wolak (2011), Allcott (2011), Faruqui et al. (2009)...
- Borenstein (2005), Borenstein and Holland (2005)
- Poletti and Wright (2020), Holland and Mansur (2008)...
- Harding and Sexton (2017) - survey

Limits to RTP for Households

1. **Efficiency:**
   - *Information*: Are households sufficiently aware/informed about price changes?
   - *Incentives*: Do they benefit enough from changing their consumption in response to price changes?

Limits to RTP for Households

1. **Efficiency:**
   - *Information*: Are households sufficiently aware/informed about price changes?
   - *Incentives*: Do they benefit enough from changing their consumption in response to price changes?

2. **Equity:**
   - Under time-invariant prices, households who consume at low-priced hours **cross-subsidize** those who consume at high-priced hours
     - How does this cross-subsidization correlate with income?
   - Low income households most exposed to extreme events
   - Also least able to adopt resilience equipment

Equity impacts during extreme events

British households face fuel poverty as energy prices skyrocket

(Reuters, 16 Feb 2022) Many people in Britain are struggling to weather a cost-of-living crisis, with rising fuel bills putting further strain on household budgets.

Whenever Sam's hand hovers over the heating control at his home in southern England, he faces a grim dilemma: turn it up and erode his meagre food budget, or turn it down and risk another spell in hospital.

Equity impacts can be devastating

WINTER STORM 2021

At least 111 people died in Texas during winter storm, most from hypothermia

> The newly revised number is nearly twice the 57 that state health officials estimated last week and will likely continue to grow.

BY **SHAWN MULCAHY** MARCH 25, 2021 4 PM CENTRAL

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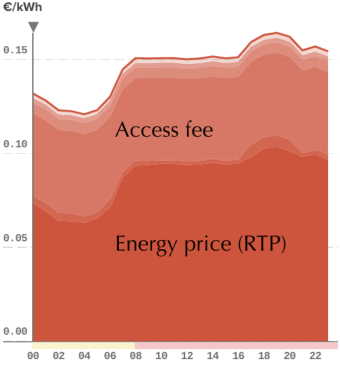
Overarching question

How to reconcile the efficiency objectives with the equity implications of policies?

Equity concerns can undermine efficient policies

RTP in Spain

Spain provides a unique opportunity to study the efficiency and equity implications of RTP



- Since April 2015, it is the only country in which RTP is the **default option for all households**.

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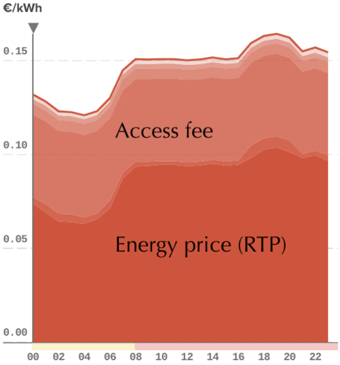


- Since April 2015, it is the only country in which RTP is the **default option for all households**.
- As of 2023, Spain will become the first country in **abandoning RTP** - as required by the EC!

Our research

Access to **hourly electricity consumption data of 2M Spanish households** has allowed us to study the efficiency and distributional impacts of RTP

1. Fabra, Rapson, Reguant, and Wang (2021) *Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market*, AEA P&P.
2. Cahana, Fabra, Reguant, and Wang (2022) *The Distributional Impacts of Real Time Pricing*

Goals of our work

1. Estimate the short-run **elasticity** to real-time prices.
2. Quantify the **distributional impacts** of RTP.
3. Identify the **drivers** of the distributional impacts of RTP.
4. Consider **counterfactual experiments**.

Data

- We obtained smart-meter data for over 2M households, from one large Spanish utility (Naturgy).
- Sample period: January 2016-July 2017.
- For each household, we have:
  - hourly electricity consumption
  - plan characteristics (pricing, contracted power)
  - postal code
- We link the postal code with detailed Census data:
  - education, income and age distribution, avg number of rooms...

A first look at the data: month vs annual variation

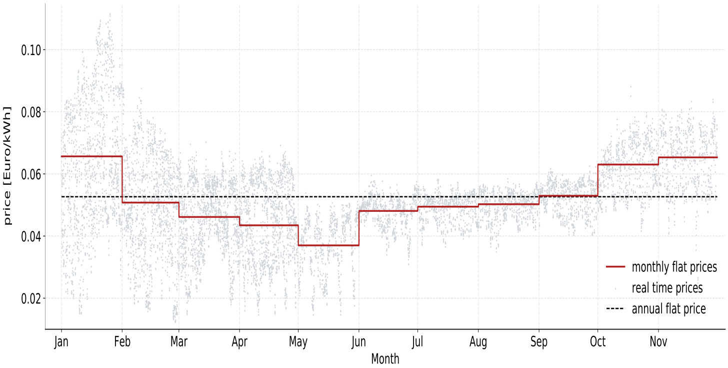


Figure: Summary of variation in energy prices (access fee not included)

Estimating the Short-Run Elasticity to Real Time Prices

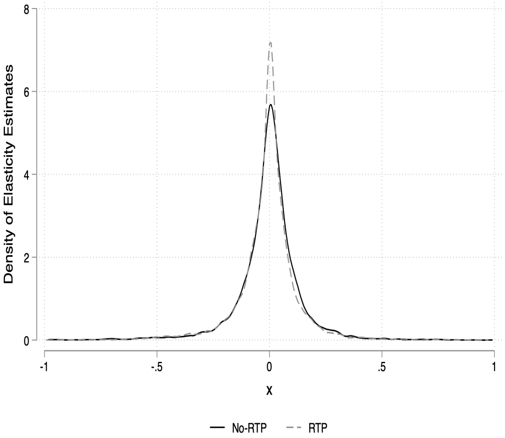
Estimating the elasticity to RTP

- We estimate the short-run price elasticity of demand for household i through 2SLS:

$$\ln q_{it} = \beta_{i0} + \beta_{i1} \ln \hat{p}_t + \phi X_t + \gamma_{it} + \epsilon_{it}$$

- In baseline specifications, we control for:
  - Fixed effects: hour x month, year x month, day of week
  - System-wide hourly electricity demand
  - Household-specific temperature bins by hour
  - IV for short-run prices: national wind forecasts

Distributions of household-level price elasticities



- Distributions centered around zero, median of no response.
- Similar distributions for RTP and Non-RTP households (defaulted into these choices at the start of the program)

Results

Why do households not respond to RTP?

- In our sample, RTP did not engage customers: why?
  1. Lack of awareness
  2. Price changes not known and not salient
  3. Rational inattention:
     - Narrow price differences $\rightarrow$ costs of changing consumption exceed the savings

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- Would demand response be enhanced...
  - with higher prices and larger price differences?
  - in the medium-run?
  - with higher penetration of solar (more predictable prices)?
  - Why is it that automatic devices have not been deployed?

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Quantifying the Distributional Implications of Real Time Pricing

Computing bills under RTP and time-invariant prices

- For each household, we compute the bill changes from time-invariant prices to RTP:

$$\Delta Bill = Bill_i^{RTP} - \overline{Bill}_i$$

where:

  - $Bill_i^{RTP}$: Bill under hourly prices (RTP)
  - $\overline{Bill}_i$: Bill under the annual average price (time-invariant)

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where:

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- We also separate hourly and monthly cross-subsidization:

"within month" and "across months" effects

$$\Delta Bill = [Bill_i^{RTP} - \overline{Bill}_i^m] + [\overline{Bill}_i^m - \overline{Bill}_i].$$

where:

  - $\overline{Bill}_i^m$: Bill under the monthly average prices

Measuring the policy impacts

- We assign households' income by exploiting the hourly consumption data and zip-code level income distributions.
    1. Classify consumers into types (*kmeans* clustering): Step 1
    2. Infer income distribution of those types based on the distribution of income and types in each zip code. Step 2

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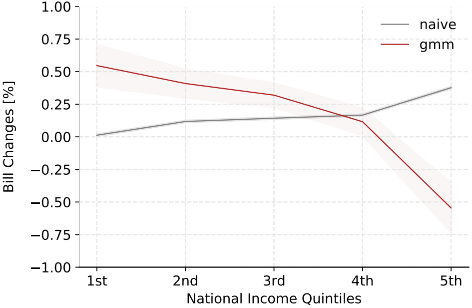
  1. Classify consumers into types (*kmeans* clustering): ▸ Step 1
  2. Infer income distribution of those types based on the distribution of income and types in each zip code. ▸ Step 2
- We use the bill impacts and the inferred distribution of income at the household level to assess the distributional impacts of RTP:
  - *What is the impact of RTP across income bins?*
  - *How can it decomposed?*
  - *What are the main drivers for the effects?*
  - *Does the within-zip-code heterogeneity matter?*

Heterogeneous impacts by income bins

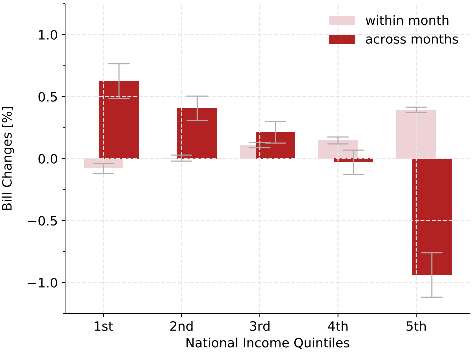
Figure: Bill changes [%] due to the switch to RTP



- RTP is slightly regressive - still, the average impact is small.
- RTP impacts are highly heterogeneous within zip-code because of income heterogeneity.
- Using zip-code level income would miss this heterogeneity, reversing the impacts.

Decomposing the impacts

Figure: Decomposition of the bill changes (two-step approach)

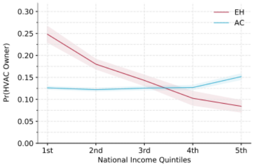


- **Within month** price changes have progressive impacts.
- However, **across month** price changes have regressive effects.

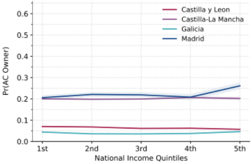
Which mechanisms explain these patterns?

- We explore different channels through which consumption of electricity relates to income and other factors.

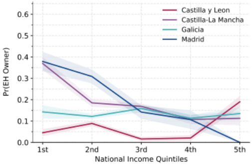
  - Consumption patterns by income.
  - Appliance ownership.
  - Locations. ▸ Go



(a) Share of electric heating owners and AC owners



(b) AC ownership by state

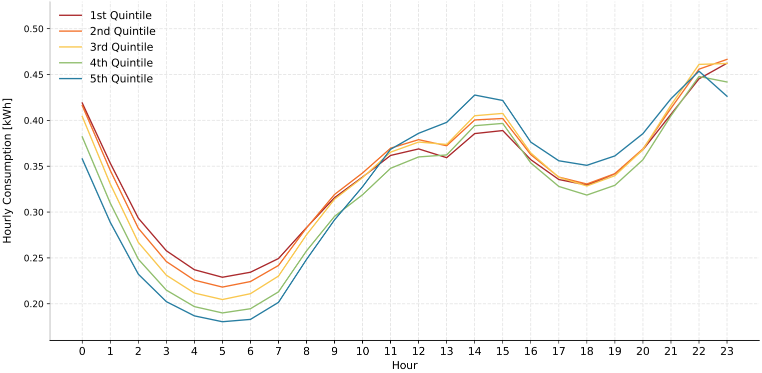


(c) EH ownership by state

Figure: Appliance ownership by income and location

Mechanisms: consumption patterns during the day

Figure: Hourly consumption during the day

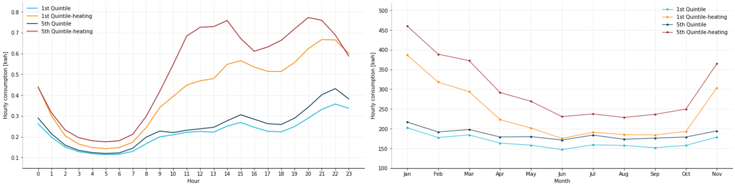


- Higher income quintiles consume proportionally more at peak.

$\rightarrow$ The within month effect is progressive.

Mechanisms: appliance ownership and consumption

Figure: Consumption curves for households with and w/o electric heating



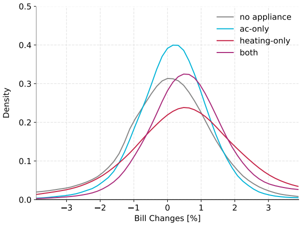
(a) Hourly consumption

(b) Monthly consumption

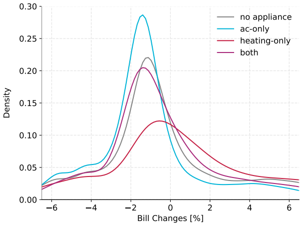
- We infer appliance ownership based on consumption structural breaks in response to local temperatures.
- Appliance ownership creates bigger differences than income, but conditional on appliance ownership, income matters.
- Households with electric heating consume more during peak hours and during winter when prices are higher. AC ownership

Mechanisms: appliance ownership and bill impacts

Figure: Bill changes by appliance ownership



(a) Within month effects



(b) Across months effects

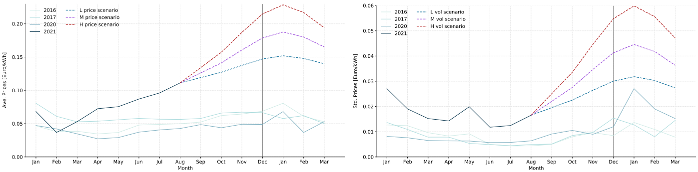
- The bigger bill increases are suffered by households with electric heating due to the across months effect.
- Low income households, more likely to have electric heating.

$\rightarrow$ The across months effect is regressive.

Counterfactual experiments

- The distributional impacts in our sample are limited and bounded (small price variation).
- However, patterns could change going forward, with increasing extreme pricing and volatility (as experienced lately).
- We explore several counterfactuals:
  - Large price shocks and volatility
  - Demand elasticity

Large price shocks and volatility

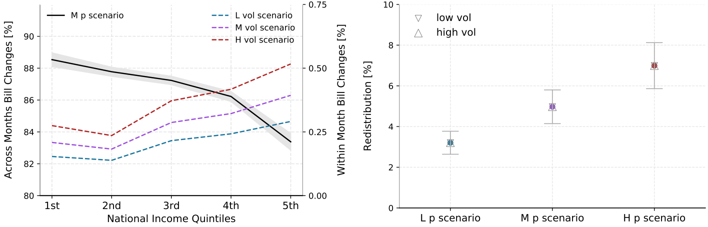


(a) Simulated prices (b) Simulated price volatility

- We consider simulated prices (with low, medium, high levels and low, medium, high volatility).
- We re-analyze the distributional implications of RTP.

Large price shocks and volatility

Figure: Distributional implications of RTP under a large price shock

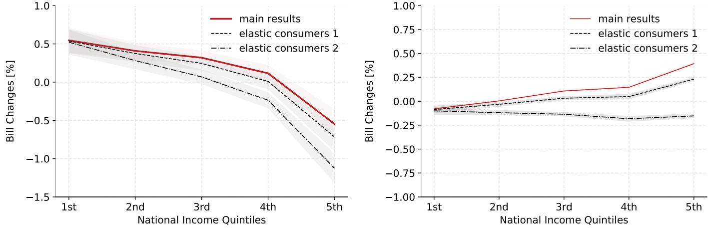


(a) Decomposition (b) Redistribution

- The (regressive) across month effects strongly dominate.
- Low-income households are relatively worse off under high prices and low volatility.
- High price levels have more adverse distributional impacts than high price volatility.

Demand elasticity

Figure: Distributional implications of RTP under demand elasticity



(a) Aggregate impact (b) Within month effect

- Suppose that elasticity is positively correlated with income (EVs, batteries, solar, automatic devices).

$\rightarrow$ RTP becomes more regressive.

- The within month effect no longer progressive: high-income households can now benefit from the within day price variation.

Summary of Results

- Distributional implications of RTP in Spain (2016-2017).
  - In this context, RTP did **not trigger demand response** and was **slightly regressive**.
- Bill impacts decomposed in:
  - within month effects (daily price variation)- progressive.
  - across months effects (seasonal price variation)- regressive.
- Key drivers: **appliance ownership** and **location**.
  - In Spain, low-income households rely more on electric heating, which exposes them to the high winter prices.

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- Key drivers: **appliance ownership** and **location**.
  - In Spain, low-income households rely more on electric heating, which exposes them to the high winter prices.

Not a general condemnation of RTP as a useful policy tool

Rather a **framework** to assess the efficiency and distributional effects of RTP so as to design it successfully

Policy questions going forward

1. How will price patterns evolve with more renewables?
   - Price levels and price volatility
   - Within day? Across the year?
   - 2030 vs. 2050?
   - Seasonal/predictable vs random price changes?

→ Strong impact on the incentives for demand response + distributional implications

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   - Devices for automatic demand response compulsory?
   - Solar+efficiency investments in low income households?
   - Time-invariant (means-tested) prices for representative load profiles + exposure to short-run price signals?

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Addressing distributional concerns is a necessary condition for efficient policy making

Thank You!

Questions? Comments?

More info at nfabra.uc3m.es and energyecolab.uc3m.es

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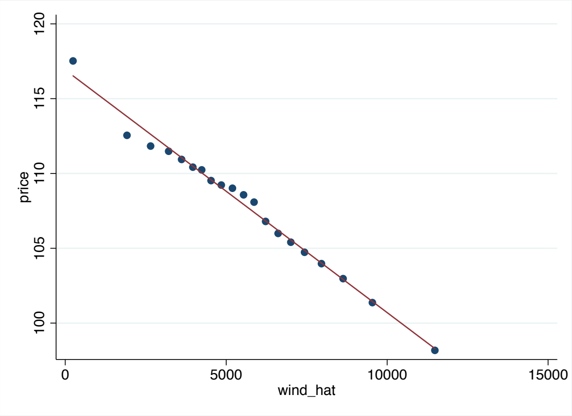
Appendix

Instrumental Variable strategy



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

Instrumental Variable challenges

- Most consumers do not consume electricity explicitly based on wind patterns, so exclusion restriction plausibly valid.
- Yet, wind patterns are intertwined with weather.
- Weather can affect electricity consumption in many ways: temperature control, sunset/sunrise, type of activities, time at home, etc.
- Difficult to control for potentially all confounders.
- High-frequency data can easily lead to significant spurious patterns due to omitted variable bias.

We consider an array of fixed-effect individual specifications together with a lasso estimator. Back

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. Back

Data: electricity consumption area

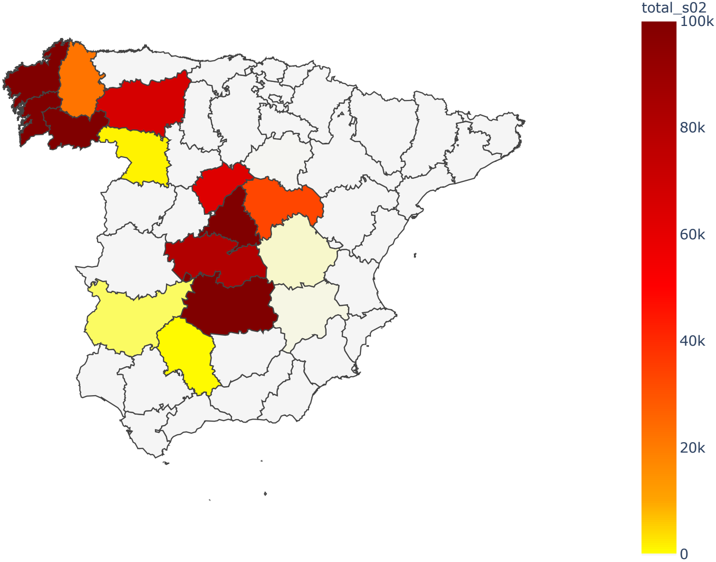


Figure: Locations of households in our data

The challenge: inferring households' income

- We observe the distribution of income at the zip code level.
- We assign households' income by exploiting the richness of hourly consumption data and zip-code level income distributions.

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Overview of our two-step approach: ▸ Details

1. Classify consumers into types (*kmeans* clustering): ▸ Step 1
   - Households with "representative" consumption patterns.
2. Infer income distribution of those types based on the distribution of income and types in each zip code. ▸ Step 2

Inferring households' income

Notation and definitions

- Zip code as $z \in \{1, \ldots, Z\}$.
- Income bins as $inc_k \in \{inc_1, \ldots, inc_K\}$.
- Households in zip code z as $i \in \{1, \ldots, H_z\}$.

- Observed zip-code income distribution: $Pr_z(inc_k)$.
- Unknown household income distribution: $Pr_i(inc_k)$.

Assigning a prob. income distribution to households

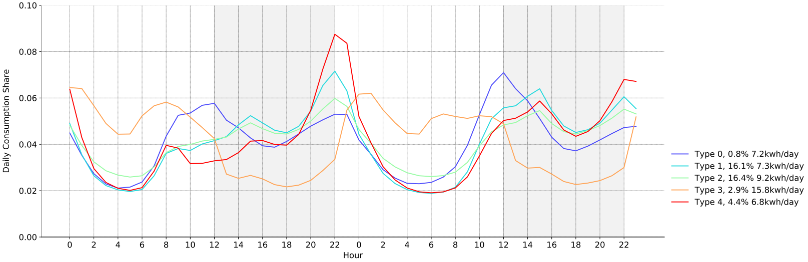
We introduce new additional objects:

- Zip code as $z \in \{1, \ldots, Z\}$.
- Income bins as $inc_k \in \{inc_1, \ldots, inc_K\}$.
- Households in zip code z as $i \in \{1, \ldots, H_z\}$.
- Discrete types as $\theta_n \in \{\theta_1, \ldots, \theta_N\}$.

- Observed zip-code income distribution: $Pr_z(inc_k)$.
- Unknown household income distribution: $Pr_i(inc_k)$.
- Unknown household type distribution: $Pr_i(\theta_n)$
- Unknown type-income distribution: η_n^k (probability that type n has income bin k).

Step 1: classify consumers into types

- We reduce the dimensionality of our data into **market shares** for daily consumption in weekdays and weekends for each individual household.
- We **group nearby zip codes** and cluster the population of consumers based on these market shares as well as the levels of consumption. Observable types based on contracted power.
- Our baseline has 5 types per observable types.



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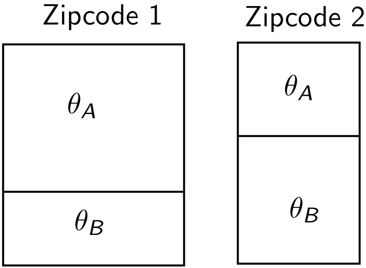
Step 2: Infer income distribution of the types



$$\eta_A^H Pr_1(\theta_A) + \eta_B^H Pr_1(\theta_B) = Pr_1(inc = H)$$

$$\eta_A^H Pr_2(\theta_A) + \eta_B^H Pr_2(\theta_B) = Pr_2(inc = H)$$

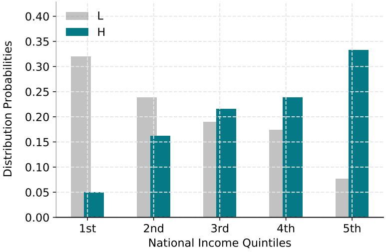
- Assume we have already inferred the distribution of types θ_i in each zip code z, $Pr_z(\theta_i)$, in Step 1.
- η_A^H is the (unknown) probability of income H for type θ_A (similarly for θ_B).
- Match zip code moments on the distribution of income, assuming same underlying types across (a set of) zip codes.

Back

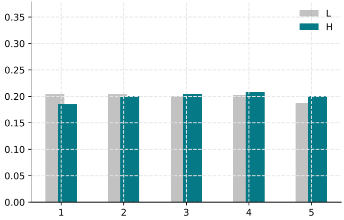
Our two-step method extracts relevant signal

- Contracted power tends to be positively correlated with income.
- Our two-step approach predicts a higher income distribution for households with high contracted power.
- In contrast, the aggregate zip-code level distribution of income would miss such correlation.

Figure: Estimated income distribution and contracted power



(a) Two-step method



(b) Naïve approach

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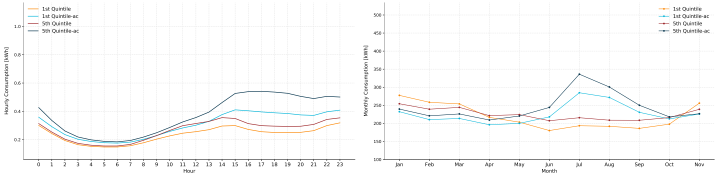
Mechanisms: appliance ownership and income impacts

Figure: Consumption curves for households with and w/o electric AC



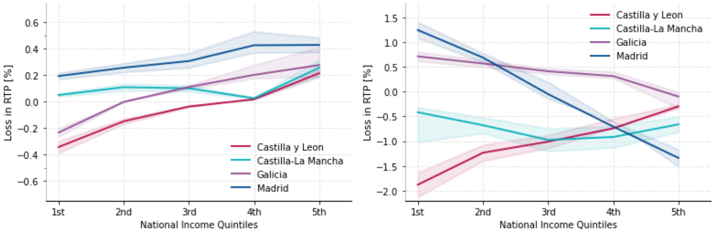
(a) Hourly consumption (b) Monthly consumption

- Households with air conditioning are affected by prices during peak hours and summer.
- AC ownership creates smaller differences than heating.

back

Mechanisms: geographical heterogeneity

Figure: Geographical heterogeneity and decomposition of the impact



(a) Within month effects (b) Across months effects

- Within month effects are similar across income and geography.
- Seasonal price variation and appliance ownership across locations drive the heterogeneous impacts.

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