The Distributional Impacts of Real-time Pricing

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Banco de España Annual Conference

June 8, 2022

The Energy transition is underway

- Need to reduce Green House Gas emissions (GHGs).
- Electricity sector ($\approx$35-40% of CO_2 emissions) has been **most active** and has the greatest potential in making the transition.
- **Carbon-free (or net zero) electricity** by 2035-2050.
  - Massive deployment of renewable energies.

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  - 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 demand response

Dynamic pricing:

- 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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- Reduce production costs.
- Mitigate market power.

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- Reduce production costs.
- Mitigate market power.

Potential concerns:

- Little awareness/scope of households for changing their consumption. ▸ Fabra, Rapson, Reguant, Wang
- Distributional implications
  - Under time-invariant prices, households who consume at low-priced hours **cross-subsidize** those who consume at high-priced hours: how does this correlate with income?

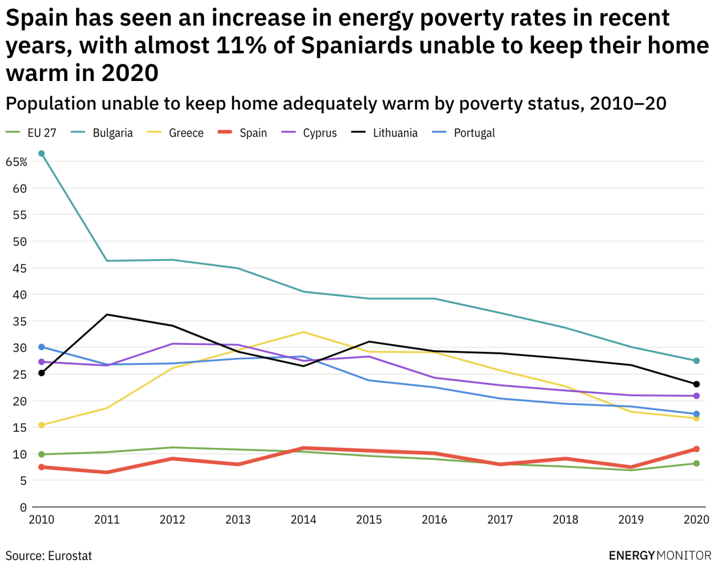
Equity concerns during extreme events

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 concerns in countries with high energy poverty



Our paper

- **Goal**: study the distributional impacts of RTP using hourly electricity consumption data of 2M Spanish households.
  1. Quantify the impacts assuming price-inelastic consumers.
     → Justified by our previous project. ▸ Fabra, Rapson, Reguant, Wang
  2. Assess the relationship of RTP impacts with income.
     → Decompose main **effects** and **channels**.
  3. Consider **counterfactual experiments**.
     → Extreme events; price-elastic households.

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- **Challenge**: we do not have detailed income information.
  - We complement aggregate patterns of distributional effects with a **method to infer individual income** using zip-code income distributions.

Preview of results

Main Finding:

- The move towards RTP was slightly regressive, with heating mode and locations as the main drivers.

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Main Effects:

- Switch from **annual to monthly prices** is regressive $\rightarrow$ low-income households tend to consume relatively more during winter when RTP prices are higher.
- Switch from **monthly to hourly prices** is progressive $\rightarrow$ low-income households consume relatively less at off-peak hours when RTP prices are lower.

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Main Effects:

- Switch from **annual to monthly prices** is regressive → low-income households tend to consume relatively more during winter when RTP prices are higher.
- Switch from **monthly to hourly prices** is progressive → low-income households consume relatively less at off-peak hours when RTP prices are lower. **Main Channels:**

- **Building/heating stock** appears to be the major driver of consumption patterns, which is correlated with income but also differs across locations.

Overview of today's talk

1. ▸ Related literature
2. Background and data
3. Inferring households' income
4. Quantifying the distributional impacts
5. Channels
   - Consumption patterns
   - Appliance ownership
   - Locations
6. Counterfactuals
   - Extreme events
   - Price-elasticity
7. Conclusions

Dynamic electricity pricing in Spain

- April 2015: Spain becomes the only country in which RTP is the **default option for all households**.
  - *The case of Spain with a regulated default dynamic price contract is unique* (EC, 2019).
- Households can opt out to time-invariant prices.

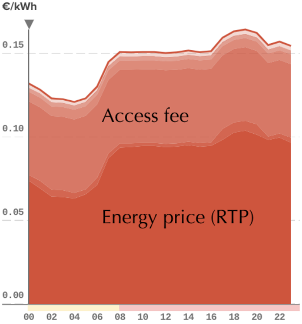

Figure: Example: electricity prices for Spanish households on 11/01/2017

Data

- We obtained smart-meter data for over 2M households, from one large Spanish utility (Naturgy).
- For each household (January 2016-July 2017), 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...

Data: electricity consumption area

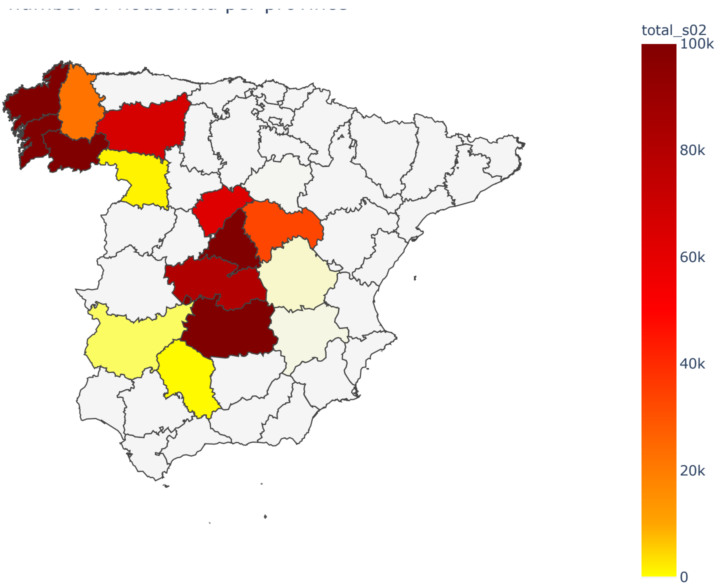

Figure: Locations of households in our data

A first look at the data: month vs annual variation

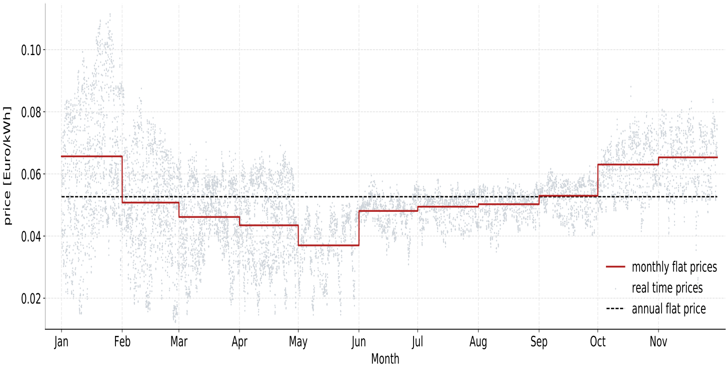

Figure: Summary of price variation

Computing bills under RTP and time-invariant prices

- We compute the bill change from being at 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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- 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

The challenge: inferring households' income

- We observe the distribution of income at the zip code level.
  - Assigning the income distribution at the zip code level to all households in that zip code (naïve approach) can miss important within-zip-code heterogeneity.
- We assign households' income by exploiting richness of hourly consumption data and zip-code level income distributions.

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Overview of our two-step approach: Details

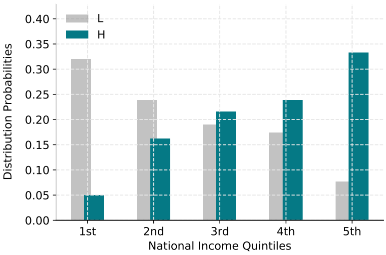
1. Classify consumers into types (*k-cluster*): Step 1
   - Households with "representative" consumption patterns.
2. Infer income distribution of those types based on the distribution of income and types in each zip code. Step 2

- **Identifying assumption:** types are shared across zip codes (what changes is the *proportion* of types in each zip-code).

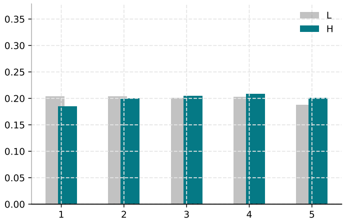
Our two-step method extracts relevant signal

- 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

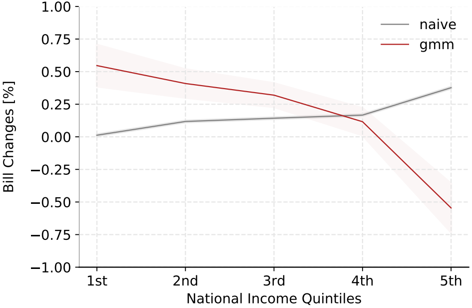
Bringing it back to measuring the policy impacts

We use 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

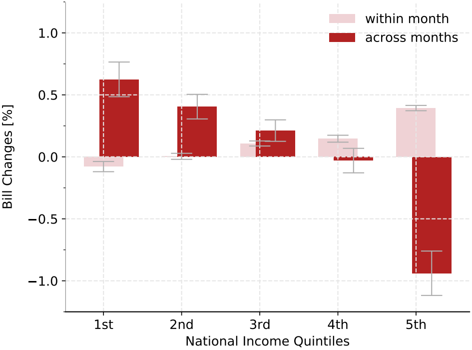
Figure: Bill changes due to the switch to RTP



- RTP is slightly regressive - still, the average impact is small.
- RTP impacts are highly heterogeneous within zip-code because of income heterogeneity.
- Distributional implications are reversed relative to using zip-code level income.

Decomposing the impacts

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

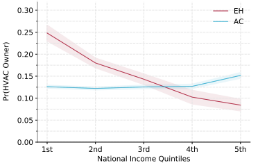


- **Within month** price changes have progressive impacts.
- However, **across month** price changes have regressive effects.

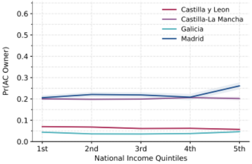
The mechanisms behind these patterns

- We explore different channels in which consumption of electricity can relate to income and other factors.

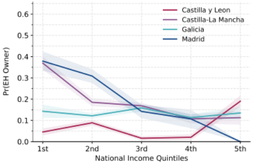
- We consider:
  - Consumption patterns by income.
  - Appliance ownership, across and by income.
  - Geographical variation related to weather/appliances.



(a) Share of electric heating owners and AC owners



(b) AC ownership by state

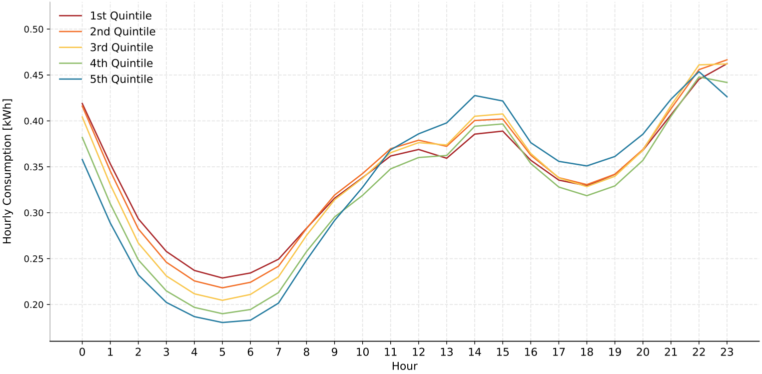


(c) EH ownership by state

Figure: Appliance ownership by income and location

Mechanisms: consumption patterns during the day

Figure: Hourly consumption during the day

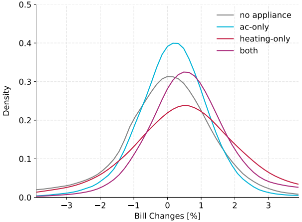


- Higher income quintiles consume more electricity.
- They also consume proportionally more at peak hours.

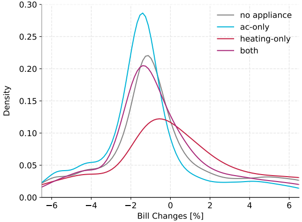
$\rightarrow$ The within month effect is progressive.

Mechanisms: appliance ownership

Figure: Bill changes by appliance ownership



(a) Within month effects

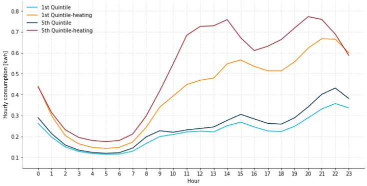


(b) Across months effects

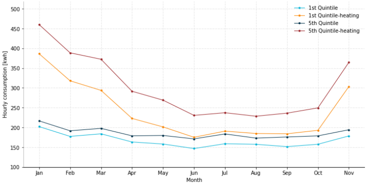
- We infer appliance ownership based on consumption structural breaks to local temperatures.
- Appliance ownership, key for the within-income heterogeneity.
- The bigger bill increases are suffered by households with electric heating due to the across months effect.

Mechanisms: appliance ownership and income impacts

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



(a) Hourly consumption



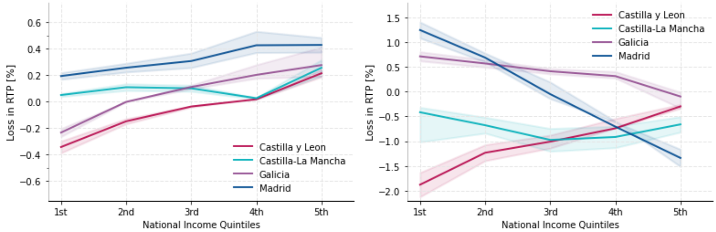
(b) Monthly consumption

- Households with electric heating consume more during peak hours and winter when prices are higher.
- Appliance ownership creates bigger differences than income.
- Conditional on appliance ownership, income still induces substantial differences.

AC ownership

Mechanisms: geographical heterogeneity

Figure: Geographical heterogeneity and decomposition of the impact



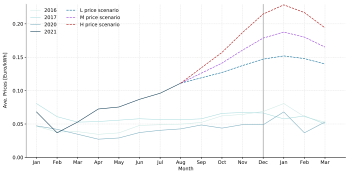
(a) Within month effects (b) Across months effects

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

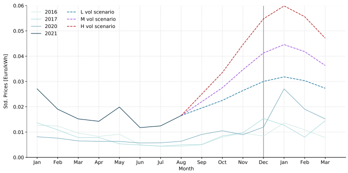
Counterfactual experiments

- 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:
  - Demand elasticity (under different correlations with income).
  - Extreme events (under alternative assumptions on price levels and volatility).

Commodity risks and energy poverty



(a) Simulated prices

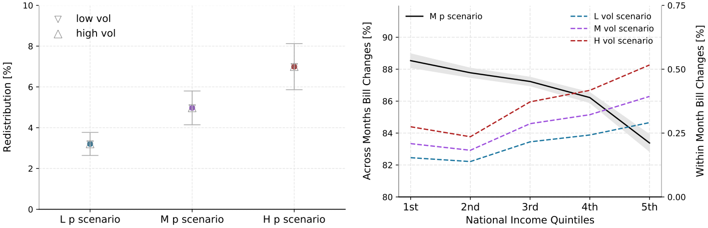


(b) Simulated price volatility

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

Commodity Risks and Energy Poverty

Figure: Distributional implications of RTP under a large price shock

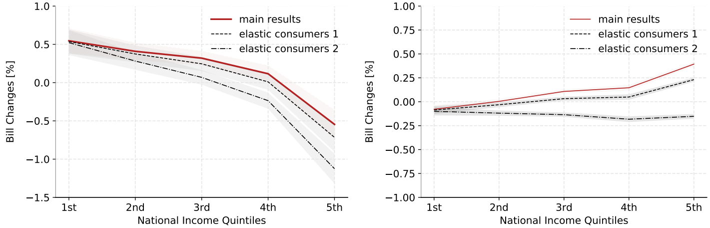


(a) Redistribution (b) Decomposition

- 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.
- The across month effects strongly dominate the within month effects.

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.
- RTP becomes more regressive.
- The within month effect is no longer progressive as high-income households can now benefit from the within day price variation.

Conclusions

- Distributional implications of RTP in Spain (2016-2017).
  - In this context, RTP was **slightly regressive**.
- Bill impacts decomposed in:
  - within month effects (daily price variation).
  - across months effects (seasonal price variation).
- 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 criticism to RTP** - results might be country specific.
- Rather, we provide a framework to assess its distributional effects so as to design an **equitable RTP system**.
  - The potential regressive of across months effects can be addressed while **preserving the hourly price signal**.

Thank you!

Questions? Comments?

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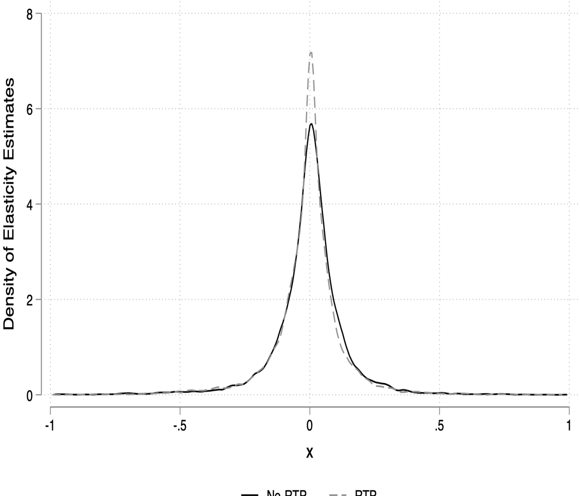
Appendix

Measuring elasticity to RTP

- We estimate the short-run price elasticity of households.
- Main regression (individual by individual):

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



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

- No effect from RTP. Back

Related literature

- Papers on the role of RTP and efficiency:
  - Borenstein (2005) among related papers.
- Papers on the role of electricity pricing and equity:
  - Borenstein (2007) (industrial), Borenstein (2012) (nonlinear pricing), Borenstein (2013) (critical peak pricing), Faruqui et al. (2010), Horowitz and Lave (2017), Zethmayr and Kolata (2018), Burger et al. (2019).
- Papers on inferring income:
  - Pissarides and Weber (1989), Feldman and Slemrod (2007), Artavanis, Morse, and Tsoutsoura (2016), Dunbar and Fu (2015), etc.
- Papers unveiling household heterogeneity:
  - BLP (1995, 2004), Petrin (2002), Fox et al. (2011), Almagro and Dominguez-Lino (2021), Bonhomme, Lamadon, and Manresa (2021).

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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

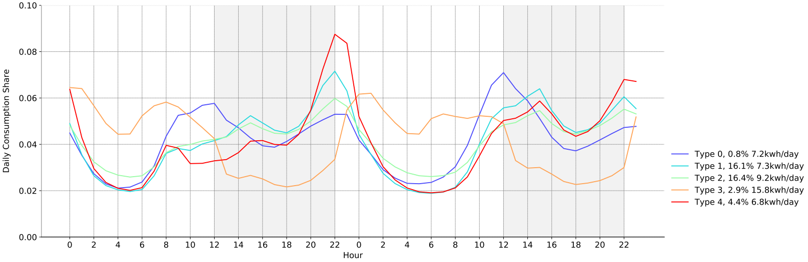
We introduce new additional objects:

- 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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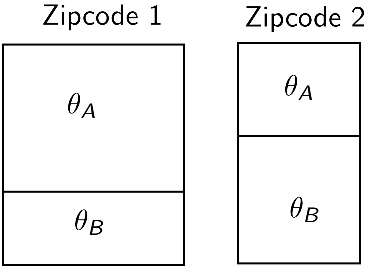
Step 2: Infer income distribution of the types



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

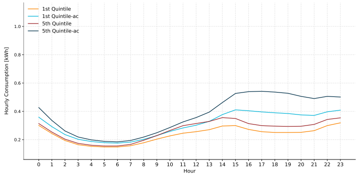
$$\eta_A^H Pr_2(\theta_A) + \eta_B^H Pr_2(\theta_B) = Pr_2(inc = H)$$

- 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.

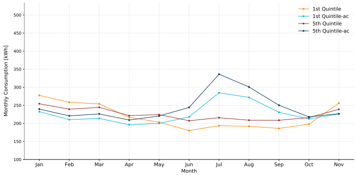
Back

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