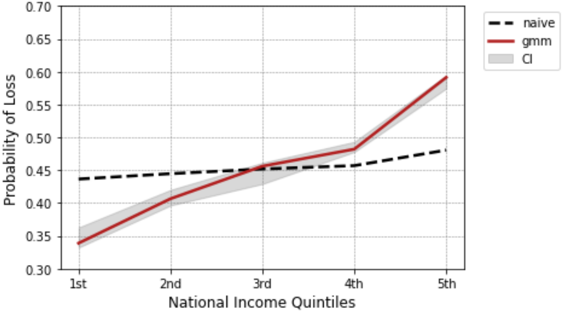
The distributional impacts of real-time pricing

- We study the distributional impacts of real-time pricing in the Spanish electricity market, which rolled out **RTP as the default tariff** for a large share of residential customers.

- However, our data **do not have** detailed income information, limiting the distributional analysis.
- We complement aggregate patterns of distributional effects with a **method to infer individual income** using zip-code income distributions.

A preview of results



- RTP is mildly progressive in the aggregate.
- Result strengthened with household income heterogeneity.
- Note: These results are in sample, future impacts need careful simulation if this was not already clear!

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), etc.

Policy implications

Goal: Analyze the **distributional effects of change to RTP**.

1. Describe RTP impacts assuming consumers are inelastic to prices in the short-run.

   → Justified by our previous project. ▸ Fabra, Rapson, Reguant, Wang

2. Assess relationship of RTP impacts with income.

   → Limited effects, not regressive.

3. Future work: consider impact of counterfactual experiments, such as responses to prices or extreme events.

Computing bills under RTP and flat tariffs

- We compute household bills with and without RTP pricing:

$$RTPBill_{im} = \sum_{h \in m} q^*_{ih} p^*_{ih}$$

$$FlatBill_{im} = \sum_{h \in m} q^*_{ih} \bar{p}_m$$

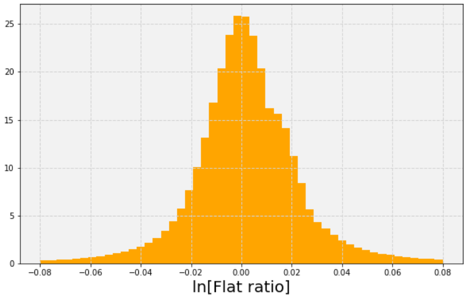
- Consider ratio of RTP bill to flat bill:

$$BillRatio_{im} = \frac{FlatBill_{im}}{RTPBill_{im}}$$

- Ratio lower than 1: consumers worse off under RTP.

Raw distribution: winners and losers

Figure: Ln[Bill Ratio] (individual, monthly)



- Centered around zero by construction (to focus on cross-subsidization due to consumption patterns).
- In practice, most consumers win under RTP (ongoing work).

Distributional impacts

	ln(kwh)	ln(kwh peak)	ln(bill ratio)
ln[IncPerHH]	0.095**	0.116***	-0.003***
	(0.036)	(0.034)	(0.001)
HHsize	0.385***	0.406***	0.001
	(0.029)	(0.027)	(0.001)
R-squared	0.617	0.701	0.508
N	685	685	685

- Income correlated with consumption.
- Modest negative correlation with RTP impacts, slightly negative.

Can we better infer household characteristics (income) exploiting the Census data?

The challenge: income data

- We observe the distribution of income at the zip code level.
- Zip codes can be substantially large.
- Inference of income common in other applications: tax fraud, subsidy fraud, refinements to coded income.
- Impacts of RTP depend on highly dimensional vector, so difficult to make intuitive bounding assumptions (e.g., Borenstein, 2012).

- **Research question**: how to better assign households' income exploiting richness of hourly consumption data?

Some 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: $Pr_i(inc_k)$.

Inferring income in this setting

- We have detailed hourly consumption data for each household–1000's of observations per HH (panel).
- We have the distribution of income at the zip code (cross-section).
- We have the zip code of each household.
- Demand system approaches are a way to infer household income at the household level (e.g., seeing someone buy a Ferrari).
- Here we prefer to remain agnostic about the demand system (lots of heterogeneity), and **directly focus on inferring income** of households.

Naïve approach

- Assign income distribution at the zip code level $Pr_z(inc_k)$ to all households in that zip code.
- Captures across-zip-code heterogeneity, but can miss important within-zip-code heterogeneity.
- One can get somewhat at within-income bin variance, but it might be overstated.
  - Heterogeneity of policy impacts conditional on the same income can be large, e.g. Cronin, Fullerton and Sexton (2019).

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).

Our approach: intuition

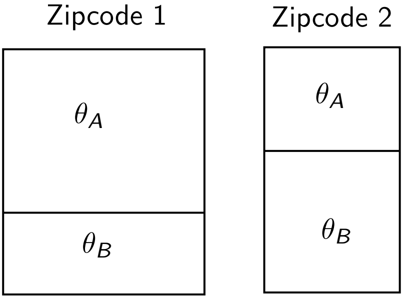
We propose an estimator in two steps:

1. Classify consumers into types (deterministic or mixtures).
2. Infer income distribution of the unobserved types based on zip code level distribution.

Key: Allow for sufficient unobserved heterogeneity to match income distribution at the zip code level.

Identifying assumption: Common types across (subsets of) zip codes.

Intuition follows similar settings (e.g., BLP, FKRB)



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

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

- Assume we have already inferred the distribution of unobserved types in each zip code.
- η_A^H represents the probability of income level H for unobserved type θ_A (similarly for θ_B), unknowns.
- Match zip code moments on the distribution of income, same underlying types across zip codes.

Identifying equations

Conditional on having identified the distribution of types for each zip code:

$$min_\eta \sum_z \omega_z \sum_k \left(Pr_z(inc_k) - \sum_{i \in z} \sum_n \eta_n^k Pr_z(\theta_n) \right)^2$$

$$\text{s.t.} \sum_k \eta_n^k = 1, \forall n,$$

where ω_z is a sampling weight and

$$Pr_z(\theta_n) \equiv \sum_{i \in z} Pr_i(\theta_n) / H_z.$$

Further discussion

Step 1: Assigning households to types

- We break the approach in two steps to facilitate the computations: millions of households with individual hourly consumption data.
- Inefficient, but consistent under the proposed assumptions.
- We have explored several classification techniques:
  - Observable discrete characteristics (contracted power).
  - Inferred discrete characteristics based on smart-meter data (appliance ownership).
  - Deterministic classification based on summary stats from high-frequency data.
  - EM algorithm based on household-level regression outcomes.
  - **k-means clustering based on load profiles**

Step 1: k-means clustering of types

- We reduce dimensionality of 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 production. Observable types based on contracted power.
- Our baseline has 5 zip codes with 5 types per observable types.
- We explore robustness of the method of choice under identifying assumptions via Monte Carlo simulation.

Step 2: GMM

- We have now a probabilistic assignment of types to each household.
  - Based on consumption patterns which correlate with price.
- We assume that types are shared across different zip codes.
  - What changes is the *proportion* of types.
- Assign unobservable income probabilities to types (η_n^k).

- Given the observed distribution of income for each zip code, we match these zip code-level moments.

GMM: income distribution

Income

1. The aggregated income distribution of each type should be consistent with the zip code level distribution.

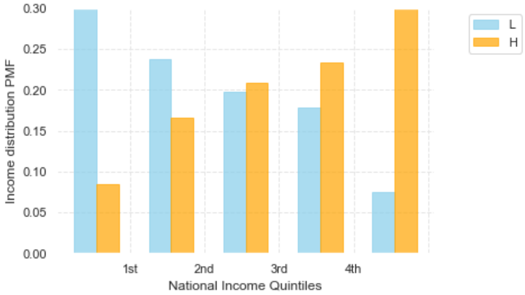
$$Pr_z(inc_k) = \sum_{n=1}^{N} \eta_n^k Pr_z(\theta_n) \qquad \forall k, z.$$

2. For each type, the probability of being in different income intervals sum up to 1:

$$\sum_{k=1}^{K} \eta_n^k = 1 \qquad \forall n$$

Results: Confirm importance of contracted power

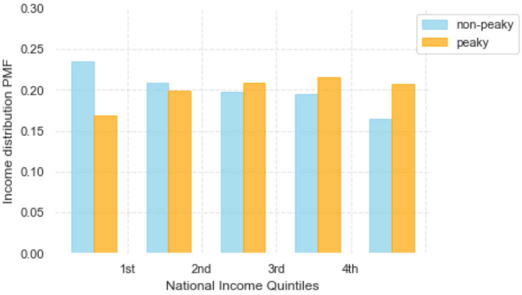
- Individual-level of contracted power predicts higher income distribution.



Results: Confirm relationship between income and peak consumption

- Individual-level monthly consumption by rich and poor

  simulated income $>$ 17,000 Euro



Bringing it back to policy impacts

- We use the inferred distribution of income to derive implications about RTP pricing.

- *What is the distribution of income for winners and losers?*
- *What is the relevance of within-zip-code heterogeneity?*

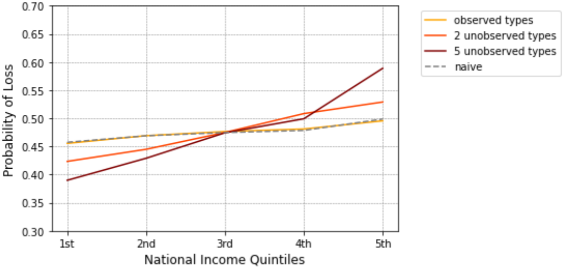
Predicting the probability of losing

- We focus on a summary statistic of the distributional income: the probability of losing under RTP.
- We assess the predicted probability of losing for each income bin under alternative income distributions.

$$Pr(lose|inc_k) = \frac{1}{H \times Pr(inc_k)} \sum_i \mathbb{1}(Loser)\ \hat{Pr}_i(inc_k).$$

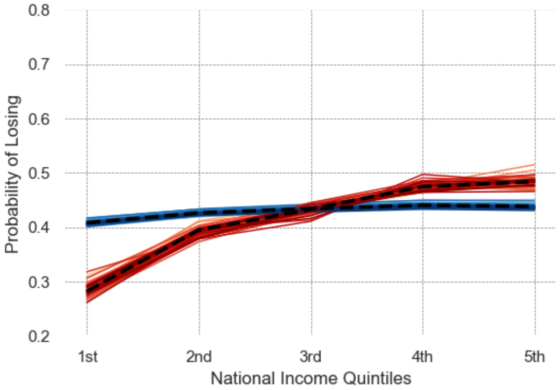
- Cases:
  - Naïve based on zip code distribution, $\widehat{Pr}_i(inc_k) \equiv Pr_{z_i}(inc_k)$;
  - Two unobservable types;
  - Five unobservable types.

K-means algorithm detects more impacts



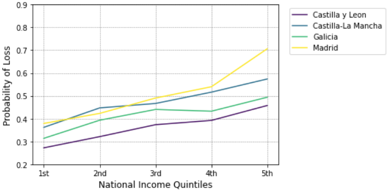
- Approach uncovers substantial within zip-code heterogeneity in impacts correlated with income.

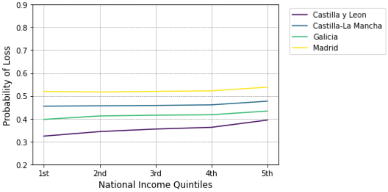
We check validity in Monte Carlo



- This will be our replication goal for today although you will see it will not look as great with limited data...
- There might be a problem in my Julia translation!!! ☠

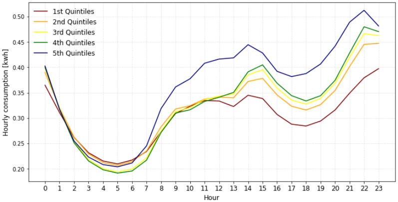
Substantial geographical heterogeneity

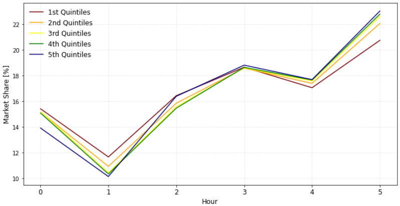




- But across-zip-code variation does not identify strong correlation of income with the policy.
- Due to geographical patterns in Spain, income vs geography cancel out in the aggregate.
- Heterogeneity within region via hidden types is driving the increase in heterogeneous impacts.

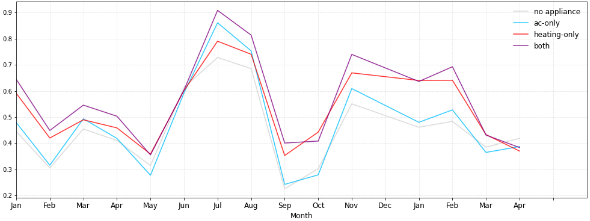
Mechanisms: consumption patterns





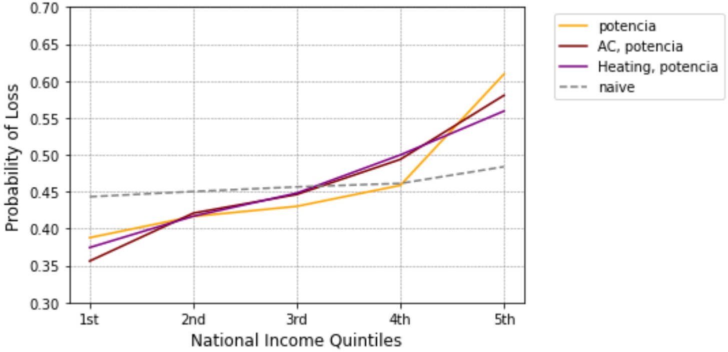
- Higher quintiles consume much more.
- They also consume proportionally more at peak.

Mechanisms: appliance ownership



- We use algorithm to infer appliance ownership by households.
- We then treat appliance ownership as an explanatory variable in heterogeneity.
- Appliance ownership is relevant to explain patterns.

Mechanisms: appliance ownership and income impacts

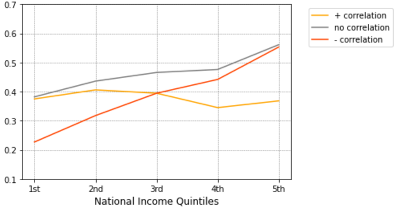


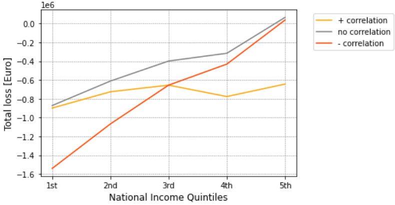
- Appliance ownership adds nuance to findings, e.g., poor households with electric heating disproportionally hurt.
- It does not affect the general average patterns if incorporated explicitly into types.
- In part due to minor role of electric heating in Spain.

Counterfactual experiments

- The distributional impacts in our sample are limited and bounded.
- However, patters could change going forward, with increasing extreme pricing and volatility.
- We plan to explore several counterfactuals:
  - Correlation of income and elasticity of demand.
  - Extreme prices under alternative assumption on their patterns and correlations of occurrence (e.g., temperature driven, peak/off-peak).

Counterfactual experiments: preliminary elasticity results





- Elasticity (if positively correlated with income) can undo some of the patterns, but not revert them in this simple calibration.
- Important as high income households can better adapt to fluctuations in prices via smart technologies and batteries.
- As price fluctuations become large, income effects can be substantial (e.g., see Texas).

Conclusions and next steps

- We use a two-step approach to infer the distribution of individual income.
- The approach exploits detailed smart-meter data.
- We are exploring several aspects of the methodology:
  - What are the advantages/disadvantages of the different practical implementations?
  - Could we do a joint approach?
  - Should the approach be tailored to the policy being evaluated?
- We are also exploring broader counterfactual impacts of RTP.

Thank you.

Questions? Comments?

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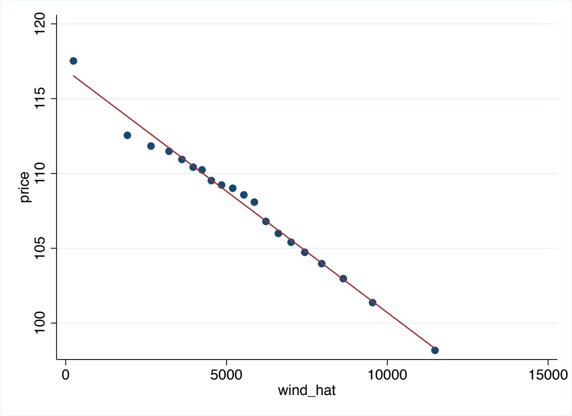
Measuring elasticity to RTP

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

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

- In baseline specifications, we control for:
  - Temperature bins by hour
  - Fixed effects: hour x month, year x month, day of week
  - Wind power forecasts as an IV for short-run price changes

Instrumental Variable strategy



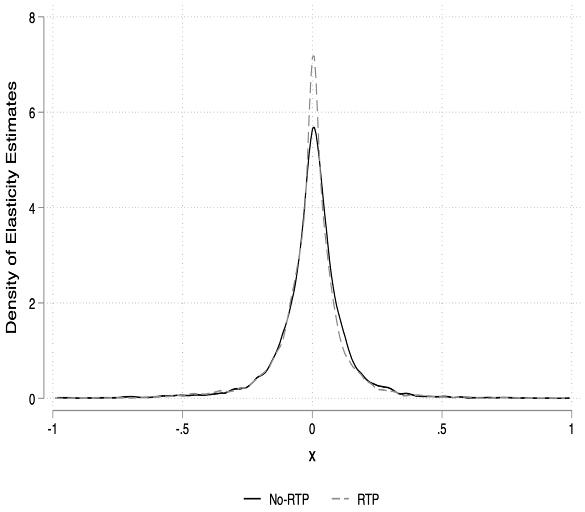
- Instrument shows strong first stage, also after conditioning
- Plausibly exogenous after controlling for local weather conditions

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.

We find similar distributions of price elasticities



- Distribution centered around zero, median of no response.

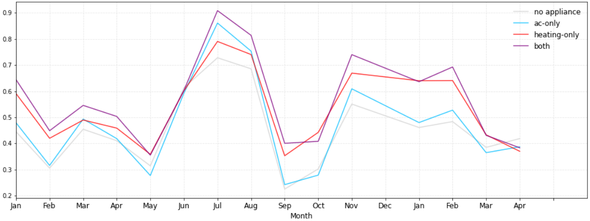
Average elasticities by group are close to zero

	(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

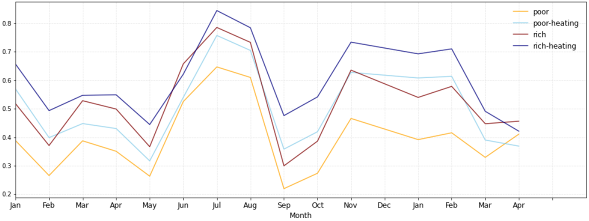
- Not much of an effect from RTP. Back distributional impacts

RTP shift affected by appliance ownership



- In spite of challenges with algorithm, we extract signal from inferred appliance ownership.

RTP shift modestly progressive: monthly



- AC explains the loss in summer
- More distributional effect in winter, poor have important share of electric heating but consumption smaller than richer households.

Back

An alternative approach

- Focus on zip-code level "aggregate" moments (cross-section).
- Make explicit parametric assumptions on the relationship between income and moments of the distribution of electricity consumption, e.g., integrating $\overline{kwh}_i(inc_i)$, $\overline{kwh}_{ih}(inc_i)$, etc. (drawing from zip-code income distribution)
- Estimate random coefficients that help explain the summarized aggregate data.
- Use Bayes rule to infer a households' income posterior.

- We did not follow this route to avoid simplifying the heterogeneity in the raw electricity consumption data for the policy analysis.

Identifying equations with aggregate moments

We could consider the zip-code level moments:

$$\sum_z \omega_z \sum_h \left(\overline{kwh}_{zh} - \sum Pr_z(\theta_n) kwh_h(\theta_n)\right)^2$$

$$\sum_z \omega_z \sum_k \left(Pr_z(inc_k) - \sum_{i \in z} \sum_n \eta_n^k Pr_z(\theta_n)\right)^2$$

$$\text{s.t.} \quad \sum_k \eta_n^k = 1, \forall n.$$

- Being fully flexible does not work here, system greatly underidentified without structure.
- E.g., if one allows as many types as zip codes, assign only one type to a zip code with probability one to perfectly match aggregate moments.

Our approach with micro data

$$\sum_z \omega_z \sum_k \left(Pr_z(inc_k) - \sum_{i \in z} \sum_n \eta_n^k Pr_z(\theta_n) \right)^2$$

$$\text{s.t.} \quad \sum_k \eta_n^k = 1, \forall n.$$

- Estimate $Pr_z(\theta_n)$ in a first step by classifying consumers into similar types with the micro data.
- Then allow up to Z types to fit income distribution system of equations.
- No longer underidentified subject to overlap in types (full rank).

Back