Empirical Methods for the Analysis of the Energy Transition

Day 5

Prof. Mar Reguant

Summer School 2024

Outline

I. Energy Efficiency

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 energy efficiency interventions.

I. Energy Efficiency

Energy Efficiency: Concepts and Evidence

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:

$$\text{Energy efficiency} = \text{energy services} \,/\, \text{energy input}$$

Examples

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

Energy efficiency - stock and flow

- Energy efficiency involves several strategies:
  - New better technology (e.g., heat pumps, better appliances, LEDs).
  - New better buildings (building codes, standards).
  - Improving energy efficiency of existing existing buildings (refurbishing).

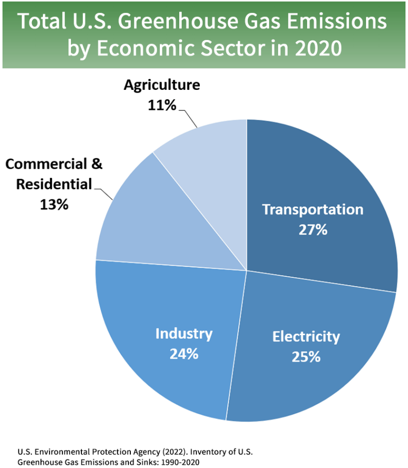
Energy Efficiency **Could** Be Essential to Decarbonization

1. Not enough battery storage for peak electricity demand
   - Consumption growing ahead of storage capability
   - **Reducing consumption lowers GHG emissions while grid mix of renewable and (mostly) non-renewable**

Energy Efficiency **Could** Be Essential to Decarbonization

2. Transitioning away from natural gas in buildings will take time

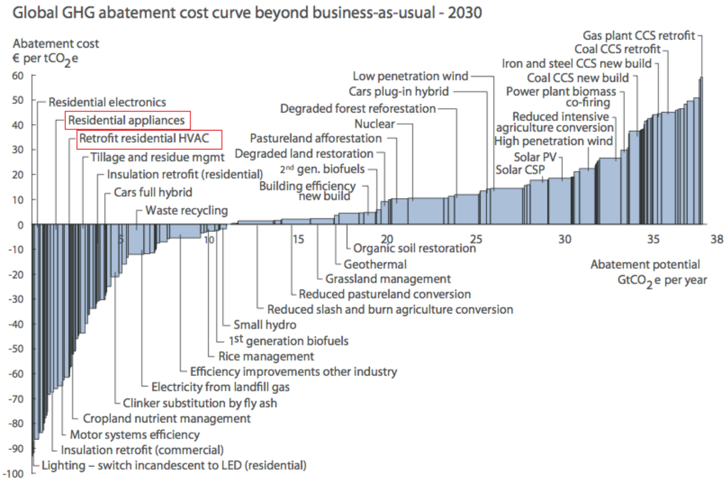
- Significant upfront costs
- Equity concerns with mandates



Energy Efficiency **Could** Be Essential to Decarbonization

3. If done cost-effectively, one of lowest cost forms of carbon abatement

Unexploited Investment Opportunities?



Source: McKinsey and Company, "Pathways to a Low-Carbon Economy", 2010

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.

- A focus on percentage savings compared to “expected” engineering savings, with numbers as low as 10 to 20 percent.

Discrepancies Between Projected and Realized Savings

- Weatherization (WAP) and home retrofits (Fowlie et al. 2018, Allcott and Greenstone 2017)
- Appliance rebate programs (Houde and Aldy 2014, Davis et al. 2014)
- Building codes/efficient housing (Levinson 2016, Davis et al. 2018, Bruegge et al. 2019)
- General efficiency rebates (Burlig et al, 2021)

Are there opportunities to allocate resources differently to achieve reductions more cost-effectively? How to explain the gap?

Recent evidence on WAP decomposes the difference

- Christensen, Francisco, Myers, and Souza (2022) decompose the performance wedge:
  1. Engineering measurement and model bias (43%)
  2. Workmanship (41%)
  3. Occupant behavior (6%)

- 2. Modifying worker incentives
  - Randomized study paying workers based on building envelope tightness– quite cost-effective
- 3. Addressing model bias
  - Predictions based on realized savings at similar homes outperform current engineering model approach
  - Targeting funds differently could improve cost-effectiveness

We will cover a couple of examples

Both of them are "natural experiments," exploiting policy interventions without randomization.

- Cash for coolers: rebate program for new fridges and AC in Mexico
- Machine learning from schools: efficiency program for public schools in CA

I. Energy Efficiency
Natural experiment example

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

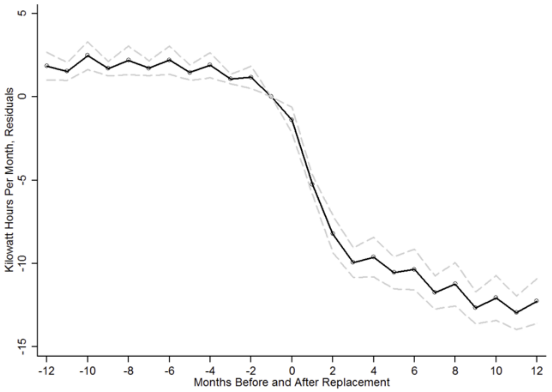
New appliance must meet exceed 2002 standard by 5%.

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 "megawatt"?
  - 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?

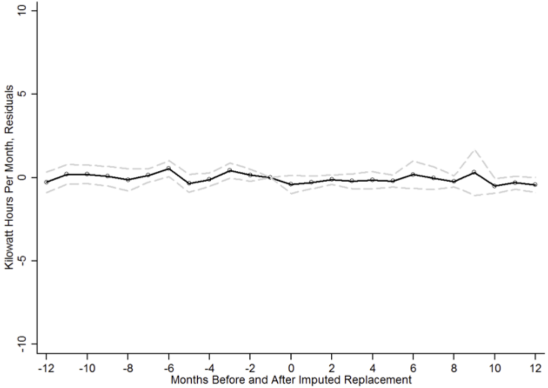
C4C impacts

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

I. Energy Efficiency
Natural experiment example with ML

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)

How effective are energy efficiency upgrades at reducing electricity consumption?

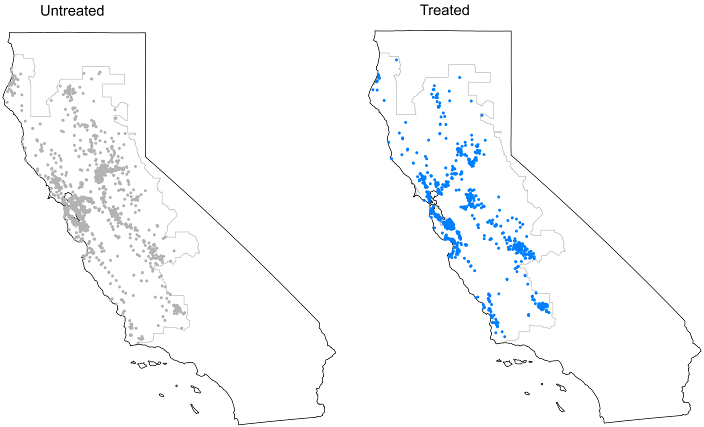
- **Context:** \$1 billion EE subsidy program in CA's K-12 schools
- **Data:** 15' interval electricity consumption
- **Research design:** Panel fixed effects meets machine learning

This question is difficult to answer empirically

Central challenge: Energy efficiency upgrades are not randomly assigned.

- It is difficult to disentangle energy efficiency from other factors.
- We must construct a counterfactual energy consumpton path.

Our sample spans the PG&E territory



Can machine learning help?

- Panel FE models are often not properly specified.
- Schools are very heterogeneous (e.g., climate, size, school calendar).
  - Ideally, introduce school-specific coefficients and trends in a very flexible manner.
- We easily came up with $\sim$6,000,000 candidate control variables by making them school-hour specific!
- No clear *ex ante* optimal choice.

Machine Learning: Advantages in this application

- Exogenous weather variation and predictable weekly and seasonal patterns drive variation in electricity consumption.
- Schools are relatively stable consumption units:
  - as opposed to single households that move around, unobservably buy a new appliance, expand family size, etc.
  - as opposed to businesses and manufacturing plants, exposed to macroeconomic shocks.

Prediction can do well!

Machine Learning: Approach

Step 1

- Use *pre-treatment data* to predict electricity consumption as a function of flexible co-variates, *for each school separately*.
    - For control schools, determine a "pre-treatment period" randomly.
    - Use LASSO method (penalized regression).
        - Minimizing the sum of the squared errors plus $\lambda \cdot \sum_{j=1}^{p} |\beta_j|$.
        - Larger "tuning parameters" lead to fewer coefficients.
        - Use bootstrapped cross-validation with training and holdout samples *within pre-treatment*.
    - Include a wide range of school-specific variables, and also consumption at control schools (a la synthetic control).
    - Also consider other alternatives (random forests).

Machine Learning: Approach

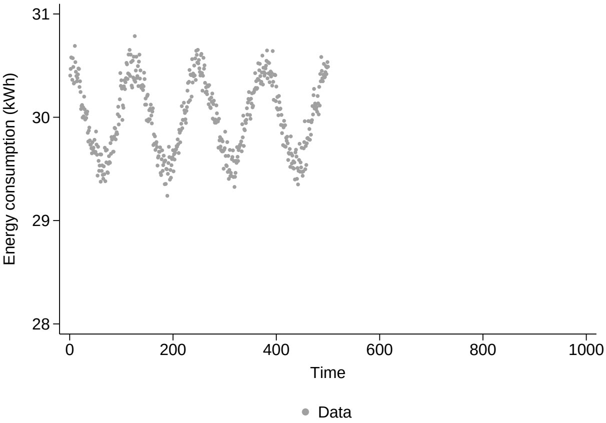
Step 2

- Regress *prediction errors* on treatment and controls.

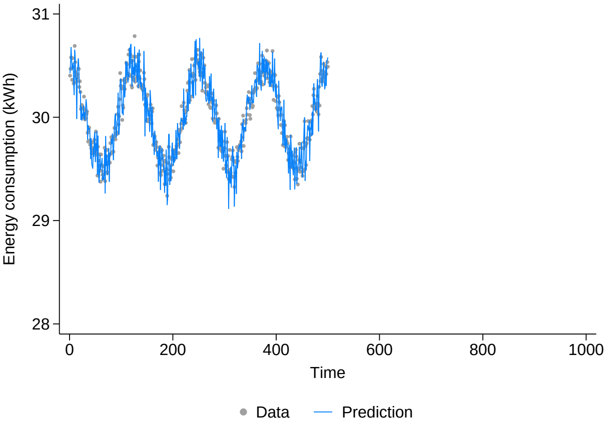
$$Y_{ith} = \beta D_{it} + \alpha_i + \kappa_h + \gamma_t + \varepsilon_{ith}$$

  - Data pooled across schools.
  - Replicates diff-in-diff approach, but Y variable is now the prediction error.

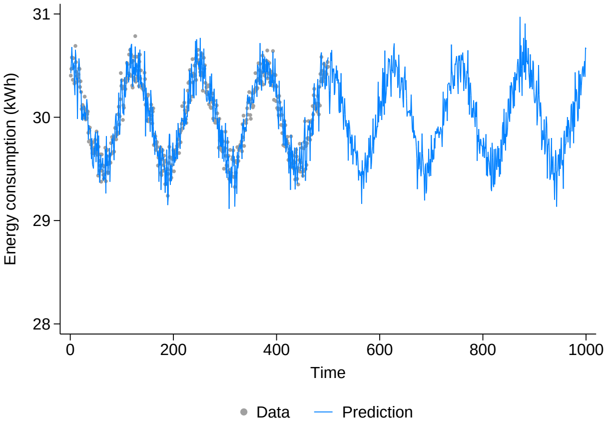
Machine Learning: Graphical intuition



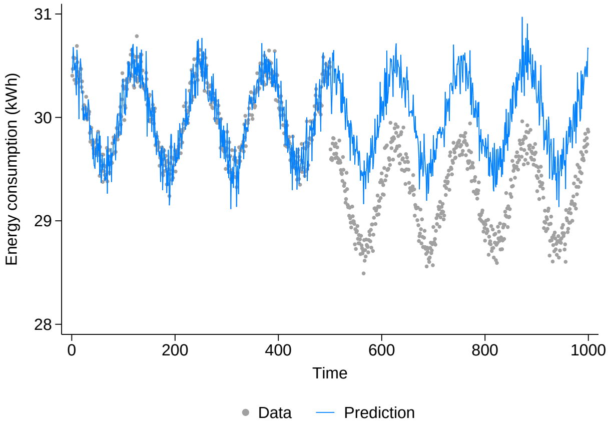
Machine Learning: Graphical intuition



Machine Learning: Graphical intuition



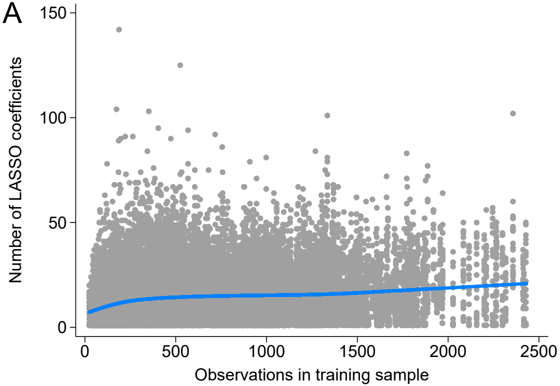
Machine Learning: Graphical intuition



ML check: model complexity scales with observations

Step 1: Each dot is a school-hour model

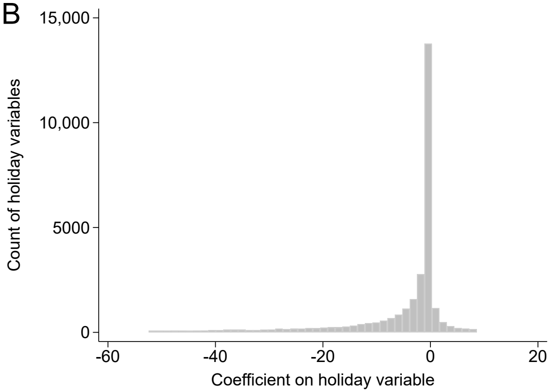
- The more data, the more controls.



ML check: holidays negatively correlated with energy use

Each observation is a school-specific holiday coefficient

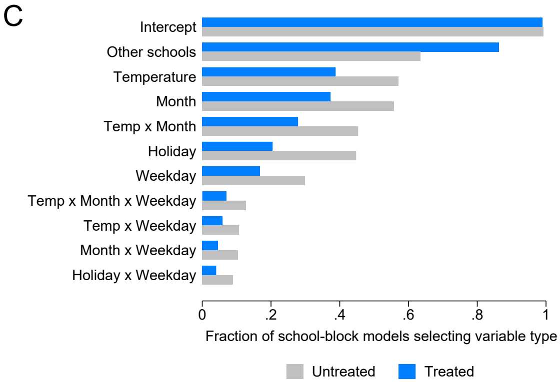
- Sanity check on sign of controls.



ML check: a wide range of variables in model

Each school-block model has different predictors

- Better taylored than a "normal" regression.



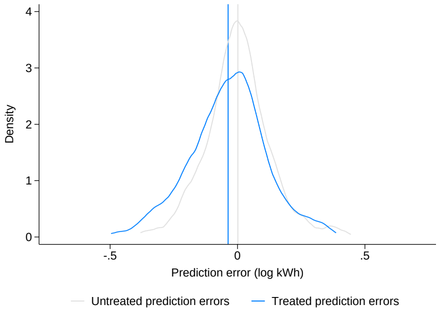
ML check: comparison across methods

	p10	p25	p50	p75	p90
LASSO optimal Lambda	-0.23	0.18	0.44	0.61	0.72
LASSO 1SE Lambda	0.08	0.21	0.43	0.58	0.69
LASSO + Synth optimal Lambda	-0.12	0.30	0.62	0.86	0.93
LASSO + Synth 1SE Lambda	0.13	0.33	0.64	0.86	0.93
LASSO Synth only optimal Lambda	-0.08	0.28	0.61	0.85	0.93
LASSO Synth only 1SE Lambda	0.12	0.32	0.63	0.85	0.93
Forest by school-block	0.09	0.30	0.52	0.67	0.76
Forest by school	-1.70	-0.15	0.42	0.63	0.71

The LASSO with control schools appears to do well out-of-sample

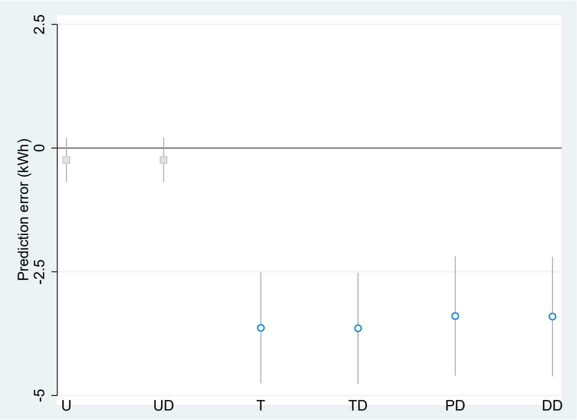
Control and treated school estimates suggest savings

- Controls: Prediction errors centered around zero well out-of-sample
- We see a shift in the distribution for schools with upgrades



ML results are stable across estimators

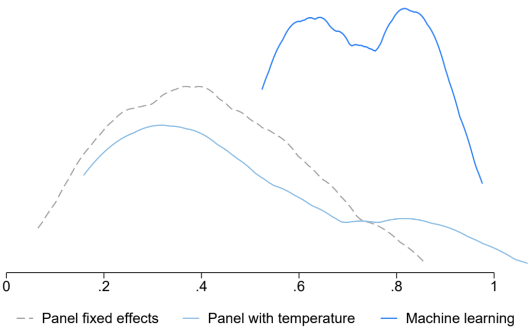
- Prediction errors suggest a reduction in energy consumption of around 2.5 KWh per day.
- However, still lots of noise across school measurements.



Implications for energy efficiency gap

- Estimates suggest savings around 0.5-0.7 of energy efficiency savings.
- Regressions are more noisy and can lead to very low estimates (0.1-0.6).
- Important to consider measurement problems when assessing the effectiveness of energy efficiency.

Figure 4: Comparison of methods across specifications and samples



Discussion: Why low realized savings?

Several potential explanations:

- General measurement error in expected savings?
  - Errors ins savings engineering model.
  - Timing of savings for which we have additional info.
- Large heterogeneity in realized savings?
  - Average effectiveness vs intervention-by-intervention.
  - Some interventions more effective than others.
  - Some interventions harder to predict.

Interactions of energy efficiency and climate impacts

- Evidence of energy efficiency is mixed: reductions in energy consumption are significant, but less than under ideal conditions.

- Energy efficiency it is yet crucial for the energy transition:
  - Reducing demand can be cheaper than reducing emissions for many settings!
  - Energy efficiency protects households from extreme events: better infrastructure, less gradient in consumption needs.

References

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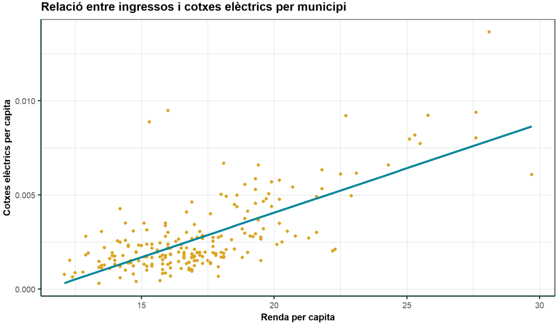
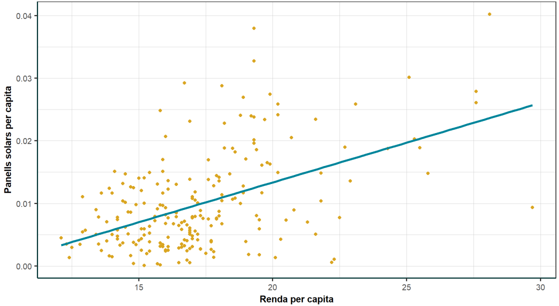
II. Inequity impacts of the energy transition

Energy transition's heterogeneous impacts

- The energy transition can have substantial impacts on households that can be highly heterogeneous.
- Example: Rich households have easier access to solar and batteries. Net-metering of solar can leave poorer households stranded without policy action.
- **Uneven impacts combined with climate change impacts**:
  - Households most exposed to extreme events tend to have the lowest income (poor building construction and insulation, heat islands).
  - Also least able to adapt and upgrade with resilience equipment (solar + backup battery, solar + EV as battery).

Example: adoption of EV and solar in Catalonia





Source: Enrich and Reguant, 2023. “Efectes distributius de la transició energètica: reptes i oportunitats per a una transformació justa.” Nota d’Economia.

Equity impacts recently in the news

The energy crisis is unprecedented and is driving the cost of living crisis. Last October, 4.5 million UK households were in fuel poverty. Now National Energy Action estimates there are 6.7 million. Come April, we are expecting there to be 8.4 million.

Read the latest policy briefing here

Across the UK, **cold homes are already damaging the lives of the poorest households**.

After Days Of Mass Outages, Some Texas Residents Now Face Huge Electricity Bills

February 21, 2021 · 12:01 PM ET

REBECCA HERSHER

Equity impacts can be devastating

Excess deaths could rise as vulnerable skimp on heating, UK charities warn

Freezing temperatures and high energy costs lead to fears that more people will die this year without action

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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Resilience preparedness will not start where most needed

NOVEMBER 16, 2022

Tax rebates for solar power ineffective for low-income Americans, but a different incentive works

Tax rebates for installing residential solar power have done little to spur adoption in low-income communities in the United States, while a less common incentive seems to succeed, according to new research using AI and satellite images.

BY EDMUND L. ANDREWS

When a new consumer technology makes its debut, whether it's a smartphone or an electric car, its adoption rate typically follows a predictable path. The first buyers come from a narrow slice of high-income users or tech enthusiasts who are willing to pay high prices. Over time, as prices fall and

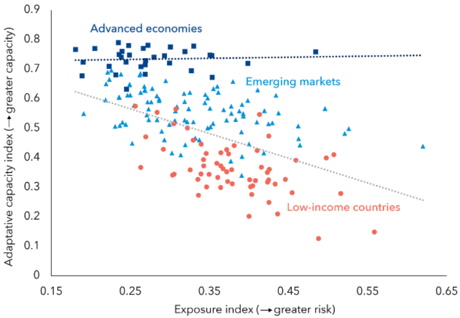
Broader impacts of climate change

- Today, we focus on "micro" aspects of the energy transition, focused on already high-energy consuming countries.
- The energy transition and impacts of climate change will be uneven within a country.
- Cross-country differences are even more dramatic, with developing countries being much more affected by climate change and extreme weather events.

Unequal costs of climate change

Poorer countries face greater risks from climate change and are less able to adapt to them.

(adaptive capacity and exposure indexes, points out of 1)



Source: IMF staff calculations based on 2015-18 data from the European Commission, the United Nations University Institute for Environment and Human Security, the University of Notre Dame, and the April 2020 World Economic Outlook.
Note: Dotted lines show estimated linear relationships for advanced economies, and for emerging market and low-income countries combined, respectively.

IMF

Equity and efficiency

- Economists had traditionally not engaged with issues such as inequity, environmental justice, etc.
- However, it is more and more obvious that inequitable policies are not feasible.
- This creates a **link between efficiency and equity**.
- For a policy to be effective, it needs to be **socially implementable**.

Explainer

Who are the gilets jaunes and what do they want?

What began as a fuel tax protest by French drivers now appeals to wider anti-government sentiment

Many open questions to address efficiency and equity

- Huge need to think about open topics concerning the energy transition that seem highly suited for economists and that touch distributional issues:
  - Equity impacts of non-linear and dynamic pricing during energy transition.
  - Stranded assets and design of tariffs for fixed costs.
  - Competition with dynamic prices and heterogeneous inattentive consumers.
  - Solar panel and battery adoption with credit constraints.
  - Transportation electrification and combustion car phase out.
  - Heterogeneous ability to engage in reliability and resilience.
  - Etc.

Examples of tools/topics in the literature

- Quantification of impacts via detailed **tax/purchase data** (Davis and Borenstein, 2016 – US energy tax credits; Borenstein, 2017 – solar PV).
- Comparisons of **pricing impacts** with micro data and aggregate income/demographic data (Borenstein, 2012 – non-linear pricing; Leslie et al, 2021 – RTP pricing using substation data; Cahana et al, 2022 – RTP pricing using household data).
  - Today's focus.
- Counterfactual **equilibrium model** of demand and supply based on household data (Wolak, 2016 – water; Feger et al., 2021, DeGroote and Verboven, 2022 – solar panels).
- Responses to uneven impacts of energy policies using **survey/voting** data (Fabre and Douenne, 2022 – Yellow Vests) and electoral data (DeGroote, Gautier and Verboven, 2022 – solar PV).

II. Inequity impacts of the energy transition
Quantification via detailed tax/purchase data

Borenstein and Davis (2016)

- Borenstein and Davis (2016) document tax credits.
- They use tax return data (IRS) to examine characteristics of recipients.
- Results suggests these are highly regressive.
- Plausably more regressive than carbon taxes, although much more popular (to a certain extent).

6

The Distributional Effects of US Clean Energy Tax Credits

Severin Borenstein, *University of California at Berkeley and NBER*
Lucas W. Davis, *University of California at Berkeley and NBER*

Executive Summary

Since 2006, US households have received more than $18 billion in federal income tax credits for weatherizing their homes, installing solar panels, buying hybrid and electric vehicles, and other "clean energy" investments. We use tax return data to examine the socioeconomic characteristics of program recipients. We find that these tax expenditures have gone predominantly to higher-income Americans. The bottom three income quintiles have received about 10% of all credits, while the top quintile has received about 60%. The most extreme is the program aimed at electric vehicles, where we find that the top income quintile has received about 90% of all credits. By comparing to previous work on the distributional consequences of pricing greenhouse gas emissions, we conclude that tax credits are likely to be much less attractive on distributional grounds than market mechanisms to reduce greenhouse gases (GHGs).

Barcelona School of Economics

Energy tax credits for EVs and solar in the US

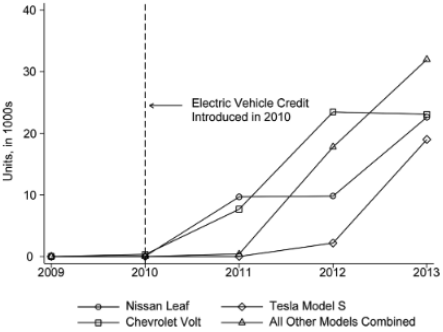


Fig. 4. US Sales of Electric and Plug-In Hybrid Vehicles

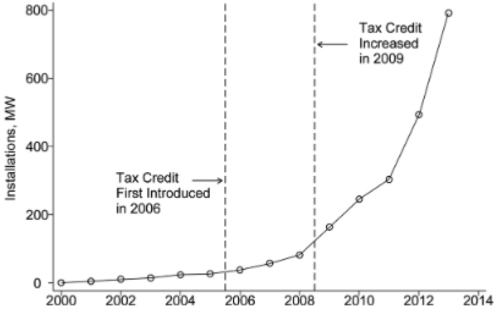


Fig. 2. US Residential Installations of Solar Panels by Year

Evolution of overall spending

- Paper focuses on a period of large energy programs via the American Recovery and Reinvestment Act (Recovery Act).
- Large programs to subsidize energy efficiency (windows, furnances, heat pumps), solar panels and alternative vehicles.
- Over $18 billion over the period of study on residential-focused subsidies alone.

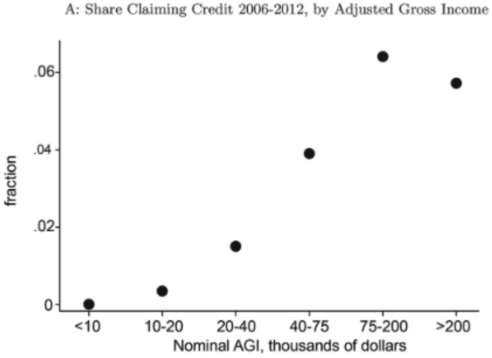
Table 1
Annual Expenditures on US Clean Energy Tax Credits, in Millions

Year	Windows and Other Energy-Efficiency Investments (NEPC) ($)	Solar Panels and Other Residential Renewables (REEPC) ($)	Hybrids and Other Alternative Fuel Vehicles (AMVC) ($)	Electric and Plug-In Hybrid Vehicles (PEDVC) ($)
2005	0	0	0	0
2006	957	43	50	0
2007	938	69	185	0
2008	0	217	49	0
2009	5,177	645	137	129
2010	5,420	754	93	1
2011	755	921	14	76
2012	449	818	20	139
Total	13,696	3,467	549	346

Sources: This table was constructed by the authors using US Department of the Treasury, Internal Revenue Service, "Statistics of Income, Individual Tax Returns," 2005–2012 and US Department of the Treasury, Internal Revenue Service, "Individual Income Tax Returns Line Item Estimates," 2005–2012.
Notes: See appendix for details. Tax credits across all four categories totaled $18.1 billion between 2005 and 2012.

Distributional analysis: access

- Thanks to the very detailed micro data from the US Treasure (IRS), authors can document that adoption of energy tax credits is very low by low income households.
- Due to the nature of these tax credits, some of these tax credits cannot be access by low income households.
- This is in addition to several other barriers (credit constraints, renter status, etc.).



Distributional analysis: concentration curves

- Authors also compute concentration curves of transfers of energy tax credits.
- x-axis: income / y-axis: transfers.
- Concentration is very large, and much larger than the distribution of income (annual gross income or AGI).
- Figure: example from EVs.

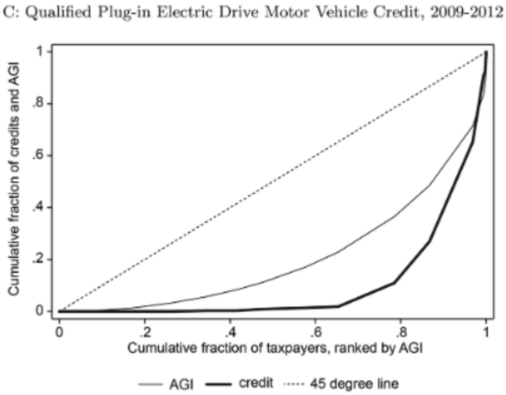
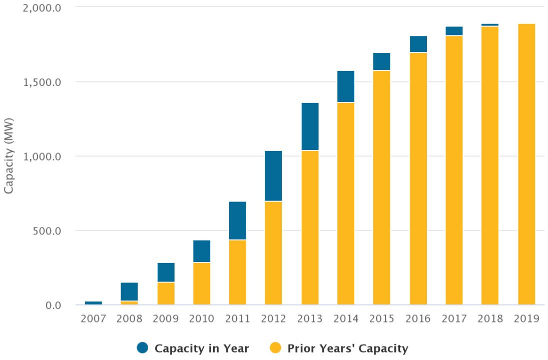


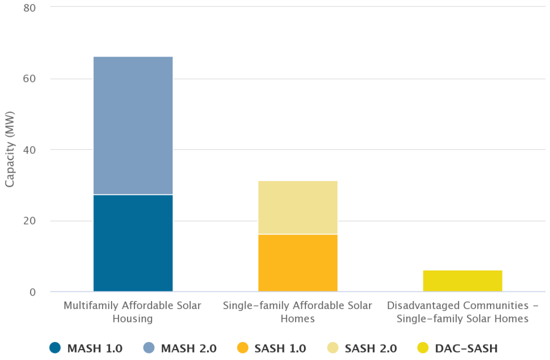
Fig. 7. Concentration Curves

Recent focus on how to include low-income, but difficult in practice

- Bottom line from mounting evidence is that inequality in energy policy is even larger than in income, which can stall progress.
- Many policies try to now explicitly **target low-income households**.
- Example: weatherization assistance program (WAP), community solar programs.
- In practice, difficult to implement in low-income neighborhoods with high participation costs and limits on ability to directly benefit from program (e.g., renters).
- Need to pool across several housing units also makes practical implementation harder (e.g., community solar rooftop: problems with community agreements, also with bureaucracy, limits on property tax credits, etc.).

But with limits... e.g., Solar PV in California





Source: California Distributed Generation Statistics, https://www.californiadgstats.ca.gov/.

Borenstein (2017)

- Paper studies the distributional impacts of solar PV in the PG&E territory.
- It uses detailed billing data with solar panel installation and production data to quantify adoption and winning by income quintiles (Census block group). Also limited hourly consumption data for a sample of households.
- Paper computes relevance of rate design in affective solar PV adoption.

Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates

Severin Borenstein

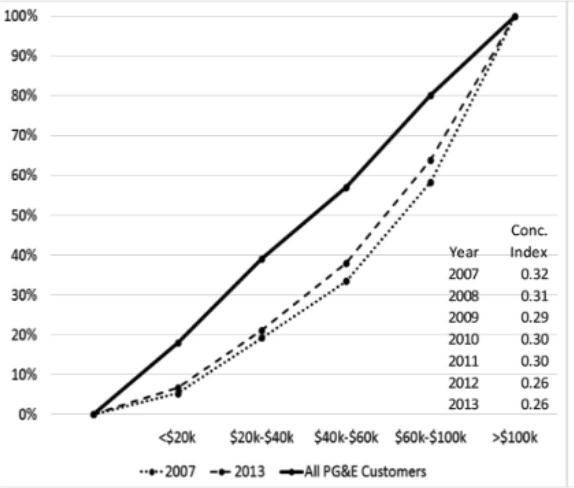
Abstract: With dramatic declines in the cost of solar PV technology since 2010, the electricity industry is in the midst of debates about whether to use this low-polluting renewable energy source in grid-scale generation or in distributed rooftop generation (DG). California has led the growth in DG solar in the United States. I use 2007 to early 2014 residential data from Pacific Gas & Electric—the utility with the largest number of residential solar customers in the United States—to examine the full range of private incentives for installing residential solar, from direct rebates and tax credits to indirect incentives that result from the residential tariff design and the crediting of solar production under "net energy metering." I then study the income distribution of solar adopters and how that has changed over time. I find the skew to wealthy households adopting solar is still significant but began to lessen after 2011. Adoption continued to be dominated by the heaviest electricity-consuming households, probably because the steeply tiered tariff structure greatly increased the private value of solar to such customers while reducing the incentive for consumers who are below median consumption. In fact, the financial incentive for those who actually adopted solar over the sample period may have been due nearly as much to California's tiered tariff structure as to the 30% federal tax credit. The California experience suggests that rate design can greatly influence the economic incentives for residential solar adoption and which customers receive those benefits.

JEL Codes: L94, Q42, Q58

Keywords: Alternative energy, Distributed generation, Energy subsidies

Concentration indices

- Concentration curves show what was already shown in the previous paper: higher concentration of adoption in high-income categories.



CSI Customers

Factors making solar very attractive in California

- Federal tax credit
- Accelerated Depreciation Value (if under lease)
- State subsidies (CSI program)
- Good solar radiation
- High electricity prices
- Rate structure (net metering)

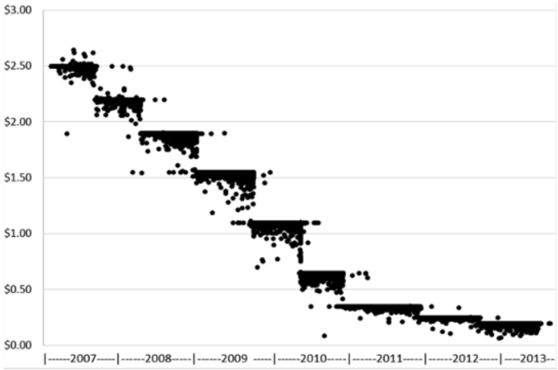


Figure 1. CSI rebate (per Watt of rated capacity) paid under PG&E program

What is net metering (NEM)?

- Under net-metering, households will get the energy produced from their solar panels substracted from their demand.
- They are only charged for their net demand, e.g., at the monthly level.
- Traditionally, energy-based, so the implicit price for solar power is the **retail price.**
- Due to non-linear pricing, net-metering is more attractive to high energy users, which on average, are higher income.

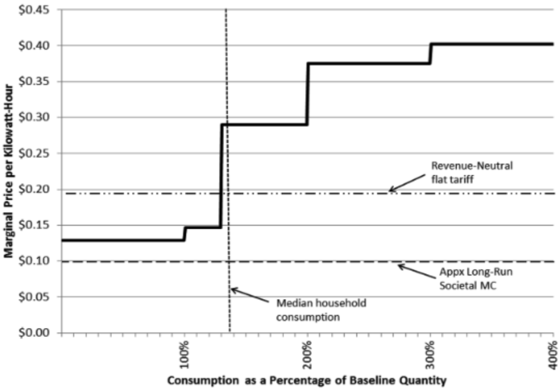


Figure 2. Average PG&E increasing block pricing tariff during 2007–13

NEM can be a substantial subsidy

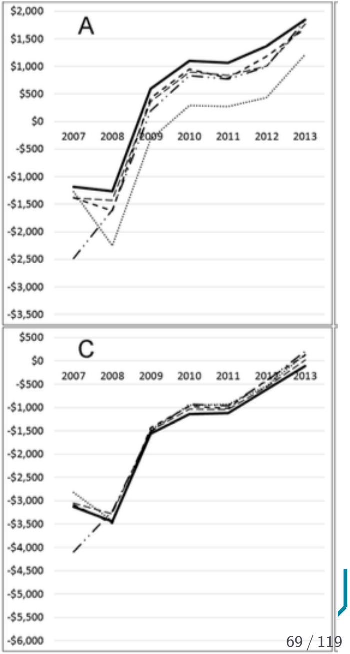
- Under traditional NEM expected the net present value (NPV) of solar panels can be much larger.
- This is due to the fact that the retail energy prices can be much larger than the marginal cost of electricity.
- In California, there were **no fixed fees**: all the distribution network is paid via retail prices that are proportional to electricity consumption.

Table 2. Average Bill Savings under Alternative Tariffs for All PG&E Residential Solar

Year	Obs.	Capacity (kW)	NPV of 25-Year Electricity Bill Savings ($): IBP with Monthly NEM	IBP with Hourly NEM	Flat Rate ($.19/kWh)	MC ($.10/kWh)
2007	5,601	3.67	20,965	18,223	14,576	7,650
2008	5,701	3.73	21,628	18,612	14,829	7,783
2009	8,393	4.00	23,338	19,794	15,943	8,368
2010	9,110	4.42	26,270	22,167	17,634	9,255
2011	11,827	4.02	23,321	19,972	16,017	8,407
2012	15,182	4.17	23,556	20,074	16,630	8,728
2013	25,654	4.46	24,726	21,024	17,793	9,339
2014*	8,411	4.65	25,729	21,789	18,600	9,762

NEW interacts with income

- Going from traditional NEM to a flat rate per solar output reduces benefits of households.
- It also reduces benefits to higher income households disproportionately more.



Policy consequences

- Net-metering policy can become socially and financially unsustainable.
- California has undergone two reforms of their net-metering policies to balance cost allocation, efficiency, equity.
- Open discussions between the winners and losers from the different alternatives.

- See bonus notebook for an example of modeling this.

II. Inequity impacts of the energy transition

Pricing impacts of the energy transition

Today: Papers about pricing

- Borenstein (2012): Distributive impacts of non-linear pricing.
- Leslie, Pourkhanali, Roger (working paper, 2021): Impact of real-time pricing.
- Cahana, Fabra, Reguant, and Wang (2022): Impact of real-time pricing and energy crisis.

A data challenge

Very ideal data

- Individual detailed smart meter data.
- Individual income.
- Individual buidling/appliance characteristics.
- Individual comfort data.

Usual data limitations

- Monthly billing data; hourly but not individual data.
- Censored income, zip code income.
- Almost never no buidling/appliance characteristics.
- Almost never comfort data.

We will discuss for each paper methods to **link consumption and income data**.

Borenstein (2012)

The Redistributional Impact of Nonlinear Electricity Pricing†

By SEVERIN BORENSTEIN*

Electricity regulators often mandate increasing-block pricing (IBP)—i.e., marginal price increases with the customer's average daily usage—to protect low-income households from rising costs. IBP has no cost basis, raising a classic conflict between efficiency and distributional goals. Combining household-level utility billing data with census data on income, I find that IBP in California results in modest wealth redistribution, but creates substantial deadweight loss relative to the transfers. I also show that a common approach to studying income distribution effects by using median household income within census block groups may be misleading. (*JEL* D31, L11, L51, L94, L98, Q41, Q48)

Can non-linear pricing help?

- Non-linear pricing is quite common in utility tariff design.
- Electricity prices are above marginal cost to pay for other costs.
- These other costs often include at least part of fixed costs, e.g., transmission lines.
- Instead of setting a fixed fee, many regulators set increasing non- linear prices.

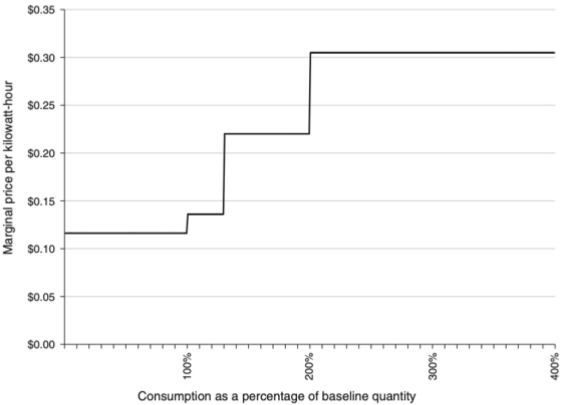


FIGURE 1. SCE's STANDARD RETAIL ELECTRICITY TARIFF IN 2006

What does the paper do?

- **Question**: Is non-linear pricing progressive? To what extent?
- **Data**: Monthly billing data for the three largest utilities in California (PG&E, SCE, SDG&E), social bonus status (CARE), median and mean income at the Census block group level (precise, small neighborhood area, but not individually).
- **Method**: ecological methods to bound redistributive impacts under assumption of perfect sorting (higher consumption $\rightarrow$ higher income) vs. no sorting vs. weighted based on survey data (most realistic).
- **Findings**: Non-linear pricing is progressive, but it fails to perfectly target households.

Basic patterns in the data

TABLE 1—DISTRIBUTION OF SCE RESIDENTIAL CUSTOMER CONSUMPTION ACROSS TARIFF TIERS IN 2006

	Residential usage (million-kWh)	Percentage of residential usage					CARE/Non-CARE shares	
		Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Percentage of usage	Percentage of customers
Non-CARE	23,046	52.9	10.7	16.5	10.9	9.0	79.3	74.8
CARE	6,016	66.0	10.7	13.5	6.7	3.1	20.7	25.2

	Percentage of customers on each tier for marginal consumption				
	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5
Non-CARE	32.4	14.2	25.0	17.2	11.3
CARE	45.4	16.7	22.7	10.9	4.3

Note: Reported results drop household accounts with consumption of less than 1 kWh/day.

Non-linear pricing is progressive

- Consumers with high levels of consumption end up paying substantially more at the margin, while consumers with low consumption get the first units at a low price.
- Higher income consumers tend to consume more even using the random approach, driven by higher income Census blocks consuming more.

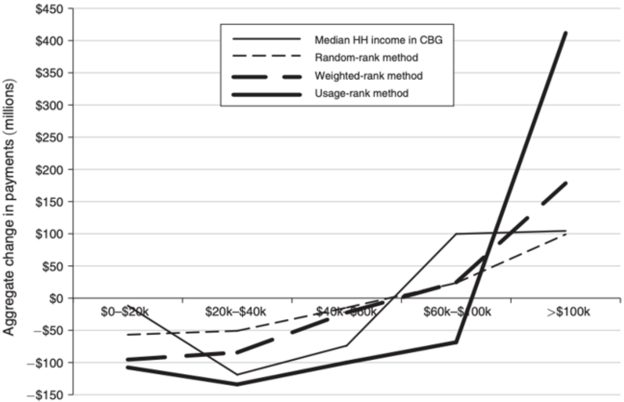


Figure 4. Alternative Estimates of Aggregate Change in Payments by Income Bracket

Main findings: complementary tools?

- Paper examines simulations with and without social bonus.
- Social bonus suspected to not be very well targeted in California.
- Under weighted method, bonus still contributes more to redistribution but non-linear pricing targets best the highest quintile.

TABLE 7—ESTIMATED AVERAGE ANNUAL BILLS WITH AND WITHOUT IBP AND CARE

	Average annualized bill				Bill change from No-CARE/flat		
	No-CARE		with CARE		No-CARE	w/CARE	w/CARE
Income range	Flat tariff	Five-tier tariff	Flat tariff	Five-tier tariff	Five-tier tariff	Flat tariff	Five-tier tariff
\$0–\$20k	\$785	\$653	\$609	\$546	−\$132	−\$176	−\$239
\$20k–\$40k	\$973	\$879	\$863	\$804	−\$94	−\$111	−\$170
\$40k–\$60k	\$1,128	\$1,098	\$1,163	\$1,115	−\$29	\$35	−\$12
\$60k–\$100k	\$1,234	\$1,260	\$1,337	\$1,327	\$26	\$103	\$93
>\$100k	\$1,646	\$1,900	\$1,790	\$1,996	\$253	\$144	\$350

Notes: All calculations using weighted-rank within-CBG allocation method. Excludes bills with daily consumption less than 1kWh/day. Includes all CARE and non-CARE customers.

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Leslie, Pourkhanali, Roger (2021)

Can real-time pricing be progressive?
Identifying cross-subsidies under fixed-rate electricity tariffs

Gordon W. Leslie* Armin Pourkhanali Guillaume Roger†

October 26, 2021

Abstract

Wholesale electricity prices can rapidly change in real-time, yet households usually face fixed-price electricity tariffs. These tariffs create implicit cross-subsidies between households, determined by the timing of consumption. We map substation data on electricity use to demographic data to identify the household characteristics associated with this cross-subsidization. We find that households in areas with low house prices and high levels of renters and elderly residents are net funders of this cross-subsidy, and may be the greatest immediate beneficiaries if real-time retail tariffs are made available. Further, cross-subsidy magnitudes are exacerbated by the wholesale price impacts from increasing solar generator penetration.

JEL classification: D12, D18, H23, L94, Q41
Keywords: Real-time pricing, Cross-subsidies, Tariff design, Clean energy transition, Energy demand.

What does the paper do?

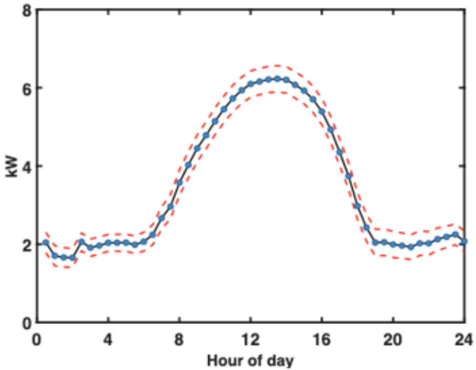
- **Question**: Is real-time pricing progressive? To what extent?
- **Data**: half-hourly substation consumption data in Victoria (AUS) matched to geographical demographic data including income and other covariates, data on number of businesses and households, weather data.
- **Method**: Regression that separates business vs. household consumption, then focus on household consumption to look at redistribution across substations.
- **Findings**: Real-time pricing favors low-income consumers on average.

Regression approach

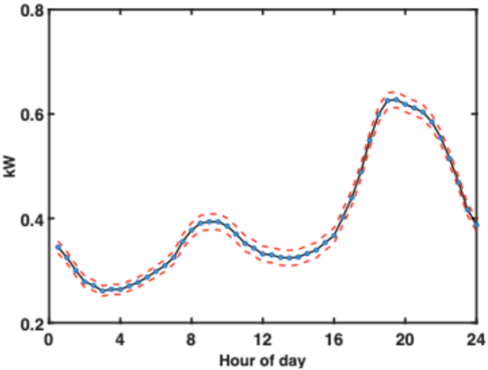
- Use regression with number of households and businesses, allowing hourly consumption to depend on neighborhood characteristics.
- Each substation ranked into terciles (high, medium, low) for 12 measures
  - Demographics: prop. of people over age 65; av. h'hold size, prop. born o'seas; prop. work from home; unemployment; av. income; prop. Uni.
  - Housing: prop. rental; median house price; residential density; prop. rooftop solar.
  - Climate: cooling degree days
- Focus on predicted household consumption β_h interacted with characteristics Z_s.

$$Q_{s,t} = \alpha_h + \boldsymbol{\beta}_h \cdot \underbrace{\boldsymbol{Z}_s}_{\text{Char's}} \cdot |I_s| + \gamma_h \cdot |J_s| + \epsilon_{s,t}$$

Method seems to extract meaningful signal

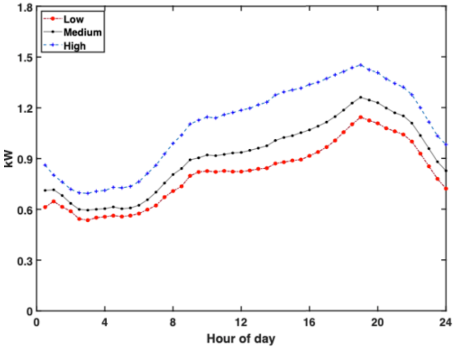


Business profiles



Household profiles

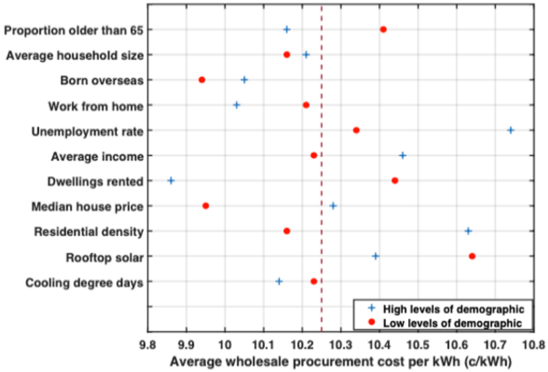
Method seems to extract meaningful signal



(e) Cooling degree days

Results are a bit mixed

- Costs per MWh under RTP go down for some sensitive demographic categories (e.g., elderly, renters).
- RTP is not necessarily regressive, although heterogeneity in impacts is substantial even with aggregate substation data.
- Some open questions:
  - Victoria has a very large share of rooftop adoption, how does interact with RTP when looking at distributional impacts?
  - How does it depend on solar pricing design, e.g., net-metering vs. other alternatives?



Cahana, Fabra, Reguant, and Wang (2022)

The Distributional Impacts of Real-Time Pricing

Michael Cahana Natalia Fabra Mar Reguant Jingyuan Wang*

October 2022

Abstract

We analyze the distributional implications of Real-Time Pricing (RTP) for electricity, which economists favor over time-invariant prices for its efficiency properties. With hourly consumption data from Spain, we find that RTP is regressive. Household consumption patterns, electric appliances, and locations explain this finding. Through counterfactuals, we find that these distributional impacts might worsen in the future with the broader adoption of enabling technologies by high-income groups. Methodologically, we propose a novel method for inferring individual household income. Capturing within zip code income heterogeneity is key for uncovering the distributional impacts of RTP.

What does the paper do?

- **Question**: Is real-time pricing progressive?
- **Data**: smart meter individual data match to zip-code level income and weather data. Income quintiles at the zip-code level.
- **Method**: Machine learning methods to infer appliance ownership and income imputation.
- **Findings**: High-frequency RTP variation benefits low income, but low-frequency hurts low-income with very inefficient electric heating.

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Main Findings Expanded

Main Finding:

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

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

A first look at the data: month vs annual variation

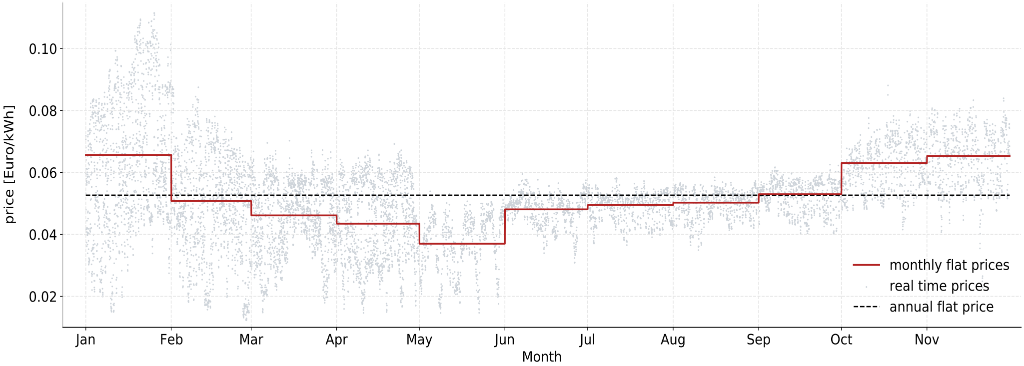

Figure: Summary of price variation

Computing bills under RTP and time-invariant prices

- Compute bill with and without RTP:

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

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

- Separate "within month" and "across months" effects:

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

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

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: $Pr_i(inc_k)$.

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

- 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).

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Our approach: intuition

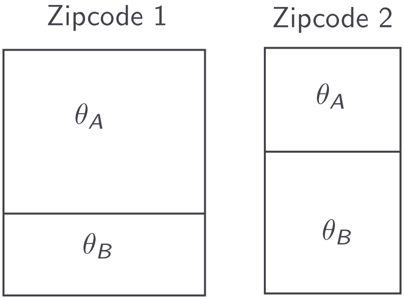
We propose an estimator in two steps:

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

Key: Allow for sufficient discrete 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 types in each zip code.
- η_A^H represents the probability of income level H for type θ_A (similarly for θ_B), unknowns.
- Match zip code moments on the distribution of income, same underlying types across zip codes.

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 12 types per province depending on contracted power, heating mode, and consumption patterns.

Step 1: Example of type assignment

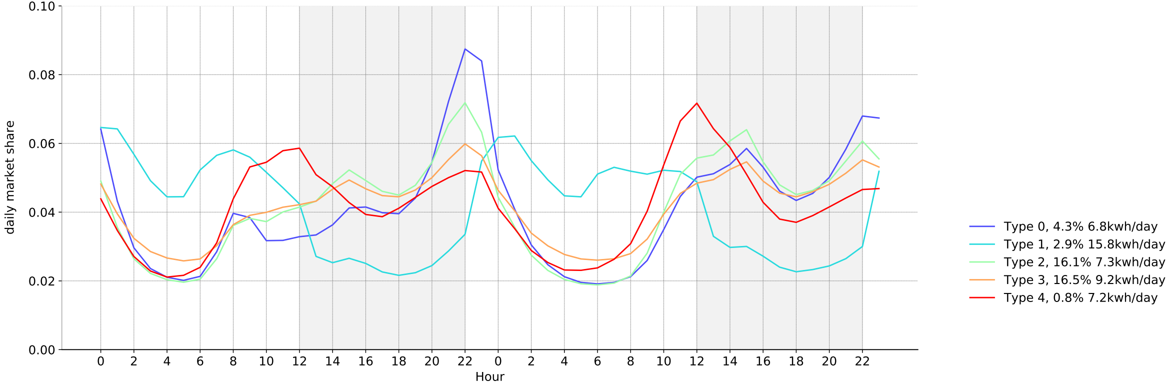


Figure: Flexible k-mean types with electric heating in a given province

Step 2: 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

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

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Step 2: Semi-parametric estimator

- Previous identification results is limited in types by the numbers of zip-codes that share types.
- We consider a semi-parametric estimator that allows the distribution of income to depend on individual and zip-code demographics.
- The distribution of income is individual and zip-code specific even for the same type.

$$\min_{\eta,\alpha,\beta} \quad \sum_{j} \omega_j \sum_{k=1}^{K} (Pr_k^j - \sum_{i \in \mathcal{I}_j} Pr_k(\theta_i, x_i, z_j)),$$

$$s.t. \quad Pr_k(\theta_i, x_i, z_j) = \frac{exp(\delta_{ijk})}{\sum_{k'=1}^{K} exp(\delta_{ijk'})}, \qquad \forall k \in [1, \cdots, K],$$

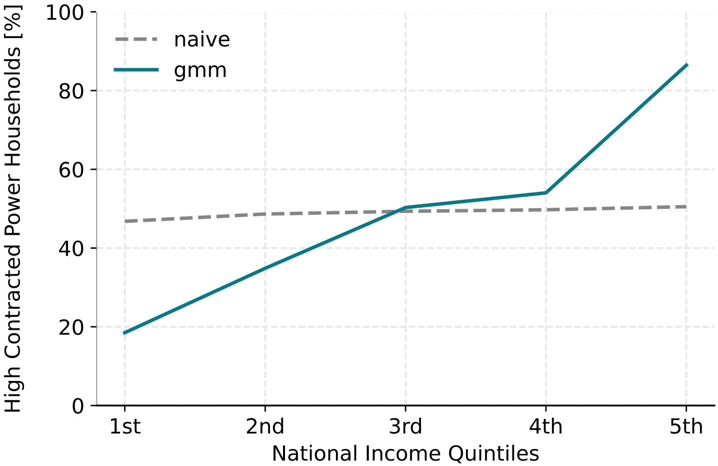
$$\delta_{ijk} = \alpha_k + \beta_0^{\theta_i} \times k + \beta_1^{\theta_i} x_i \times k + \beta_2^{\theta_i} z_j \times k.$$

Step 2: Results

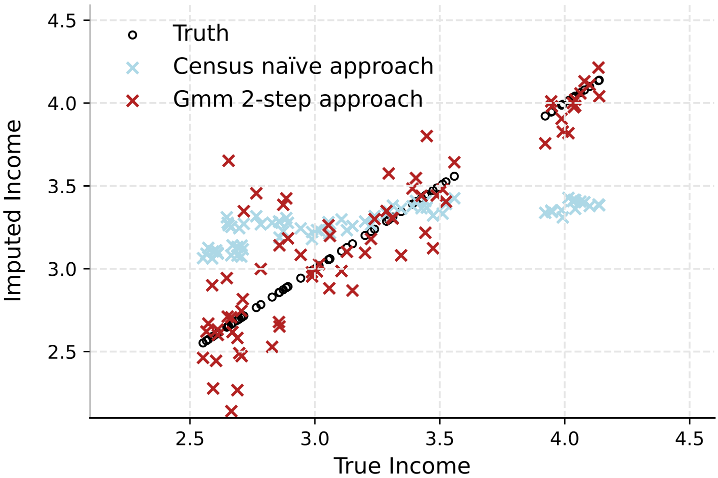
- The above estimator gives us an estimated probability of a given household belonging to a certain income bin.
- Estimator does not say exact income of a given households (still measured with error).
- We show it can help correct the association between income and the policy impacts even if income is not perfectly observed, which can be biased with zip-code level income.

Step 2: Confirm relationship between income and contracted power

- Individual-level of contracted power strongly associated with higher income distribution, but not with naïve zip-code level data.



Monte Carlo: Income estimation



Monte Carlo: Policy impacts

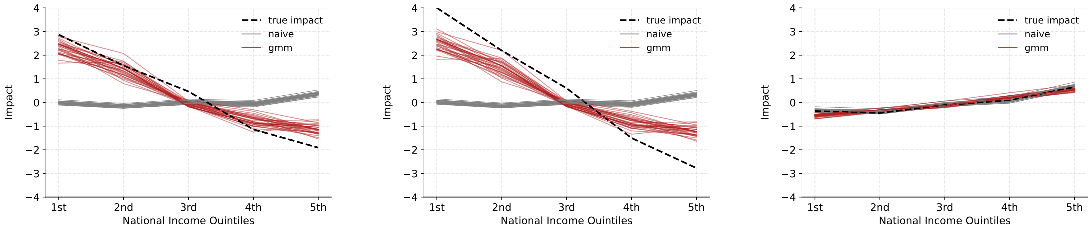
We perform a Monte-Carlo simulation to inform this discussion. Assume that the true data generation process behind the distributional impacts is governed by the following equation:

$$impact_{i,z} = t \times \theta_i + k \times inc_i + \sigma_z \times (\phi_z + \overline{\phi}_{zipgroup}) + \sigma_e \times \epsilon_{iz}.$$

- t: Heterogeneity captured by the types.
- k: Direct income heterogeneity.
- σ_z: Across zip code heterogeneity.
- σ_e: Remaining unobserved heterogeneity.

Monte Carlo: Policy impacts

Figure: Assessing the method with a Monte-Carlo simulation



(a) Full bias correction (b) Partial bias correction (c) No naïve bias

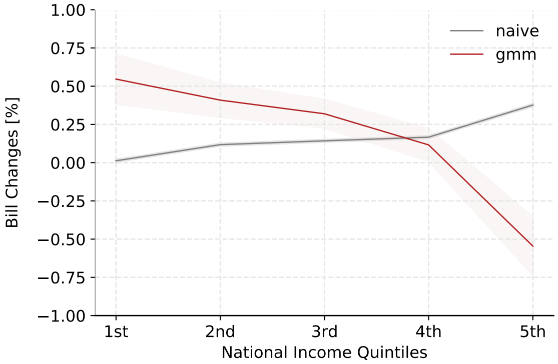
Bringing it back to measuring the policy impacts

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?*

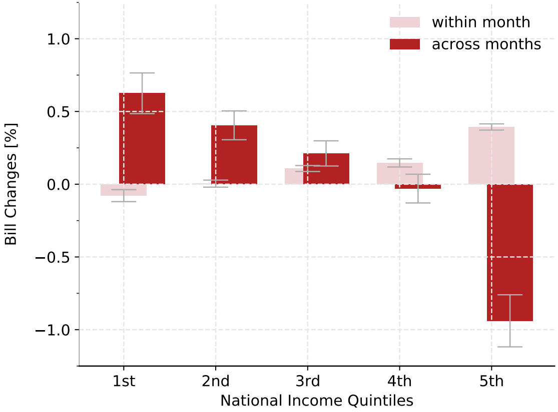
Heterogeneous impacts by income bins

- 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.



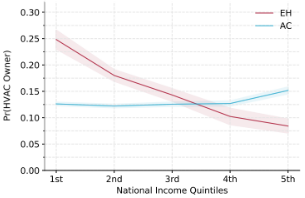
Decomposing the impacts

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

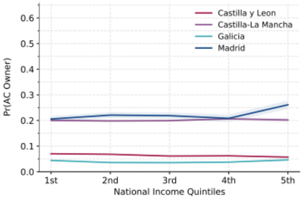


The mechanisms behind these patterns

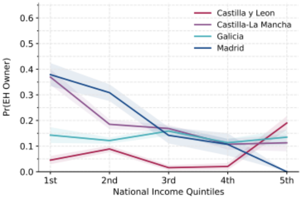
- We consider:
  - Consumption patterns by income.
  - Appliance ownership, across and by income.
  - Geographical variation related to weather/appliances.



(a) Share of electric heating owners and AC owners



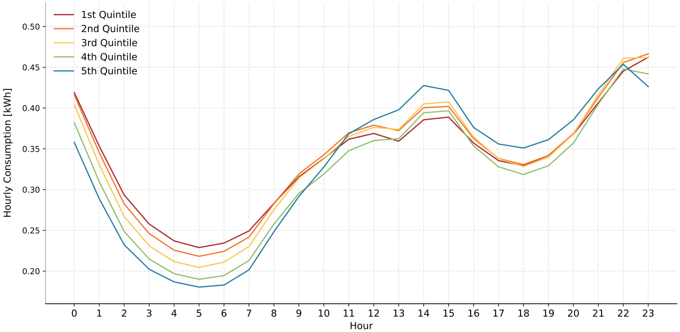
(b) AC ownership by state



(c) EH ownership by state

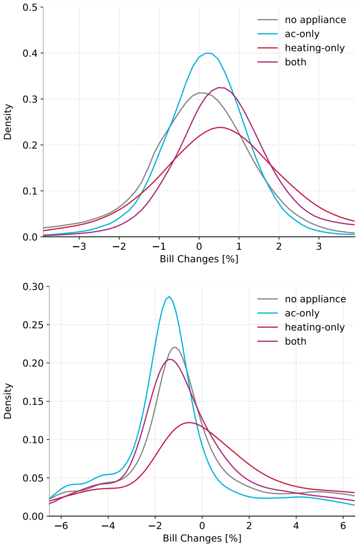
Mechanisms: consumption patterns during the day

- Higher income quintiles consume more electricity.
- They also consume proportionally more at peak hours.
- [→] The within month effect is progressive.

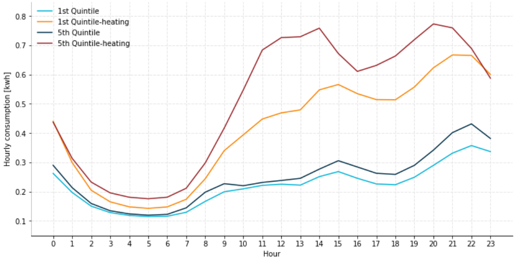


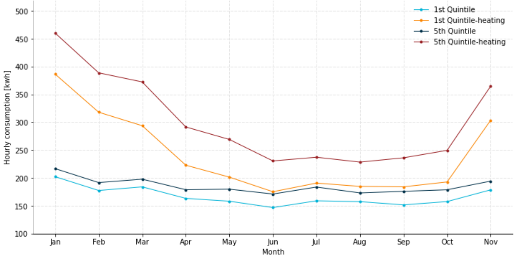
Mechanisms: appliance ownership

- 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

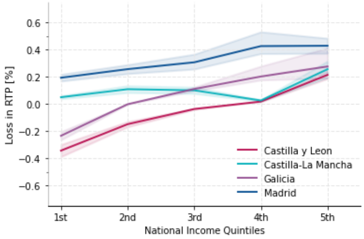




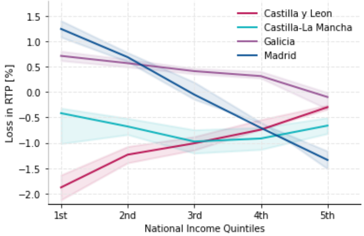
- Households with electric heating consume more during peak hours and winter when prices are higher.
- Appliance ownership creates bigger differences than income.
- Conditional on appliance ownership, income still induces substantial differences.

Mechanisms: geography

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



(a) Within month effects

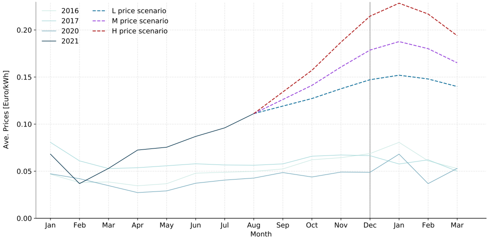


(b) Across months effects

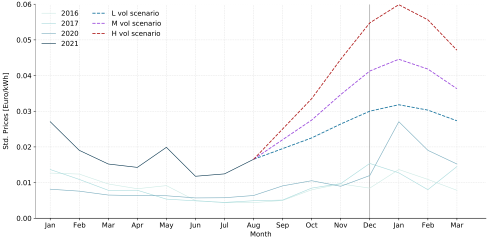
Counterfactual experiments

- 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

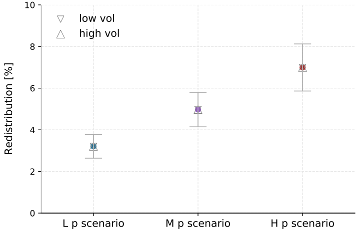


(b) Simulated price volatility

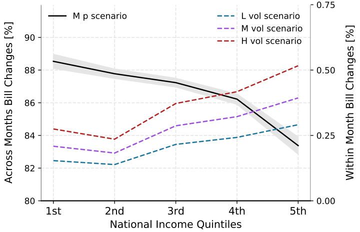
- We consider simulated prices (with low, medium, high levels and low, medium, high volatility).
- We re-analyze the distributional implications of RTP.

Commodity Risks and Energy Poverty

- 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.



(a) Redistribution



(b) Decomposition

Conclusions: energy crisis, RTP, and equity

- 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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