Smart Rationing: Designing Electricity Blackout Policies for Extreme Events

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Today's plan

- I will talk about two papers:
  - "Smart Rationing: Designing Electricity Blackout Policies for Extreme Events," with Mayra Wagner
  - "The Distributional Impacts of Real-Time Pricing," with Natalia Fabra, Jingyuan Wang, and Michael Cahana
- Focus on the first one, but use and explain tools from the second one.
- Both examine efficiency-equity implications from the energy transition/climate crisis.

- **Note**: Results on rationing still preliminary, heterogeneity analysis in progress.

Rationing electricity

- I will talk about early work on **rationing** in the presence of energy scarcity.
- During 2022, growing concerns about the possibility of energy shortages in Europe.
- Several leaders announced potential consumer-level planned systemic blackouts (e.g., Austria, France).
- Large blackouts have occurred recently in California and Texas.

- While system-wide sustained blackouts are *relatively unlikely*, it is important to study its design due to their welfare relevance and the more likely blackouts due to climate change.
  - Supply-side failures due to extreme weather
  - Demand spikes correlated with extreme weather

Persistent blackout conditions are costly

NEWS // HOUSTON & TEXAS

Texas energy demand may exhaust supply this summer, ERCOT warns

Texas' energy grid operator warned that extreme scenarios may lead to rolling blackouts this summer.

Michael Murney, Chron
May 5, 2023

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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Individual/public investments can help, but highly unequal

- High-income households can avoid blackouts with solar + battery systems that are oversized absent blackout concerns.
- With the raise of solar + batteries (microgrids), blackouts, one can also build electrical shelters (see Brehm et al., 2024).
- All these solutions will ease the burden on some households and neighborhoods. The impact of rolling blackouts falls on HHs that cannot afford resilience preparedness.

How to improve blackout policies?

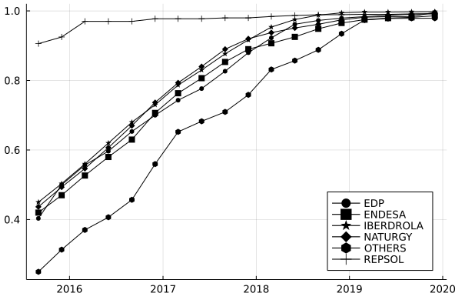
Our proposed solution

- Traditionally, "rolling" blackouts for system-wide shortages have been used to deal with scarcity.
  - Very costly and "secret recipe" often undisclosed.

- We propose to use power limits, which are now feasible with smart meters.
- The proposed solution is technologically feasible and a clear welfare improvement.
- We are still exploring its design when targeting is allowed.

From smart meters to smart rationing

- Smart meters are now commonplace in many electricity markets.
- Multiple benefits: potential for dynamic pricing, reduction in distribution losses, better solar pricing, etc.
- Smart meters can also contribute to improved rationing via maximum power limits.



From "Smart Meters and Retail Competition: Trends and Challenges."

Maximum power limits offer a better solution

- Consumers in many countries can contract their maximum power level at any instantaneous point for the duration of a certain period (limited changes).
  - Used for cost-allocation purposes: consumers with high power contribute more to fixed system costs, highly correlated with usage and income.
- If a user goes over their contracted power, the circuit breaker trips.
- The user has to disconnect enough appliances to be back in balance (aka, below the limit).
- Traditionally, this maximum limit was a "bug" in the device and had to be adjusted manually.
- Nowadays, it can be adapted digitally and become a feature.

Smart rationing as a partial blackout

- In the traditional blackout setting, a customer was disconnected.
- Smart meters allow to limit the available power to a user partially.
- Even using a crude rule and method, **better in many situations**!

- **Preview:**

  Get *blackout-equivalent policies*
  while bothering *fewer* people
  and with no consumer at zero.

When can this be useful?

- This is not useful for blackouts that happen unexpectedly or need immediate action due to the communications protocol with the smart meters.
- This is also less useful when network topology is essential (e.g., wildfires).

- Useful for situations like European crisis, Texas, California (non-fire): expected and persistent.
- In some sense, similar to water scarcity problems, as a way to reduce demand once other channels have failed (or might not be feasible).

Will this be useful?

- Some conversations with the transmission system operators in Spain and France!
  - Seen as a last resource option in Europe, less common than in places like Texas and California.
  - Large rationing programs for the industrial sector and higher investment in reliability/redundancies.
  - However, implementation cost is very low and could still be useful under unprecedented events.
- In the US, smart meters do not always have this capability.

(Partial) Literature review

Growing area of study due to recent events (systemic blackouts in USA, geopolitical instability in Europe).

- **Theoretical literature**: Weitzman (1997), Joskow and Tirole (2007), Gerlagh, Liski and Vehviläinen (2023), Bobtchef, De Donder and Salanie (2022), Tokasrki et al (2023), Akbarpour et al (2023).

- **Empirical literature**: Brehm, Johnston and Milton (2024), Lee et al. (2022), Ryan and Sudarshan (2022).
- **"Tools" literature**: Borenstein (2012), Dyson et al. (2014).

Overview

Framework

Data

Results with simple mechanisms

Adding heterogeneity

- Inferring end-uses (Cahana et al.)
- Inferring income (Cahana et al.)
- Preliminary findings without using the fancy individual measures...

Next steps

Framework

Framework

- Consider the following individual net utility from electricity (Weitzman, 1977):

$$w_i(p; \lambda_i, \epsilon_i) \;\equiv\; u_i(x_i(p); \epsilon_i) - \lambda_i \; p \; x_i(p),$$

  where x_i is individual-specific and can depend on ϵ_i and λ_i.
- In a shortage situation, at $\overline{p}$,

$$D(p) \equiv \sum_i x_i >> S(\overline{p}).$$

Traditional "rolling" blackouts can have very large costs

- Define $\kappa \in [0, \overline{\kappa}]$ as the degree of rationing at a given moment.
- Let $\kappa = 0$ be full rationing and $\kappa = \overline{\kappa}$, none.

- Under *random rationing*, we can use the aggregate welfare and establish that total welfare equals

$$W^B(p, \alpha_t) = \alpha W(p, 0) + (1 - \alpha) W(p, \overline{\kappa}),$$

  where W represents aggregate welfare, i.e., $W(p, \kappa) = \int_i \theta_i w_i(p, \kappa) di$.

- Notice that α might be small, but costs to selected consumers can be considerable if the blackout is severe (e.g., Texas).

Smart rationing

- Under very reasonable assumptions, it is trivial to show that a form of “smart rationing” should be preferable to full blackouts for a small subset of the population.
- Consider a set of smart rationing rules that can be flexible and allow for individualized rationing policies,

$$\Phi : i \to \phi_i.$$

Blackout-equivalent smart rationing

- Under a general setting, we define the optimal unconstrained smart rationing rule to achieve a demand reduction equivalent to a blackout of size α, as

$$W^*(p,\alpha) \equiv max_\Phi \int_i \theta_i w_i(p,\phi_i)di \quad \text{s.t.} \quad \int_i x_i(p,\lambda_i,\epsilon_i)di = (1-\alpha)D(p).$$

- Notice that ϕ trivially includes the simple blackout rationing.

- Intuitively, having some power should be much preferable than none at all, so potentially $W^*(p,\alpha) >> W^B(p,\alpha)$.

Power limits as a special case

- Under power-limit random rationing, a fraction β gets selected for partial rationing.
- If selected, a household gets *possibly* limited power ($\kappa \in (0, \overline{\kappa})$), while the rest remains with full provision of service ($\kappa = \overline{\kappa}$).

- Under partial rationing to a share β of households, with a limit κ, welfare becomes:

$$W^P(p, \beta, \kappa) = \beta W(p, \kappa) + (1 - \beta) W(p, \overline{\kappa}).$$

- For a given β and κ, one can obtain demand cuts equivalent to a blackout α.

Limits to power limits

- Because power limits provide an allowance to rationed households, they can never be equivalent to a full blackout.
- It is useful to understand the blackout size that they can approximate, which will be maximized at $\beta = 1$.

- We define the maximum amount of rationing that can be achieved by a partial rationing policy ϕ as
$$\overline{\alpha}(p, \kappa) = 1 - D(p, \kappa)/D(p),$$
where $D(p, \kappa) \equiv \sum_i x_i(p, \kappa)$.

Wthout heterogeneity, stylized optimal policy is simple

- With decreasing utility of consumption and no heterogeneity, it is optimal to set $\beta = 1$ and maximize κ.
- For a blackout-equivalent policy of size α, the optimal policy becomes:

$$\beta^* = 1, \kappa^* \text{ s.t. } D(p, \kappa) = (1 - \alpha)D(p).$$

Technical considerations

- Even without heterogeneity, reasoning abstracts away from discrete costs of being rationed (e.g., power tripped at home).
- It also abstracts away from empty houses at the time of the event (cannot respond actively, however this should be minor as usually below limit).
- Reasoning also abstracts away from telecommunication limits and might not be able to safely communicate with all smart meters simultaneously.

Heterogeneity/welfare considerations

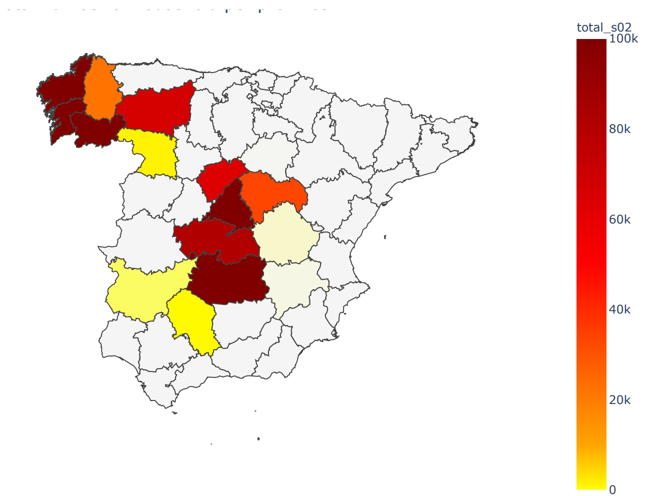
- What if κ is allowed to be individual specific?
- Optimal blackout-equivalent policy depends critically on:
  - Idiosyncratic value of ϵ_i
  - Income distribution λ_i
  - Social weights θ_i
- If ϵ_i and λ_i negatively correlated, then monotonic ordering equity-efficiency.
- Typical assumption: higher income consume more, true on average, but plenty of heterogeneity $\rightarrow$ an empirical question.

Data

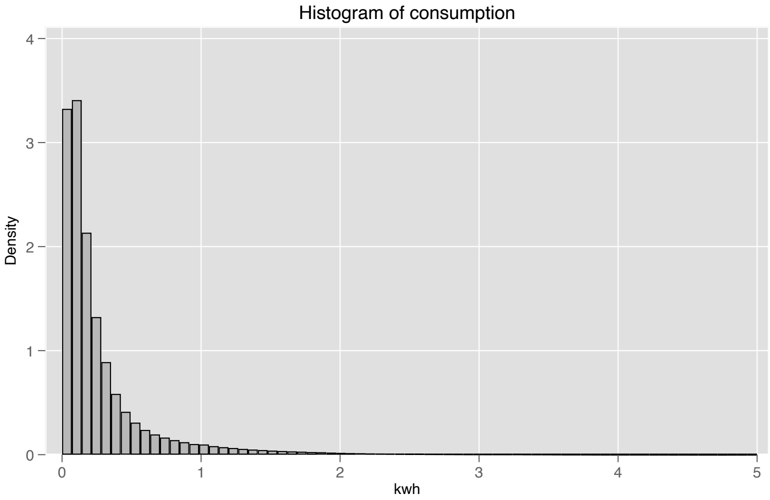
Data

- Data as in Fabra et al (2020, 2023).
- We obtained over 4M smart meters data from one large Spanish utility (Naturgy).
- For each meter (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 on zip-code income.
- From previous work, use ML tools to infer heating mode and individual income distribution.

Data: electricity consumption area



Data: consumption distribution



Data: some notes

- For this first analysis, we consider all meters as valid (even if they appear to be empty houses).
- We want to focus on realistic distributions of demand available for rationing, and traditional blackouts include "infra-marginal" meters (empty houses).
- When looking at distributional implications, we might narrow it down to "households" that are active, as in Cahana et al (2023).

Results with simple mechanisms

Simulations

- We simulate simple rationing policies with our smart meter data to understand the blackout-equivalent policies.
- We only use a couple of months of data for now.

- We assume random rationing, which can be complete (blackout) or partial (reduced maximum power).
- We also consider geographically correlated blackouts, which reduce household heterogeneity and might limit the effectiveness of smart rationing policies.

Simulation details

- For each household i, with our implementation of "smart" rationing, demand equals to:

$$x_{it}(p, \kappa) = \min\{x_{it}(p), \kappa\}.$$

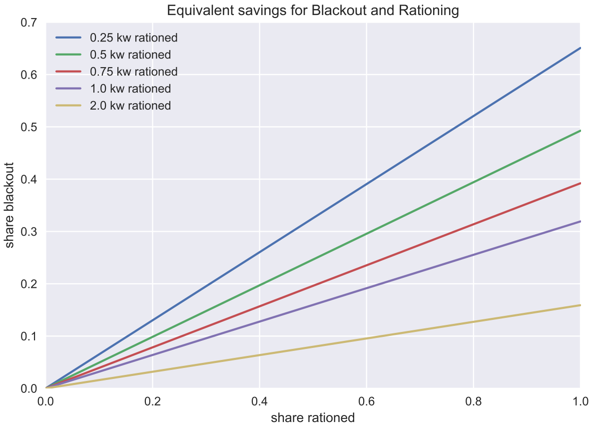
- κ is the limit per household (in kW).
- We consider $\kappa = \{0.0, 0.5, 0.75, 1.0, 2.0\}$.
- This allows us to trace an equivalence frontier for different levels of partial rationing.

- **Note:** This is a large estimate of the consumption of households after the smart-rationing event, assuming that they manage to stay at the limit, thus, conservative for rationing effectiveness.

Equivalence frontier

- All lines are below the 45-degree line: partial random rationing must select more households.
- Due to random assignment, also by construction linear (in expectation and precise due to LLN).

- Example: to equal a 10% full blackout, 20% of households need to be rationed at 0.5 kW.



Some notes

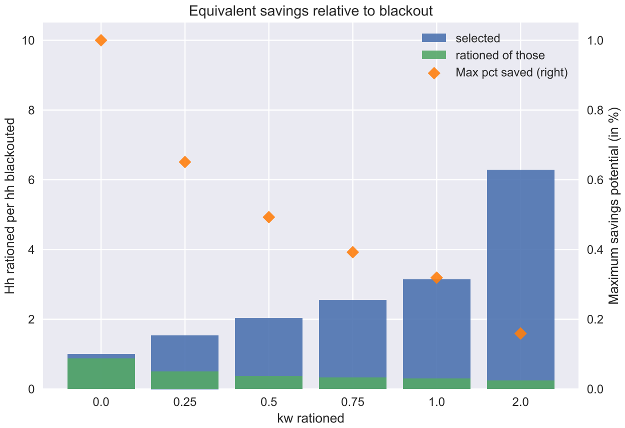
- Under partial rationing, not all households are partially rationed.
- We separate **effectively rationed** vs. **selected but unrationed** households.
- This is a useful concept to think about welfare and incidence.

- Under random rationing, conditional on a given κ, the *share* of "effectively rationed" and "selected but unrationed" remains constant.

- Also important to notice that there are natural limits to partial rationing: a 100% full blackout cannot be replicated by any partial rationing policy.

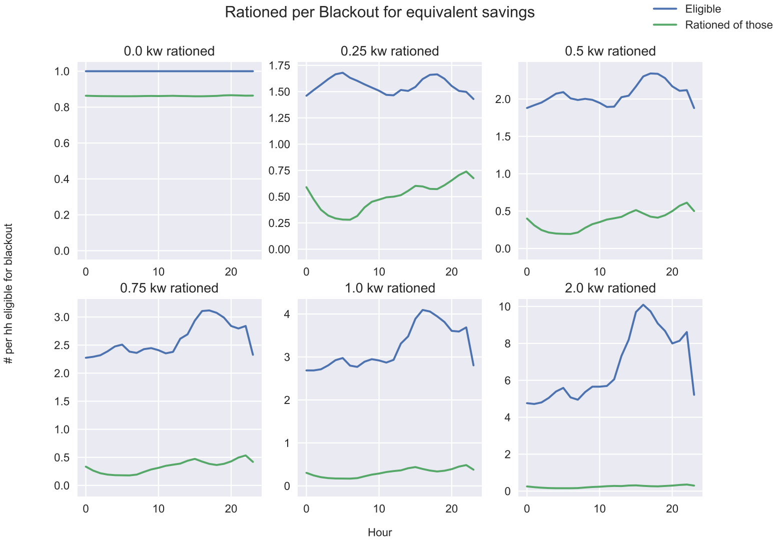
Impacted consumers and limits to partial rationing

- The more generous the partial rationing, the more people must be selected.
- However, rationing de facto affects fewer and fewer people.
- Note: this is an empirical question driven by the shape of consumption.
- Generalized partial blackouts can mimic large blackouts affecting *much fewer* people.



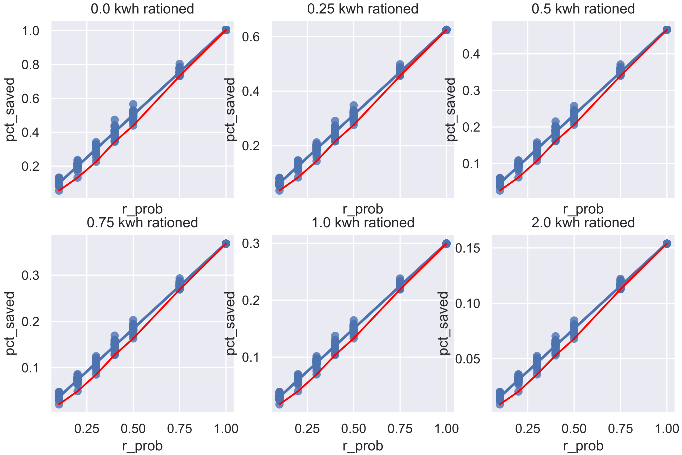
Impact of the rule depends on demand patterns

- Rationing policies have less impact at night.
- More homogeneous consumption across households during the night–it impacts the number of selected households and rationed households.



Geographical aggregation matters

- If rationing has to be done at the zip-code level, there is less randomization.
- Lower envelope to ensure α-equivalent blackout is achieved becomes more aggressive.
- Particularly relevant for small blackouts where only one or two zip-codes must be rationed.

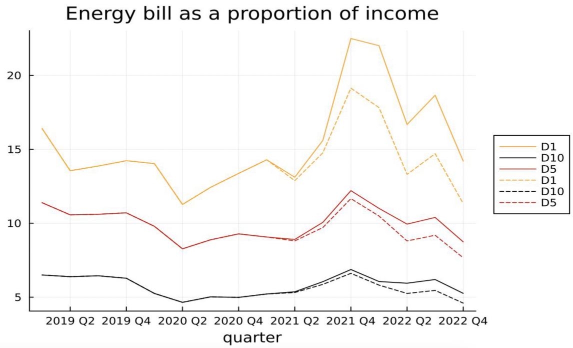


Adding heterogeneity

How are income and consumption correlated?

Should households have limits proportional to their typical consumption?

- Income + marginal declining utility of consumption suggests consumption could be socially less valuable, λ_i.
- However, high consumption reveals higher utility than other households (e.g., heating mode), ϵ_i.



Getting at ϵ_i and λ_i

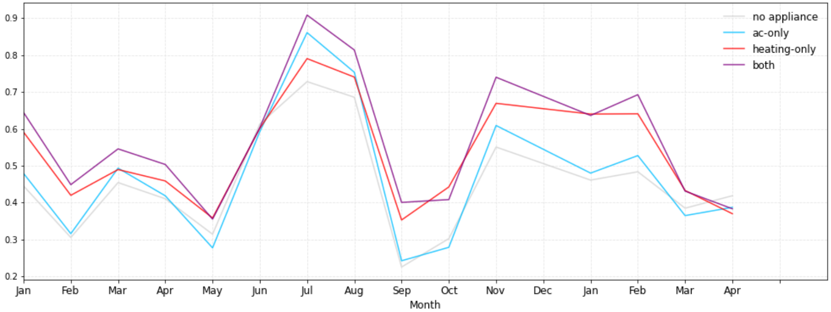
Both heterogeneous parameters are unobserved.

- We account for ϵ_i by focusing on HVAC mode (still residual heterogeneity remains).
- We account for λ_i by an estimating procedure exploiting zip-code income distributions.

Adding heterogeneity

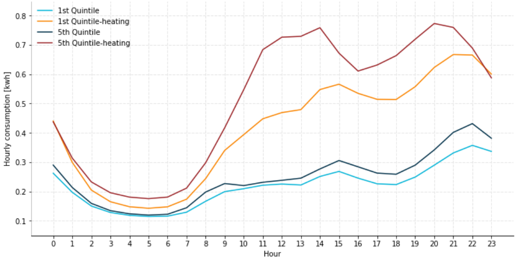
Inferring end-uses (Cahana et al.)

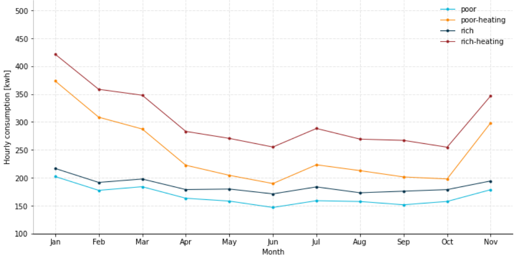
Mechanisms: appliance ownership



- We use algorithm to infer appliance ownership by households based on consumption structural breaks to local temperatures.
- We then treat appliance ownership as an explanatory variable in heterogeneity.
- Appliance ownership is very relevant to explain patterns, key driver behind within-income heterogeneity.

Mechanisms: appliance ownership and income impacts





- Poor households with electric heating disproportionally hurt.
- Appliance ownership can create bigger difference than income alone.
- Income still induces substantial differences conditional on appliance ownership.

Adding heterogeneity

Inferring income (Cahana et al.)

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 due to the lack of classification.

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).

Our approach: intuition

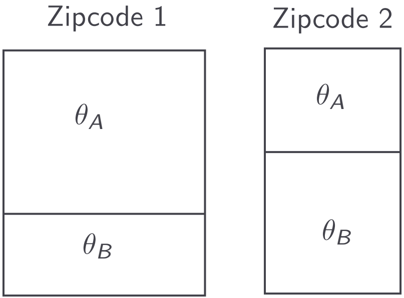
We propose an estimator in two steps:

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: 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

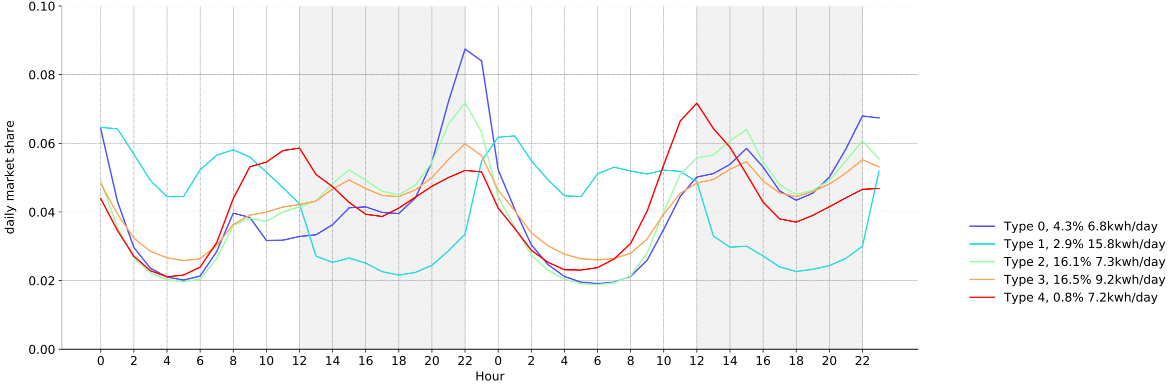


Figure: Flexible k-mean types with electric heating in a given province

Step 2: Non-parametric 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 Monte Carlo

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.

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

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

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

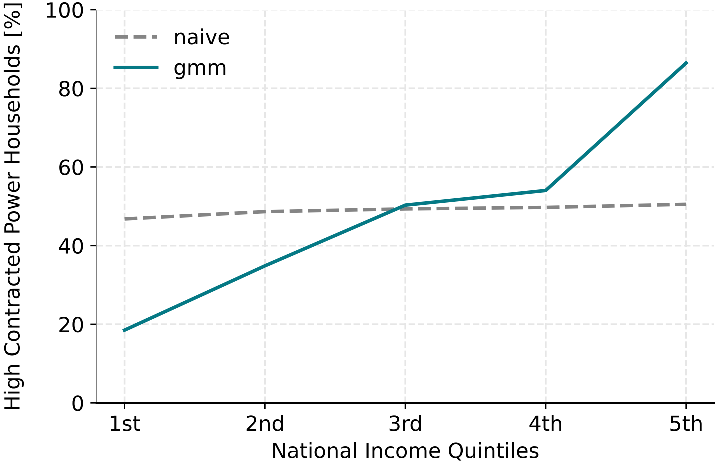
Step 2: Results

- 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.

▸ Monte Carlo

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.
- Provides suggestive evidence that on average high income types will be rationed more, but still subject to heterogeneity.



Adding heterogeneity

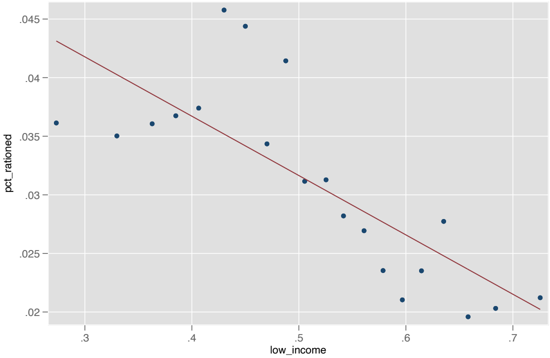
Preliminary findings without using the fancy individual measures...

Zip-code level results for now, preliminary

Disclaimer: Zip-code level results with "naïve" measures of income for now (and no appliances!).

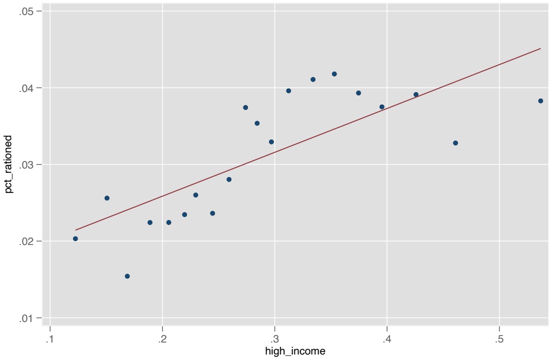
Low-income, less rationed *on average*

- Low-income share (Q1+Q2) predictive of less rationing.



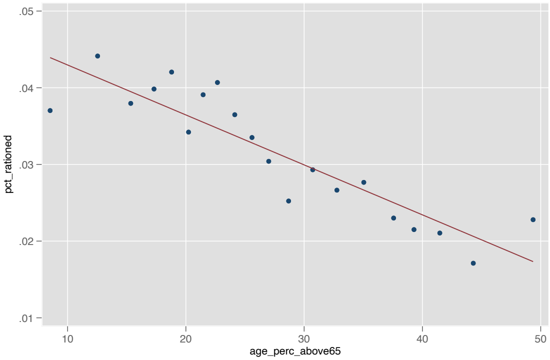
High-income, more rationed *on average*

- High-income share (Q4+Q5), the opposite.



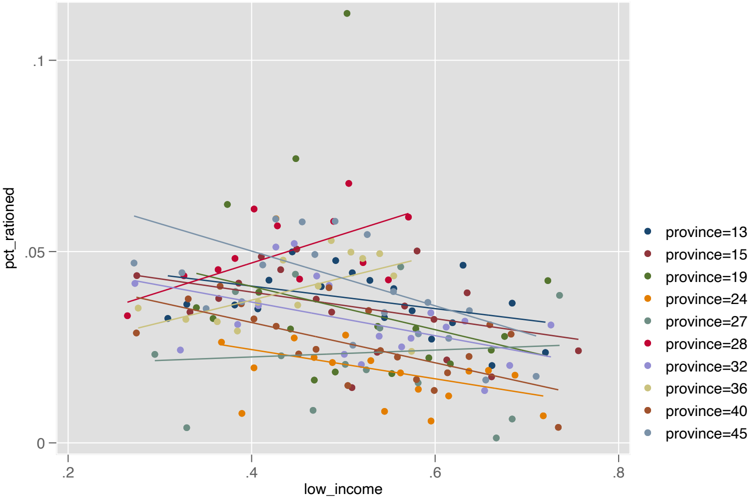
The elderly, less rationed *on average*

- The elderly share correlates negatively with the probability of rationing



Just starting to examine individually predicted heterogeneous effects...

- Even with zip-code level analysis, substantial heterogeneity across provinces.



Next steps

Many open questions to make this an implementable mechanism

- What are the smart rationing protocols that ensure $\alpha D(p) = D(p, \phi)$ (technical aspects, notions of uncertainty/reliability)?
  - How does it depend on the communication protocol, e.g., if only a portion $\beta_t \geq \alpha_t$ can be modified in time? $\rightarrow$ "smart rationing" not always optimal
  - What if only a region at a time can be reached?

- What are the impacts of smart rationing on households of different income levels?
  - Should rationing depend on consumption levels or contracted power? What are the dynamic incentives?
  - Should rationing depend on heating mode / season and other relevant aspects of electricity use? What are the investment incentives?
  - Should some of this be contractible via further increases in p? Why or why not?

Next steps

- Explore limiting factors to communication protocol: number of smart meters that can be reached at any time, minimum length of blackout for it to be optimal.
- Explore notions of welfare under rationing, budget constraints, and extreme events.
  - Incorporate appliance ownership and household-level income predictions from Cahana et al. (2023) $\rightarrow$ should be quite immediate once we fix our server problem!

Thank you.

Questions? Comments?

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Identifying equations with aggregate moments

We could consider the zip-code level moments:

$$
\begin{aligned}
&\sum_z \omega_z \sum_h \left(\overline{kwh}_{zh} - \sum Pr_z(\theta_n) kwh_h(\theta_n) \right)^2 \\
&\sum_z \omega_z \sum_k \left(Pr_z(inc_k) - \sum_{i \in z} \sum_n \eta_n^k Pr_z(\theta_n) \right)^2 \\
\text{s.t. } &\sum_k \eta_n^k = 1, \forall n.
\end{aligned}
$$

- 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

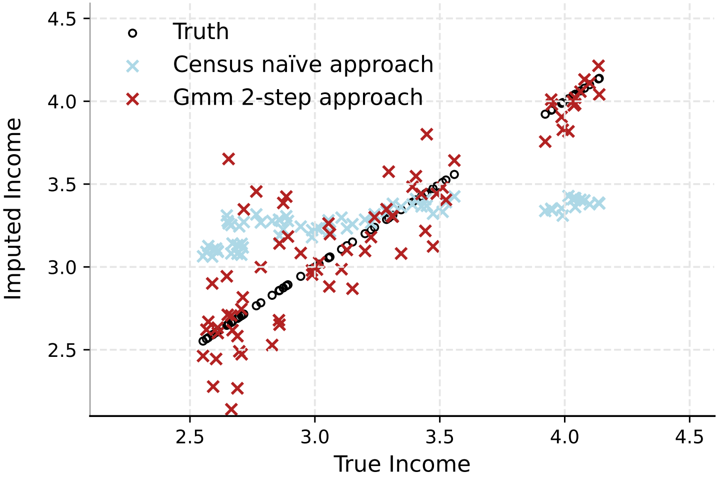
$$\sum_z \omega_z \sum_k \left(Pr_z(inc_k) - \sum_{i \in z} \sum_n \eta_n^k Pr_z(\theta_n) \right)^2$$

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

- 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

Monte Carlo: Income estimation



▸ Back

Monte Carlo: Policy impacts

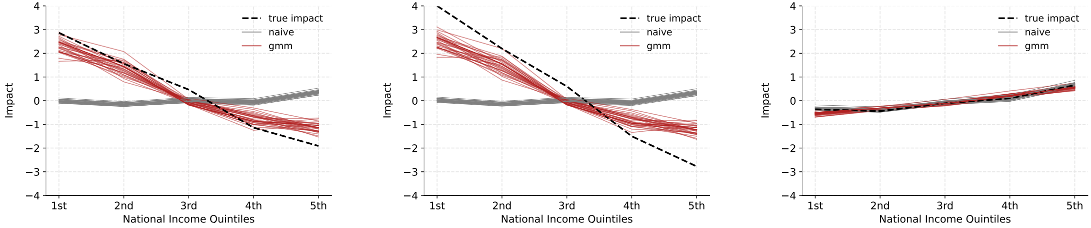
We perform a Monte-Carlo simulation to inform this discussion. Assume that the true data generation process behind the distributional impacts is governed by the following equation:

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

- 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

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Northwestern