

Empirical Methods for the Analysis of the Energy Transition

Slide Set 2

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2025/2026

Roadmap

I. The Economics of Electricity Markets

Overview of functioning

II. Dimension reduction techniques

Overview of methods

Reguant (2019)

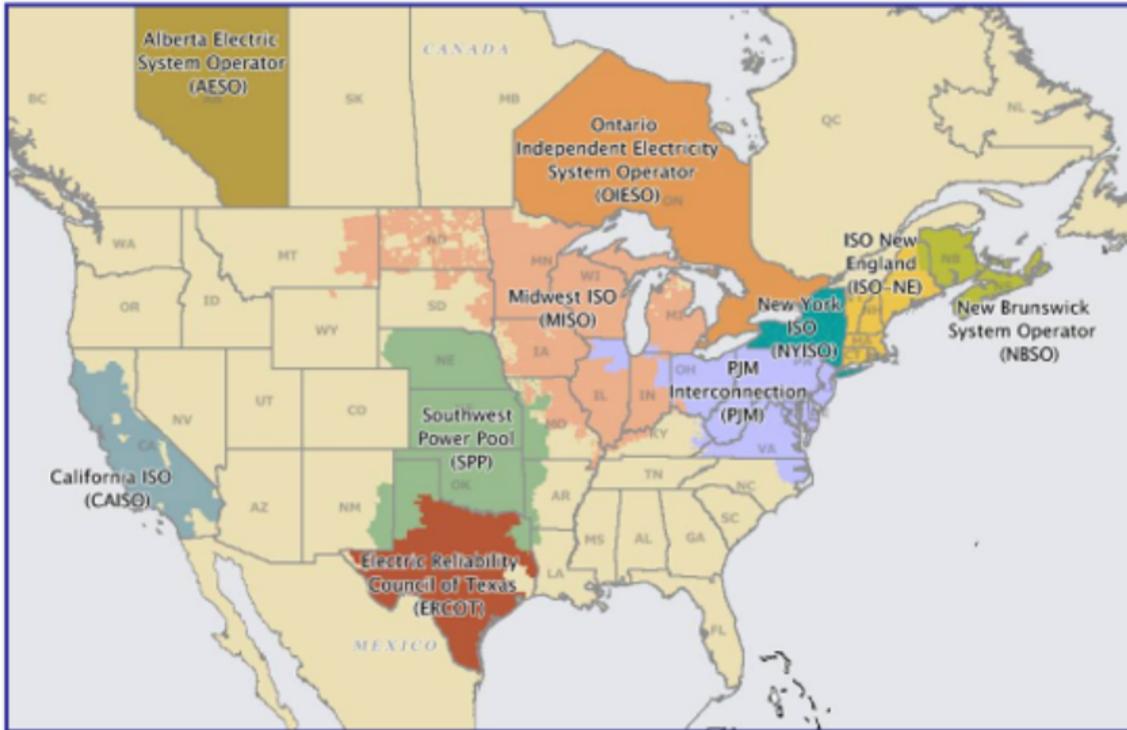
Mercadal (2021)

Clustering our Data (today)

Dispatching electricity markets

- Basic structure is typically designed around a wholesale market for electricity.
- Generators submit bids for electricity every day!
 - ▶ The complexity of these bids varies significantly across markets
 - ▶ Bid just one price for energy vs. include start up costs.
 - ▶ Have separate products for capacity and energy vs. only energy.
 - ▶ Etc.
- Demand also submits bids for electricity
 - ▶ Can be sloped or not
- Lots of other details that we will discuss
 - ▶ Price caps, “capacity markets”, etc.

US liberalized markets

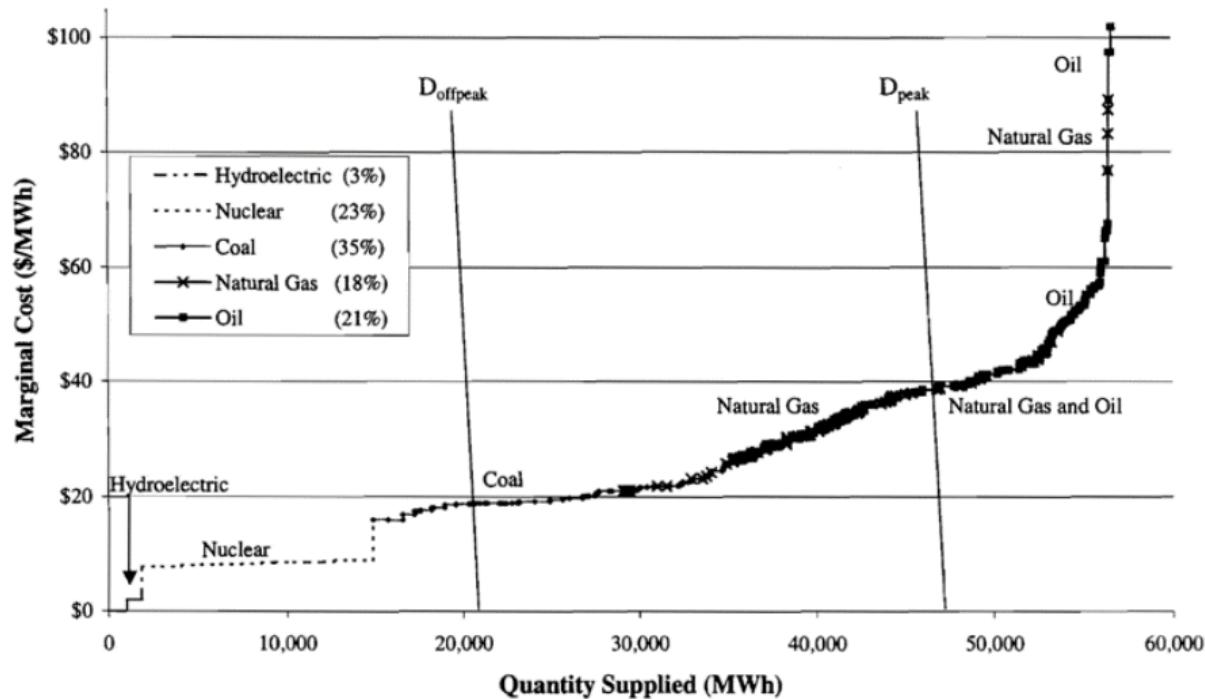


An example: bidding in Chicago

- Imagine a power company in Chicago.
- It will offer its power on a *daily basis* to the PJM market.
 - ▶ The typical offer will consist of several price-quantity offers for every hour of the day.
 - ▶ Example: at 8 am, the firm is willing to produce 200 MWh as long as the price is at least \$45/MWh with one of their plants.
- Many other companies will also offer their power at the PJM market.
- The system operator will collect all the bids from all the power plants.
- It will then cross supply with demand and determine the **marginal price** that all accepted units get.

A supply example for PJM

Figure 2. Competitive supply and demand in Pennsylvania-New Jersey-Maryland (PJM)



What do the bids represent?

- If the market is very **competitive**, the bids will tend to represent the **marginal cost of a given firm**.
- If there is **market power**, then firms might bid above their marginal cost, to increase prices.
- For the case of hydro power, bids will tend to represent the opportunity cost of water.
 - ▶ Note: the opportunity cost of water can be quite high for markets with limited hydro availability or during scarcity conditions (droughts).
- For renewables, bids will tend to be quite low or reflect market power considerations.

What about demand?

- Demand also participates in the market, although it is typically quite inelastic.
 - ▶ Final consumers do not directly demand power: the distribution utilities or retailers do it on their behalf.
- Big industrial consumers or commercial customers might participate in the market, and avoid consuming electricity if prices are too high.
 - ▶ Much more elastic, extensive contracting that may require firms to respond in moments of high prices.
 - ▶ Some big industrial producers participate directly as generators (co-generators, direct generation).

Nodal vs. zonal markets

- The crossing of demand and supply may or may not account for bottlenecks in the electricity grid.
 - ▶ **Nodal markets:** Typical in the US, each node in the grid has its own price (thousands of different marginal prices every hour).
 - ▶ **Zonal markets:** Typical in Europe, large areas all share the same price, e.g., Spain, Portugal, four regions in Germany, etc.
- Several studies have highlighted the advantages of having more granular prices (Green, 2007; Joskow 2008; Holmberg and Lazarczyk, 2015; Graf et al., 2020).

Day-ahead vs. real-time markets

- The crossing of demand and supply may happen at different points in time.
 - ▶ **Day-ahead markets:** A few hours in advance, a preliminary schedule of what will happen (most commonly with a financial commitment).
 - ▶ **Real-time markets:** A few minutes before the dispatch happens (e.g., 5 to 30 min).
- In many areas, consumers pay the day-ahead price (or a forward price that uses the day-ahead as reference).
- Therefore, a lot of focus goes into day-ahead markets, which clear the most volume.
- After the real-time market, last-minute adjustments are handled with automatic decisions (but still receive compensation ex-post).
- However, some markets do not have a day-ahead market and clear the market in real-time and with bilateral contracts.

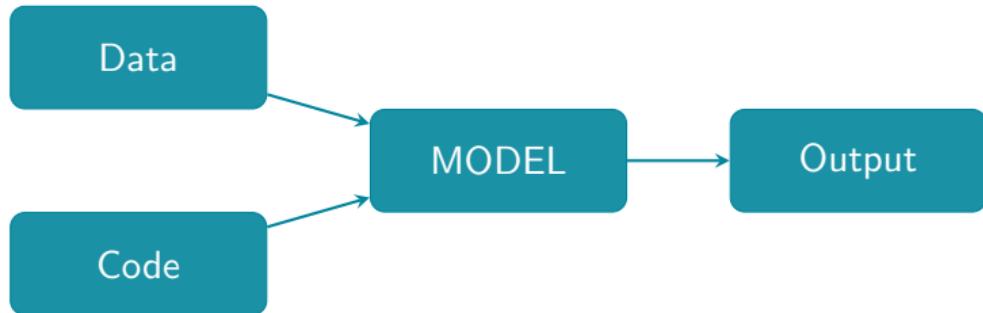
In practice, much more complex

- As we discussed, demand and supply need to balance at all time.
- Electricity markets tend to have a day-ahead auction to plan in advance.
 - ▶ Tends to clear the largest economic volume.
- But there are many follow up markets and products to ensure balance in real time.
 - ▶ Very complicated, and often market-specific!
 - ▶ Some of these markets are related to congestion.
- Electricity operators solve **complex problems every hour/half-hour** to determine the dispatch allocation over a **wide-range of products** (energy, reserves, transmission rights, etc.).

Modeling economics in electricity markets

- At its heart, all electricity market models have firms/technologies and information about demand (as a curve or fixed) to find the best allocation that ensures demand = supply (called **economic dispatch**).
- If the model takes into account discrete decisions about which power plants to turn on/off, it is called a **unit commitment problem** (more difficult to solve).
- Depending on the question at hand, the electricity markets in economic analysis are modeled abstracting away from many features.
- E.g., big long-run policy questions like climate policy might be answered with a simplified version of the market.
- Depending on the question, some more detailed features need to be brought back (e.g., transmission congestion regarding renewable expansion).

Building models of electricity markets



- Model used to simulate impact of alternative configurations, profitability of investments, impacts of climate policies, etc.
- Does output for baseline match data? If not, do we need to expand code?
 - ▶ Not always, keep an eye on things that are important to our question and that we might not be matching well. A model is a simplification of a complex reality.

Building models of electricity markets

Common elements and options

■ Supply side

- ▶ Competitive (cost curves) or strategic (firms max profit)
- ▶ At tech, firm, or plant level
- ▶ With or without geography (transmission, usually with direct current approximation)
- ▶ With or without startup costs (non-convexities)

■ Demand side

- ▶ Inelastic or responsive
- ▶ Granular or aggregated

Horizon and temporal linkages

■ Level of aggregation

- ▶ Hourly, daily, etc.

■ Links between hours

- ▶ Every hour independent from each other vs. temporal linkages (important for storage or startup costs)

■ Horizon of choice

- ▶ Day-to-day operations
- ▶ Seasonal water storage
- ▶ Capacity expansion model (investment)

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Reguant (2019)

Mercadal (2021)

Clustering our Data (today)

Outline

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Dimension reduction techniques

- Electricity markets are highly complex.
- Electrical engineers often work with representative cases to make their contributions comparable, but they have limited empirical relevance.
- When analyzing one market in detail with historical data, analysis can become slow.
- Slow computations can lead to limited sample sizes (e.g., three months) or limited counterfactual/econometric analysis (e.g., no standard errors, limited policy analysis).
- Machine learning techniques can be used to reduce the size of the data.

Clustering of different dimensions

- Dimension reduction techniques can be used in many ways to reduce the computational demands of electricity market models.
- Today: application simplifies the time dimension.
- Other examples:
 - ▶ Types of consumers with highly dimensional smart-meter data (see later in the course, as in Cahana et al, 2022).
 - ▶ Geographical granularity to simplify nodal market data (e.g., see Mercadal, 2021; Gonzales, Ito and Reguant, 2022).
 - ▶ Types of production units to simplify technologies in the model.

The k-means clustering algorithm

- Input data: matrix where each column represents a “unit” that we want to classify, rows are the number of observations per unit.
 - ▶ Examples: what are the rows? what are the columns?
- Tuning parameter: a parameter or set of parameters to decide how much granular the clusters will be (e.g., directly choosing number of clusters n).
- Output: an assignment of units to clusters, cluster centers (representative observations) and cluster weights (how important a cluster is).

Reguant (2019)

- **Question:** Examine current practice of charging renewable costs mostly to residential sector.
- **Data:** California market data to calibrate a stylized model of an electricity market with 3 types of end users (I, C, R).
- **Methods:** Ramsey pricing theory with externalities, computational tools for quant assessment.
- **Finding:** Charging residential HH cannot be justified by Ramsey pricing unless industrial sector leaks.

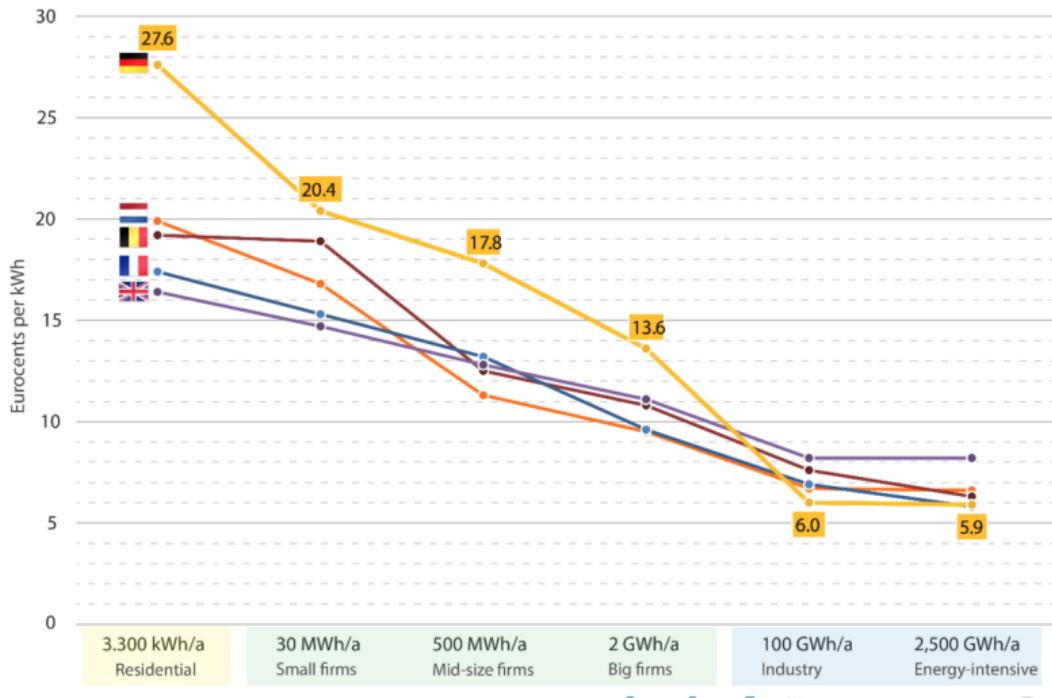
Policy and Tariff Design

- Previous work on large-scale renewable policies tends to model wholesale demand for electricity (Fell, 2013; Wibulpolprasert, 2014).
- Implementation of wholesale renewable policies can have impacts to electricity consumption also through its impacts on retail tariffs.
- Example:
 - ▶ If RPS, how do consumers pay for it through retail rates?
 - ▶ If production subsidies are used, how is the revenue raised?

Small German power consumers massively cross-subsidize industry

Electricity prices by consumer groups and annual consumption in 2013

Source: PwC, "Prijsvergelijking elektriciteit" for Dutch Economics Ministry, 2014



Source: energietransition.de

Table 4: RPS impact by retail sector

	Effect of Renewable Portfolio Standards on Electricity Prices, by Sector				
	Total (1)	Total (2)	Residential (3)	Commercial (4)	Industrial (5)
$\delta_1: 1(RPS)$	0.714** (0.298)				
$\delta_1 + 5\delta_3$		1.119**	1.499***	0.827	0.681
p-value		0.022	0.003	0.109	0.107
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	1224	1224	1224	1224	1224

Notes:

- 1) Coefficient estimates for states with data seven years before and five years after RPS effective date.
- 2) Standard errors clustered at the state level.
- 3) Asterisks denote significance at the 90% (*), 95% (**), and 99% (***) levels

Source: Greenstone and McDowell, 2016.

Proposed approach

- Integrate two elements:
 - ▶ Supply-side model with endogenous dispatch and capacity.
 - ▶ Demand-side model for residential, commercial and industry sectors, with tariff design.
- Use framework to simulate:
 - ▶ Carbon tax
 - ▶ Feed-in tariff/production subsidy
 - ▶ RPS/Standards

Key: Renewables mostly about fixed capital costs. How do we recover their costs?

→ Affects *both* efficiency and distributional implications.

Stylized overview of the model

Demand

Demand Industrial:

$$D_{rt}^I(P_{rt}, X_{rt}; \theta^I)$$

Demand Commercial:

$$D_{rt}^C(P_{rt}, X_{rt}; \theta^C)$$

Demand Residential:

$$D_{irt}^R(P_{irt}, X_{irt}; \theta^R)$$

Supply

$$\min_{q, K} \quad \sum_g \left(F_g K_g + \sum_t C(q_{gt}, K_g, \tau) \right)$$

$$\text{s.t.} \quad \sum_g q_{gt} = \sum_r \left(D^I + D^C + \sum_i D^R \right)$$

Policy and Regulation

Which renewable policy? How are prices set at retail?

Renewable policies considered

- 1 **Carbon tax:** Puts a price τ on carbon. Not necessarily about large-scale renewables.
- 2 **Feed-in tariff/subsidies:** Gives a flat rate per MWh of renewable production. Often technology specific. Also common to have subsidies at the margin, on top of the market price.
- 3 **Renewable Portfolio Standard:** Sets a percent goal in renewable generation, typically at the utility level. Trading of certificates to induce compliance and reveal market price. Similar in spirit to subsidies, but utilities are directly responsible to charge these costs.

Adding retail tariffs...

- Some of these policies generate revenues or policy costs that are not accounted for by the model.
- Typical partial equilibrium assumption is to treat them as lump-sum transfers, maybe with a multiplier (large body of work looking at how they might impact general equilibrium).
- In practice, some of them might be priced directly into electricity consumption, e.g., with environmental charges to the price of electricity.
- Two extreme cases:
 - ▶ lump-sum charges, no multiplier
 - ▶ full cost recovery at the margin within the electricity sector

Retail tariffs considered

- 1 Flat or real-time plus lump-sum:** assumed to be allocated equally across sectors.
- 2 Flat or real-time plus marginal fee:** assumed to be allocated equally across sectors.
- 3 Ramsey:** potential reallocation of costs across sectors (only for environmental fixed costs).

Can Ramsey prices justify shifting the burden on residential consumers vs. industrial consumers?

Theory detour on Ramsey prices

Typical Ramsey formula:

$$\frac{p_s - c}{p_s} = \frac{\lambda}{1 + \lambda} \frac{1}{\epsilon_s},$$

- Given that industrial consumers are more elastic, serves as a justification for the type of pricing that we see.
- Burdensome on consumers, but potentially still efficient.
- Importantly, these are optimal Ramsey prices ignoring the presence of an externality.

Theory detour on Ramsey prices

Adding externality to the Ramsey formula:

$$\frac{p_s - c}{p_s} = \frac{\lambda}{1 + \lambda} \frac{1}{\epsilon_s} + \frac{1}{1 + \lambda} \frac{e_s \times SCC}{p_s},$$

- No longer as clear whether Ramsey formula is optimal or prescriptive in its standard form.
- Can depend substantially on marginal emissions rate, e_s .
- If consumers see too low prices due to renewable subsidies, possible to justify charging more to the *more* elastic.
- As long as they are also elastic *in terms of emissions*, i.e. no leakage.

Ramsey prices considered

- 1 **Ramsey:** Ramsey prices that recover costs of renewables and maximize welfare (ignoring externality).
- 2 **Ramsey enviro:** Ramsey prices that recover costs of renewables and take into account externalities.
- 3 **Ramsey enviro + leak:** Ramsey prices when emissions reductions in the industrial sector leak (decoupling between electricity response and emissions response).

Note: For all of them, additional markups exactly cover renewable costs. Of course, in practice many other reasons why retail prices are above marginal cost.

Data

Use data from California to build a simulation framework, 2011-2015.

- Load data

- ▶ Hourly, by utility and customer class (dynamic load profiles).
- ▶ Monthly, by utility, zipcode and customer class.

- Generation data

- ▶ Generation by type and imports, hourly.
- ▶ Wind and solar potential based on actual production.
- ▶ Combine with assumptions on marginal and fixed costs.

Demand

- Use hourly demand by class to account for correlation between demand and renewables.
- Make assumptions about elasticity of different sectors (residential, commercial, industrial).

Sector	Elasticity	Share
Residential	0.15	41%
Commercial	0.30	45%
Industrial	0.50	14%

Imports

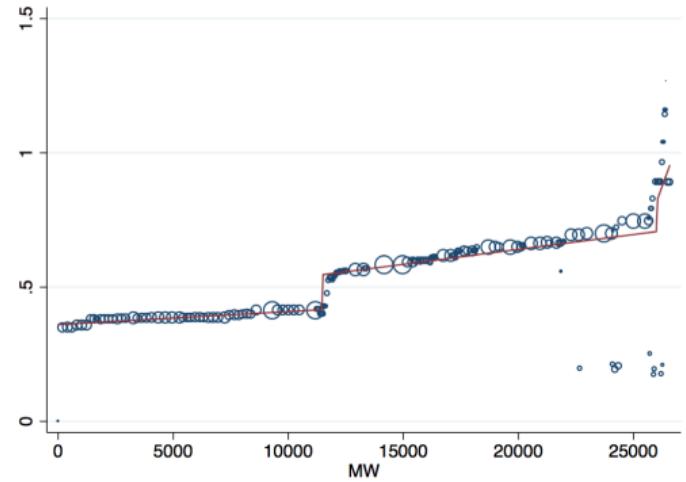
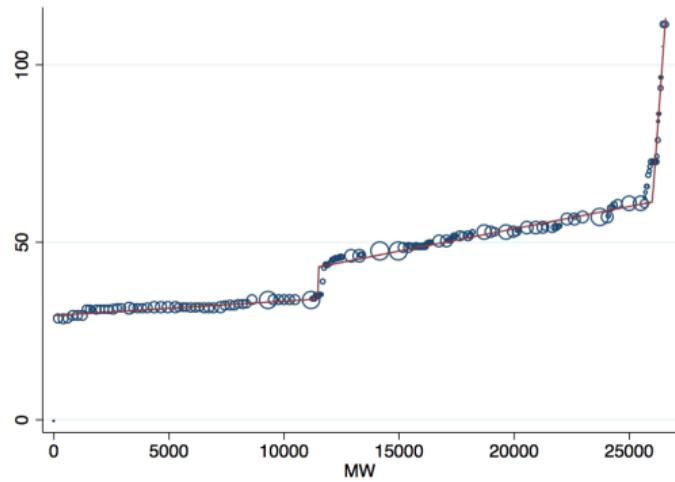
- Estimate import supply from data.

	(1) Log Imports	(2) Log Imports	(3) Log Imports
Log Price	0.3103 (0.0055)	0.2902 (0.0037)	0.2912 (0.0032)
Observations	43,364	43,364	43,364
Weather controls	Yes	Yes	No
Year and Month FE	No	Yes	No
YearXMonth FE	No	No	Yes

Generation

- Construct incumbent supply curve based on existing generation mix for thermal plants and emissions rates.
- Take as given hourly hydro and nuclear production.
- Use EIA construction cost data from new investment to calibrate costs of new plants.
- Researchers are also starting to use k-means to simplify the number of power plants. In this application, not much machine learning was needed...

Generation supply curve and emissions rate fit



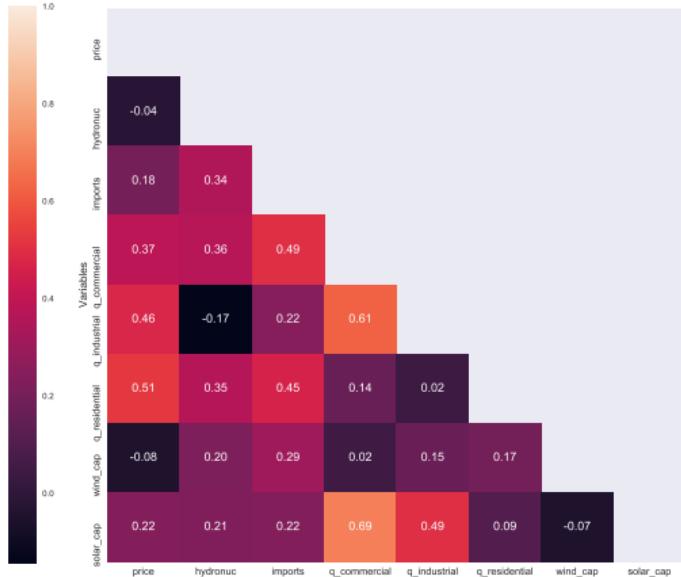
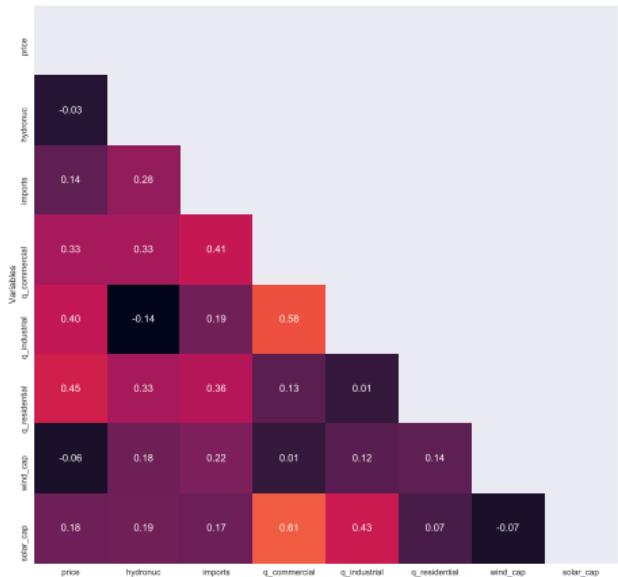
Renewables

- Renewable output by category from 2013 onwards.
- Used to generate different renewable profiles (distribution of utilization factors during the day and over the seasons).
- Model has only a single region, so variation is limited to different technologies.
- Investment costs based also on EIA realized cost data.

Computational use of k-means

- I use the data to build a model with long-run investment in new gas, wind and solar.
- Data based on several years (up to 43,000 hours in the sample).
- I have found it very practical to use clustering methods to reduce the dimensionality of the data.
- It works really well, and I very much recommend it!

Making simulations tractable



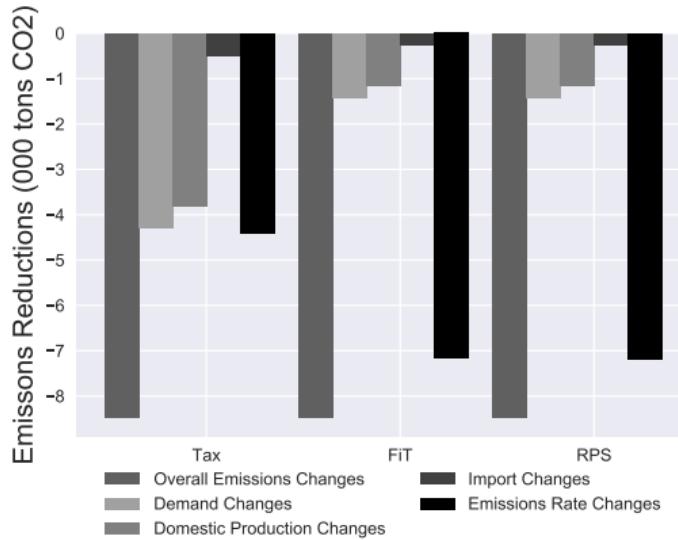
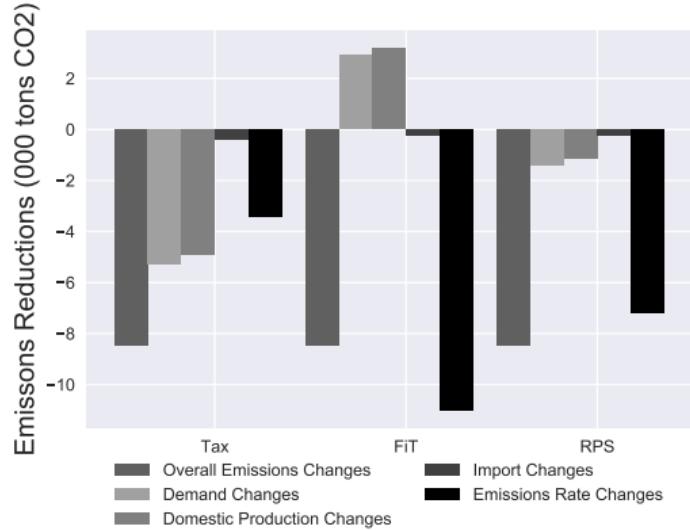
Efficiency and Distributional implications

- Do policies induce the right investment?
- How is this reflected in abatement?
- Who are the winners and losers?
- How much does it all change as the cost of renewables is passed through to consumers?

Efficiency decomposition

- Reduction of emissions held fixed across policies.
- Decompose source of reductions between:
 - ▶ Demand/supply changes
 - ▶ Emissions rate becoming cleaner
- Two sets of results:
 - ▶ Carbon tax, subsidies, and RPS
 - ▶ Carbon tax with marginal rebate, subsidies charged at the margin, and RPS

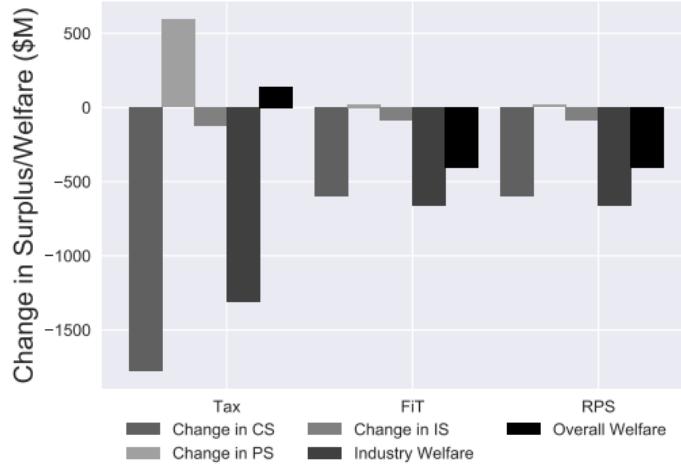
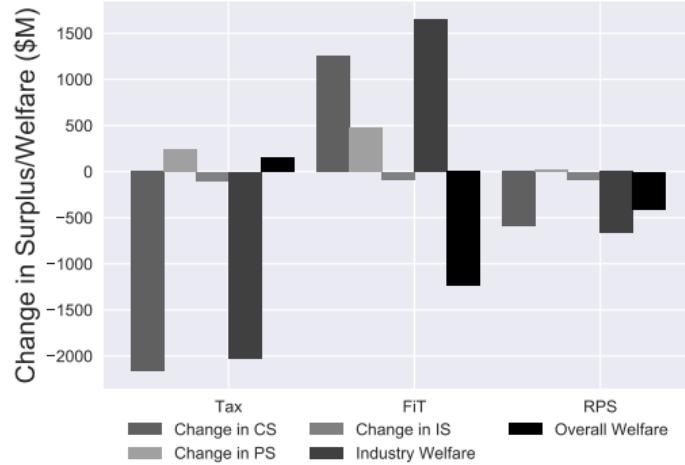
Efficiency implications with and without demand charges



Distributional implications

- Who are the winners and losers?
- How does it depend on retail pass-through?
- For now, look at producers vs consumers:
 - ▶ Consumer surplus
 - ▶ Producers surplus
 - ▶ Import surplus

Distributional impacts with and without demand charges



Getting at sectoral redistribution

- I consider three different Ramsey scenarios:
 - 1 Standard Ramsey formula (ignores externality).
 - 2 Optimal Ramsey taking into account externality for welfare.
 - 3 Optimal Ramsey when industrial emissions leak.
- Also important to consider different levels of renewables subsidies.
- Helps consider situations far from first best, as Ramsey pricing can be used as corrective tool.

Results for Ramsey pricing

Low renewable target – FiT \$107

	Prices			Δ Surplus			
	Res.	Com.	Ind.	Res.	Com.	Ind.	Δ W
Flat	40.84	40.84	40.84	-0.05	-0.09	-0.14	-1028.86
Ramsey	45.19	38.72	36.92	-0.08	-0.06	-0.05	-1047.02
Ramsey Enviro	39.51	41.14	43.14	-0.04	-0.09	-0.19	-1026.54
Ramsey Enviro Leak	40.86	43.14	34.65	-0.05	-0.12	-0.00	-1044.23

Ramsey prices are not welfare improving

High renewable target – FiT \$148

	Prices			Δ Surplus			
	Res.	Com.	Ind.	Res.	Com.	Ind.	Δ W
Flat	59.19	59.19	59.19	-0.18	-0.33	-0.51	-3702.68
Ramsey	76.48	47.50	47.19	-0.29	-0.18	-0.28	-3641.29
Ramsey Enviro	69.78	52.42	47.80	-0.25	-0.25	-0.29	-3611.35
Ramsey Enviro Leak	72.36	52.47	41.73	-0.26	-0.25	-0.16	-3622.08

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Ramsey prices with externality reverse!

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Subject to no leakage assumption

High renewable target – FiT \$148

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If prices above first best, then traditional qualitative result holds

Getting at sectoral redistribution - insights

- Ramsey pricing can be detrimental to the extent that it prevents reductions from most elastic sectors.
- Ramsey pricing accounting for externalities prescribes prices that are closer together (if renewable goal large enough), or even reversed in the presence of too modest targets (increase reductions of electricity instead of avoiding them).
- All of this crucially depends on whether elasticity of electricity is correlated with elasticity of emissions:
 - ▶ If electricity-elastic sectors are not truly reducing emissions, then a further motive to strengthen Ramsey result.

Conclusions

- Paper builds a model to understand the trade-offs between charging different types of customers.
- I find it is key to understand whether elasticity is for electricity or for emissions.
 - ▶ If elasticity is for emissions, Ramsey undoes potential environmental goal.
- Model is silent about distributed generation as it doesn't have household granularity, but also a big part of the discussions on equity.

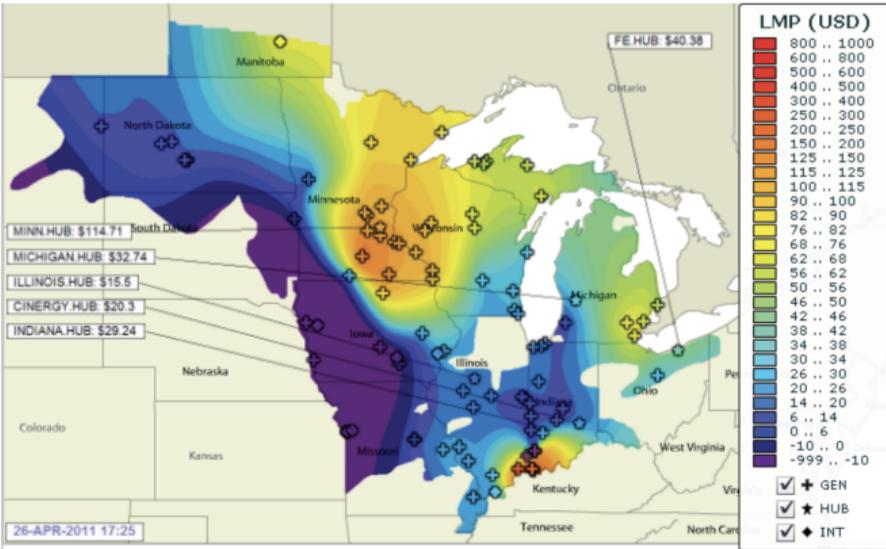
Another example: Mercadal (2021)

Dynamic Competition and Arbitrage in Electricity Markets: The Role of Financial Players[†]

By IGNACIA MERCADAL*

I study the effects of financial players who trade alongside physical buyers and sellers in electricity markets. Using detailed firm-level data, I examine physical and financial firms' responses to regulation that exogenously increased financial trading. I show that the effect of speculators on generators' market power depends on the kind of equilibrium they are in. I develop a test of the null of static Nash equilibrium and reject it. To implement the test, I present a new method to define markets using machine-learning tools. I find that increased financial trading reduced generators' market power and increased consumer surplus. (JEL C45, D83, G13, L13, L94, L98, Q41)

How clustering plays a role? Nodal markets can be a challenge



Source: MISO

Proposed solution: infer a finite number of independent markets

- Idea: prices should move together if firms are in the same market (Stigler and Sherwin, 1985).
- Group firms according to price correlation.
- How? Hierarchical clustering (machine learning tool).
- Clustering algorithm requires to specify the number of markets.
 - ▶ Use bid data to select “best fitting” market definitions.
 - ▶ Clear each independent market using bids submitted at those locations.
 - ▶ Compare simulated and observed prices.

Clustering comparison to previous paper

- In previous paper, k-means clustering was used in a somewhat ad-hoc fashion: number of clusters chosen exogenously: enough clusters to produce equivalent results but in an informal manner.
- Here, Mercadal (2021) uses hierarchical clustering to determine the number of relevant markets in a nodal market.
- She disciplines the model by adding an additional loop searching for the number of clusters that best fit the data.

Some challenges with clustering approach

- Clustering done for each hour-month combination of the sample to reflect congestion conditions.
- But congestion patterns can change before and after a policy takes into effect.
- This approach can limit the counterfactual analysis if one were to build a computational model.
- Specialized software can also create a simplified representation of complex grids.
- We will also review an application to Chile using k-means clustering to create a simple grid.

Concluding remarks

- Clustering techniques can be very useful in many settings to reduce complexity.
- Here we explored applications to electricity reducing number of periods (which can often be repetitive), nodes, and number of power plants.
- Clustering is not innocuous, need to think about what we need to keep track of:
 - ▶ Time interactions?
 - ▶ Particular time periods?
 - ▶ Firm level heterogeneity?
 - ▶ Relevant geographical areas?
 - ▶ Implications for counterfactuals?
 - ▶ Etc.

Today's application paper

- We will be building the simplest version of an electricity market with data from Reguant (2019).
- Paper has investment and retail equilibrium prices, but today we will focus on simple short-run model.
- Analogous to models in Bushnell, Mansur, and Saravia (2008) and the second stage of Ito and Reguant (2016), but without market power.
- **Main goal** is to get some familiarity about how these models are formulated as mathematical programming objects and how they are built in Julia.

Equilibrium model for this paper

■ Model needs to solve for:

- ▶ Supply and demand choices, market and retail prices.
- ▶ Investment level of each technology. This step makes model more expensive, cannot solve each hour fully separately.
- ▶ Retail prices that include subsidies to renewable power, with taxes that can be split in different ways and designed optimally. This step makes the problem more expensive as well, not nice equations, need to solve iteratively many times.

■ How to simplify the model?

Simplifying the data and the model

Simplifying the data

- You will learn how to use k-means clustering to vastly reduce the number of hours that are used.
- Results are still very similar, but it takes a much shorter time.

Simplifying the model

- The model will be simple: supply aggregated at the technology level, without hydro modeling.
- Demand will be aggregated (one category today, three in the paper).
- Model will treat firms as competitive, offering their power at their marginal cost (social planner equivalent).

Simplifying the data

- Key idea is to identify “representative hours” with some “weights” for how important each hour or location is.
- These representative hours can then be used in the model (together with the weights) to ensure that the model is representative (but runs much faster).
- Note: The hourly clustering is easiest, but it treats each hour as independent. Depending on the problem, clustering days or weeks might be better.
 - ▶ E.g., for a short-term battery problem, need to look at battery behavior for at least three days; for hydro, very difficult to cluster due to seasonal rains and long-term storage.

The k-means clustering algorithm in practice

Let's try it out!

Next class

■ Supply I

- ▶ Modeling the electricity market