Empirical Methods for the Analysis of the Energy Transition

Slide Set 3

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IDEA

Fall 2024

Outline

I. Re-cap

Clearing a simple model

- Clearing in electricity markets
- Modeling with JuMP

Dimension reduction techniques

Empirical examples

- Reguant (2019)
- Mercadal (2021)

I. Re-cap

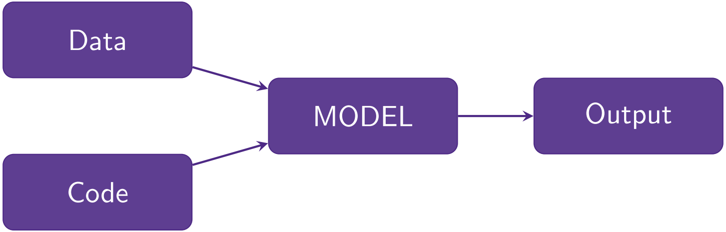
Modeling economics in electricity markets

- 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 committtment 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)

Market power modeling

- We have focused on a Cournot formulation of electricity markets.
- Strategic players compete in quantities while taking the competitive supply curve and imports as given.
- Alternative representations are models of supply function equilibria (SFE) and models of conjectural variations, also agent-based formulations not uncommon in electrical engineering.
- The Cournot formulation is best for counterfactual modeling (in my opinion and experience). We will see today that it can be formulated as a set of first-order conditions.

Clearing a simple model

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Auctions in electricity markets

- To decide supply and demand, the centralized planner clears an auction.
  - Suppliers submit willingness to produce.
  - Consumers submit willingness to pay.

- Planner maximizes the net surplus based on these offers, sometimes considering **constraints** due to the complexities of electricity generation and delivery.
- This is not an abstraction, every single day, several times, electricity market operators are solving these optimization problems.

Inputs to the auction

- At the very least:
  - Demand curve.
  - Supply curve.
- Often:
  - Some additional rules and constraints.

Our goal today

- Our goal today is to create these inputs based on the data from last week (CAISO).
- We then need to solve for the objective function.

$$\begin{aligned} \max_{q} \quad & S(q) - C(q) \\ s.t. \quad & \text{demand=supply,} \\ & \text{other constraints.} \end{aligned}$$

- We solve for the quantities that maximize the gross surplus S minus the costs of generation C.
- Implicitly or explicitly, there is a price to electricity consumption.

Outline

Solving the model with JuMP

- JuMP makes the formulation of electricity dispatch models relatively seamless.
- One code to express the model, one can then call several solvers depending on the needs.
- I will give you a “hint” of what JuMP can do.
- Example of highly configurable electricity expansion model based on Julia + JuMP:
  - https://github.com/GenXProject/GenX
  - https://netzeroamerica.princeton.edu/

Ingredients to a mathematical model

- Parameters/Inputs
- Variables
- Constraints
- Objective function
- Sense of the objective function
- The solver we want to use

Note: In mathematical programming, the terms ‘variables‘ and ‘parameters‘ are used the opposite way as in econometrics! Variables: what we are trying to solve. Parameters: what we already have, the inputs.

Solvers

- There is an array of optimization resources that are tailored to be particularly efficient in certain problems.
- Developed/used more in engineering and operations research.
- Examples:
  - Quadratic programs
  - Linear programs with integer variables
  - Nonlinear programs with integer variables
  - Programs with complementary conditions

Steps to building model

1. Gather data
2. Simplify data
3. Build first model
4. Improve model

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 tin 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.

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.

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 chosing number of clusters n).
- Output: an assignment of units to clusters, cluster centers (representative observations) and cluster weights (how important a cluster is).

Empirical examples

Reguant (2019)

The Efficiency and Sectoral Distributional Impacts of Large-Scale Renewable Energy Policies

Mar Reguant

Abstract: Renewable energy policies have grown in popularity. Given that renewable energy costs are mostly nonmarginal, due to the large presence of fixed costs, there are many different ways to implement these policies in both the environmental design and retail pricing margins. I show that the efficiency and distributional implications of large-scale policies crucially depend not only on the design of wholesale policies to incentivize renewables but also on how the costs of such policies are passed-through to consumers. Using data from the California electricity market, I develop a model to illustrate the interaction between large-scale renewable energy policies (carbon taxes, feed-in tariffs, and renewable portfolio standards) and their pricing to final consumers under alternative retail pricing schemes (no pass-through, marginal fees, fixed flat tariffs, and Ramsey pricing). I focus on the trade-off between charging residential versus industrial consumers to highlight tensions between efficiency, distributional, and environmental goals.

JEL Codes: L51, Q42, Q58

Keywords: renewable policies, efficiency, distributional impacts

Motivation

- Renewable policies have grown in popularity across states in the US, and also worldwide.
- The costs and benefits from renewable policies are unevenly distributed across several margins.
  - Stakeholders.
  - Regional heterogeneity in resources (and correlation of resources with demand).
  - Heterogeneity across consumer types, e.g. residential vs commercial.
  - Heterogeneity in consumption, e.g., across income groups.

Goal: Quantify (some of) these distributional impacts under alternative policy assumptions, focusing on redistribution across sectors (customer classes). *Who to charge?*

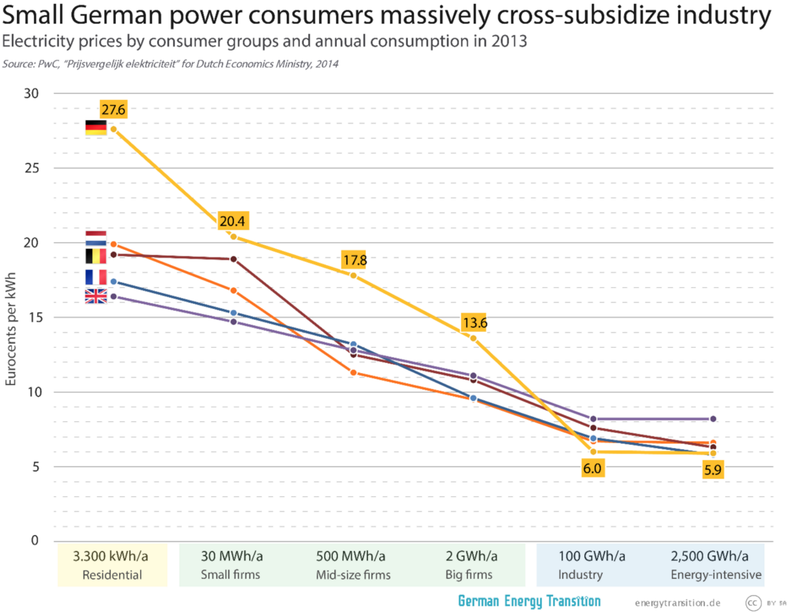
- Carbon tax, feed-in tariff, production subsidy and renewable portfolio standards (RPS).
- We will do much more about distributional effects later in the course.

Policy and Tariff Design

- Previous work on large-scale renewable policies tends to model wholesale demand for electricity (**??**).
- 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?

Feed-in tariffs do not necessarily depress *all* prices



Source: energietransition.de

Northwestern

Also in the US

Table 4: RPS impact by retail sector

Effect of Renewable Portfolio Standards on Electricity Prices, by Sector

	Total (1)	Total (2)	Residential (3)	Commerical (4)	Industrial (5)
δ_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?

$\rightarrow$ Affects *both* efficiency and distributional implications.

Stylized overview of the model

Demand

Demand Industrial:	$D^I_{rt}(P_{rt}, X_{rt}; \theta^I)$
Demand Commercial:	$D^C_{rt}(P_{rt}, X_{rt}; \theta^C)$
Demand Residential:	$D^R_{irt}(P_{irt}, X_{irt}; \theta^R)$

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:

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

- 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 to 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.

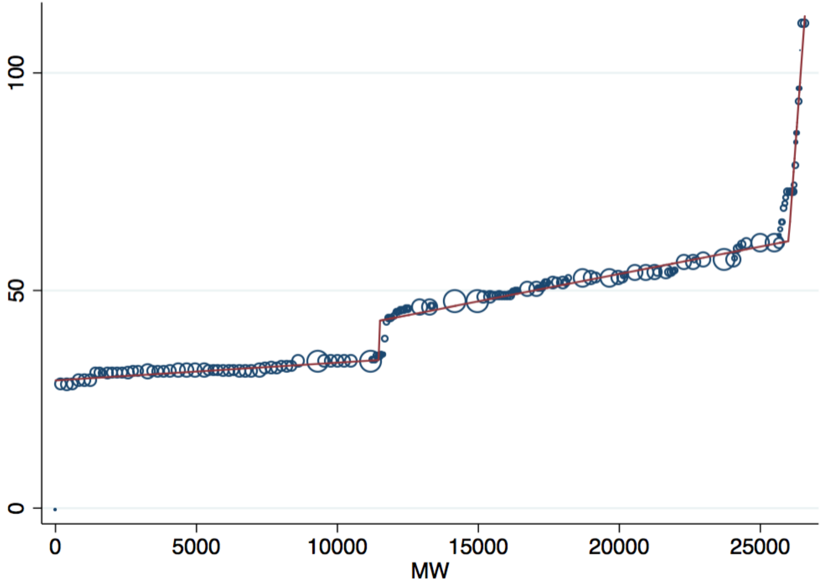
	(1) Log Imports	(2) Log Imports	(3) Log Imports
Log Price	0.3103	0.2902	0.2912
	(0.0055)	(0.0037)	(0.0032)
Observations	43,364	43,364	43,364
Weather controls	Yes	Yes	No
Year and Month FE	No	Yes	No
YearXMonth FE	No	No	Yes

Generation

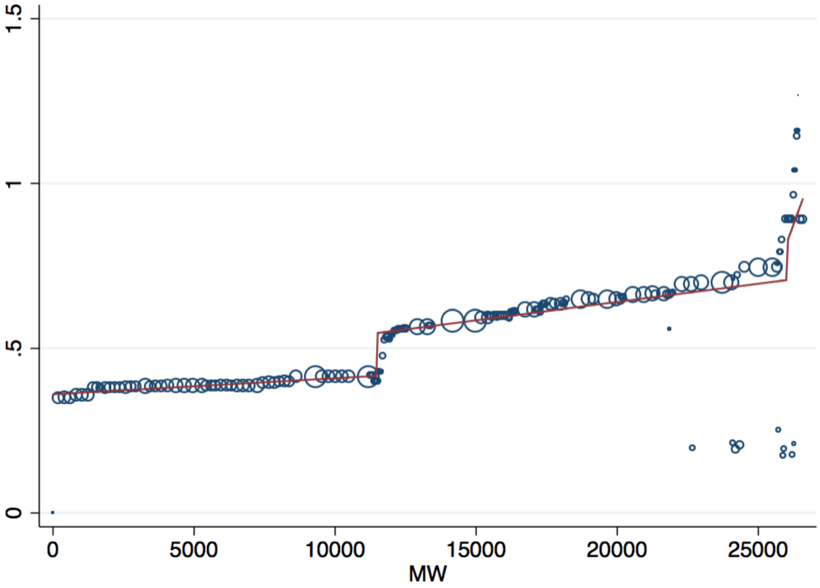
- Construct incumbent supply curve based on existing generation mix for thermal plants and emissions rates.
- Take as given hourly hydro and nuclear production.
- Use EIA construction cost data from new investment to calibrate costs of new plants.

- 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



Emissions rate supply curve



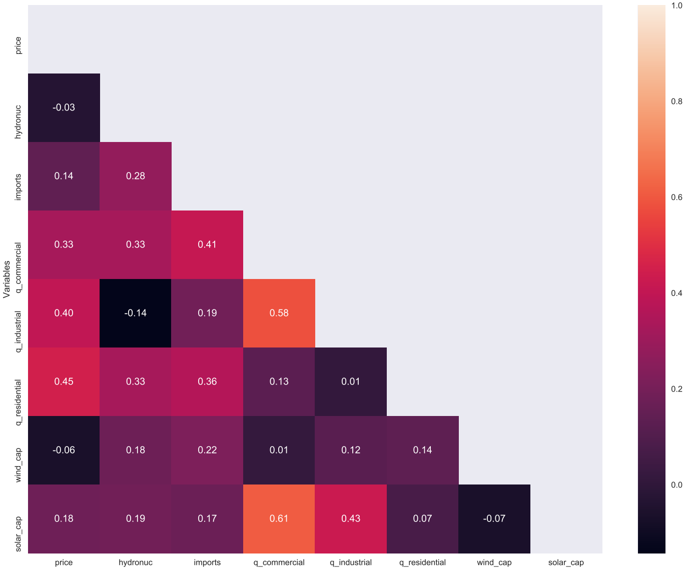
Renewables

- 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



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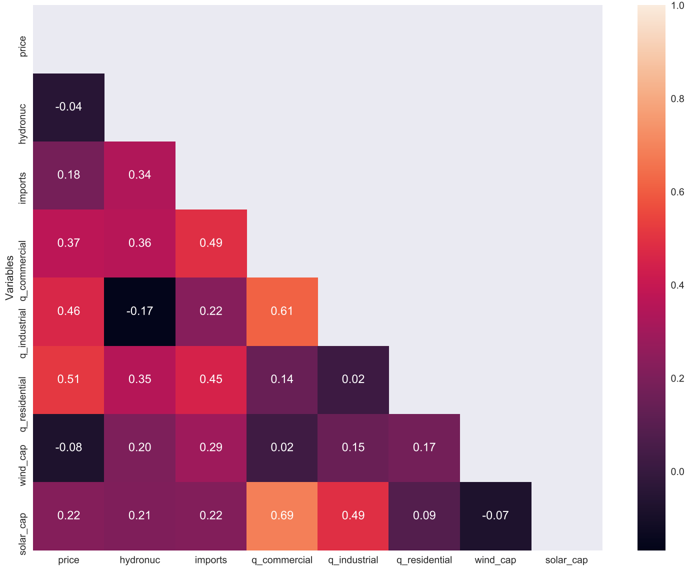

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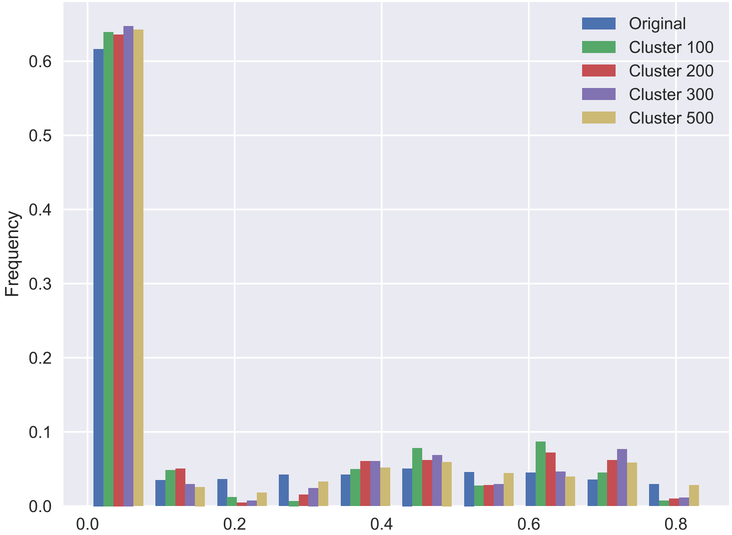


Efficiency and Distributional implications

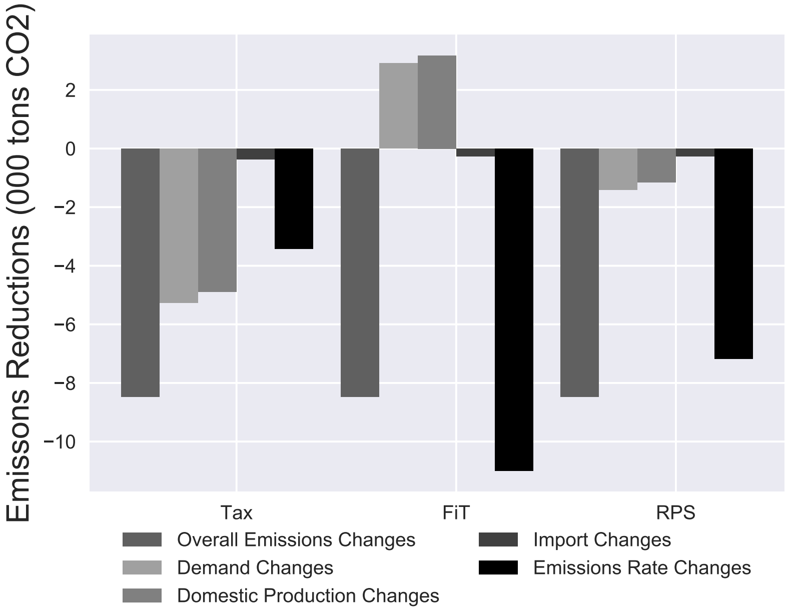
- Do policies induce the right investment?
- How is this reflected in abatement?
- Who are the winners and losers?
- How much does it all change as the cost of renewables is passed through to consumers?

Efficiency decomposition

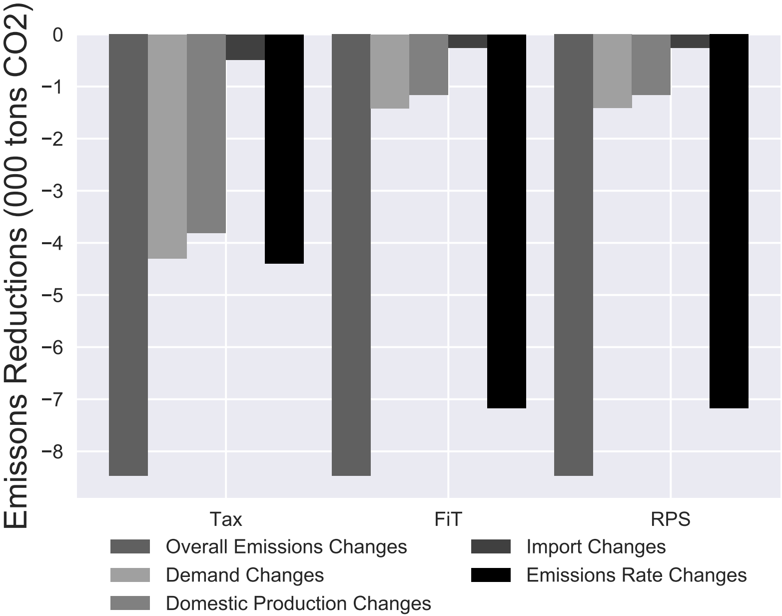
- Reduction of emissions held fixed across policies.
- Decompose source of reductions between:
  - Demand/supply changes
  - Emissions rate becoming cleaner

- Two sets of results:
  - Carbon tax, subsidies, and RPS
  - Carbon tax with marginal rebate, subsidies charged at the margin, and RPS

Efficiency implications



Efficiency implications

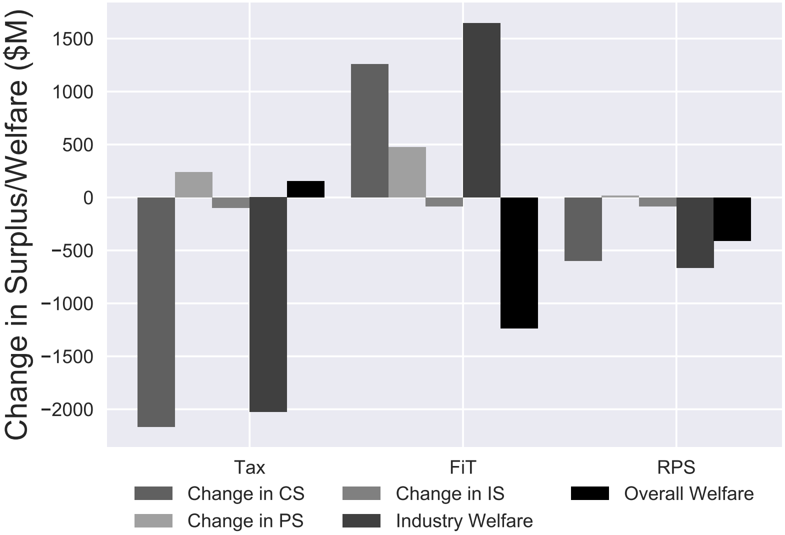


Distributional implications

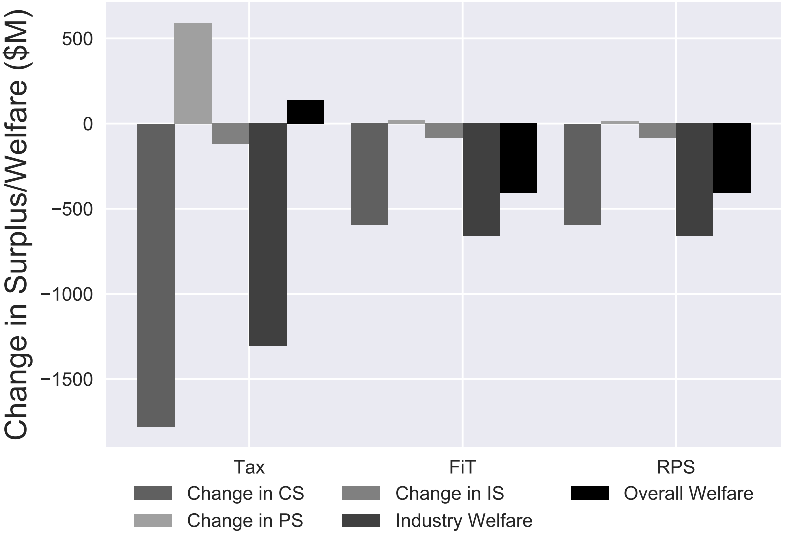
- Who are the winners and losers?
- How does it depend on retail pass-through?

- For now, look at producers vs consumers:
  - Consumer surplus
  - Producers surplus
  - Import surplus

Distributional impacts



Distributional impacts



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.

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)

The role of financial speculators is controversial

- Increase liquidity and informational efficiency.
- Blamed for higher prices in oil, food, electricity.
- Accused of price manipulation in several markets.
  - US Senate investigation: Aluminum, oil, uranium
  - Electricity: Louis Dreyfus (Midwest)
  - Onion Futures Act (1958)

- **Paper**: Exploit a regulatory change that led to increased trading using detailed bidding data on firm behavior.

Physical and financial players

Physical sellers

- Produce electricity
- Intertemporal price discrimination (Ito and Reguant, 2016)
  - Withhold sales in the forward market
  - Results in a forward premium

Financial or virtual traders

- Financial or virtual traders
- Do not own physical assets.
- Compete with physical producers: "virtually" arbitrage.
- Forward premium $\rightarrow$ sell in the forward and buy in the spot

$$\Pi = (P^F - P^S)Q$$

Regulatory change

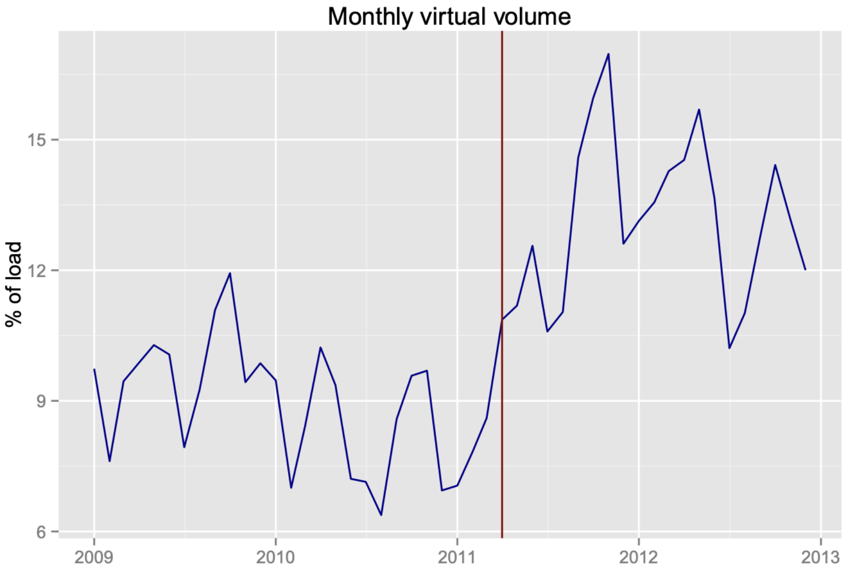
Before April, 2011

- Positive forward premium
- Virtual supply marginal profits: $P^F - P^S - c$
- Charges c were as high as the premium $\rightarrow$ arbitrage was limited

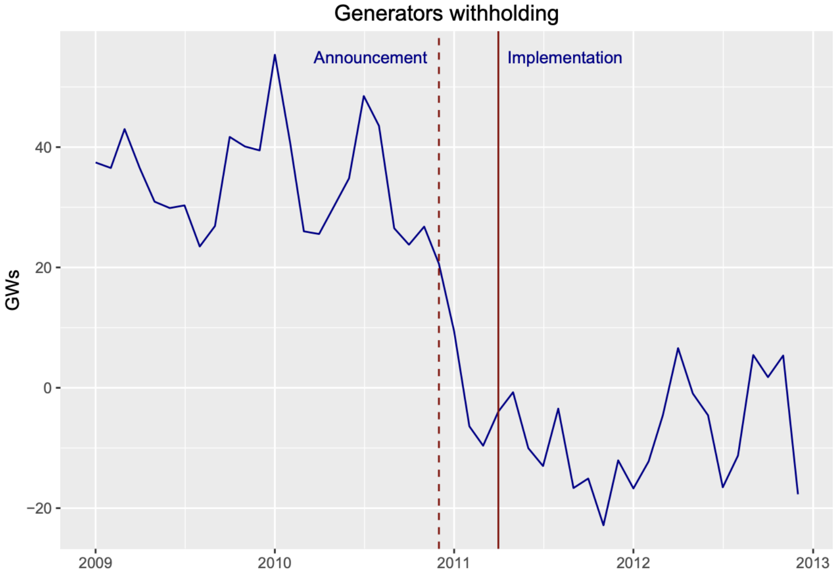
After April 2011

- Charges significantly decreased.
- Proposal submitted on December 1, 2010 (Announcement)

Result 1: Financial trading increased



Result 2: Producer withholding decreased



Hypotheses

Null: Static Nash equilibrium

- Firms play static best response to the competitive conditions they face.

Alternative: Dynamic equilibrium
Do they exert more or less market power than under the static best response?

1. Tacit collusion: Firms do not play static best response: they act as if the market were less competitive than it is.
2. Entry deterrence: Firms do not play static best response: they act as if the market were more competitive than it is.

Static model for a generator

Static model

- Generator deciding how to bid in a sequential market.

$$p^F - p^S = -\left[Q^*(p^F) - x^F\right]\frac{1}{R'(p^F)} \tag{2}$$

$$p^S - c' = -\left[S^*(p^S) - Q^*(p^F) - x^S\right]\frac{1}{R'(p^S)}. \tag{3}$$

Test of conduct

- The optimal forward bid can serve as a test of conduct.
- Define the best response deviation (BRD) as:

$$BRD \equiv p^F - p^S + \left[Q(p^F) - x^F\right] \frac{1}{R'(p^F)}$$

- Test:

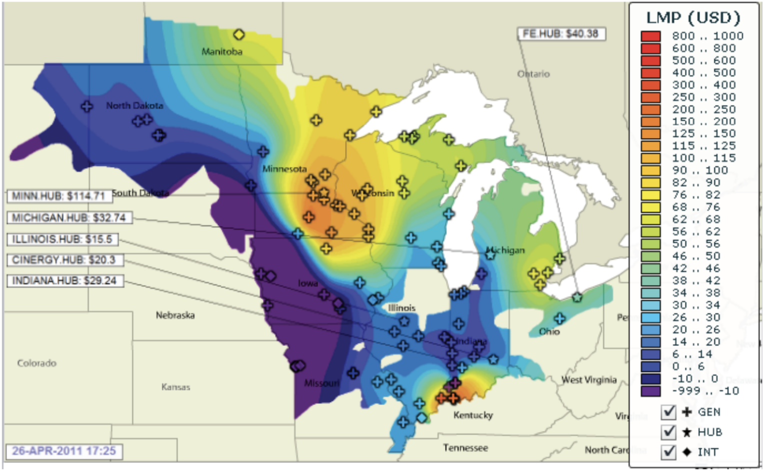
$$BRD = \begin{cases} = 0 & \Rightarrow \quad \text{Static model holds} \\ > 0 & \Rightarrow \quad \text{Consistent with tacit collusion} \\ & \quad\;\; \text{They act as if the residual demand were less elastic} \\ < 0 & \Rightarrow \quad \text{Consistent with entry deterrence} \\ & \quad\;\; \text{They act as if the residual demand were more elastic} \end{cases}$$

Implementation relies on knowledge of the demand

- Demand is "almost observable"
- Hourly bid data: willingness to buy/sell at each price
- One can construct the slope of the residual demand flexibly at any hour.

- Practical notes: Estimation of residual demand requires smoothing.
- Taken too literally, it can be unstable due to "step" nature of bids.
- My preferred approach: locally linear or Kernel with "wide-enough" catchment.

Challenge: 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.

- We will see a different paper in which we use clustering to define the grid $\rightarrow$ one can do counterfactuals.
- Paper takes advantage of Chile being a "linear" country.
- Congestion can be endogenous to the model, not a ex-post classification of the algorithm.

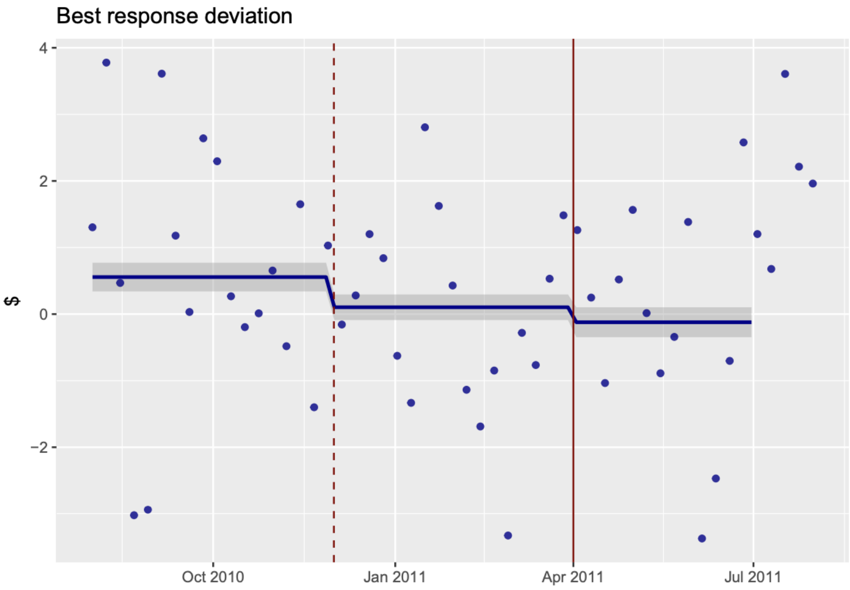
Test of conduct: implementation

- Paper runs a simple regression to assess changes in BRD before and after the policy change:

$$BRD_t = \alpha_0 Before_t + \alpha_1 Interim_t + \alpha_2 After_t + \epsilon_t$$

- Examine if BRD goes up or down after the policy change.

Best Response Deviation



Test of conduct: results

TABLE 2—BEST RESPONSE DEVIATION ANALYSIS

	Dependent variable: best response deviation					
	OLS (1)	OLS (2)	Quantile regression (3)	OLS (4)	OLS (5)	OLS (6)
Interim	−0.71	−3.71	−0.62	−1.98	−0.02	−0.03
	(0.23)	(4.52)	(0.09)	(0.34)	(0.26)	(0.26)
After	−0.46	−9.52	−0.14	−0.73	0.06	0.02
	(0.16)	(7.41)	(0.06)	(0.38)	(0.18)	(0.18)
West					0.75	
					(0.16)	
West × Interim					−1.40	
				(0.28)		
West × After					−1.02	
					(0.23)	
Frequent interaction						0.65
						(0.17)
FI × Interim						−1.79
						(0.28)
FI × After						−1.25
						(0.24)
Constant			2.71	−184		
			(0.18)	(12.94)		
Controls	N	N	N	Y	N	N
Expectations	RE	PF	PF	RE	RE	RE
Mean fixed effects	0.39	−3.94	−0.52	0	0.2	0.28
Between = After = 0	0.37	0.1			0.26	0.01
Hour and month fixed effects	Y	Y	Y	N	Y	Y
Observations	63,480	63,480	63,480	63,421	63,421	63,480
R^2	0.01	0.001		0.10	0.01	0.01

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.