HARVARD ENVIRONMENTAL ECONOMICS PROGRAM

Research Workshop
for
Pre-Doctoral Fellows and Alumni

Thursday-Friday, September 19 – 20, 2019
Harvard Kennedy School
Cambridge, Massachusetts

The Cost of Adapting to Climate Change Through the Grid

Steve Cicala

University of Chicago

19 September 2019

Research Questions

- What will adaptation to climate change through changes in electricity usage cost?
- How would generation costs have been different if US were warmer in the recent past?
    - Upper bound of adjustment costs through this channel.

Motivation

- Cooling is a principle channel of adaptation
  - Barreca, Clay, Deschenes, Greenstone, and Shapiro (2016)
- Climate change is anticipated to increase electricity demand
  - Deschênes & Greenstone (2011), Auffhammer & Mansur (2014), Davis & Gertler (2015), Aufhammer, Baylis, Hausman (2017)
- High demand periods have high marginal costs
  - Davis and Boomhower (2017)

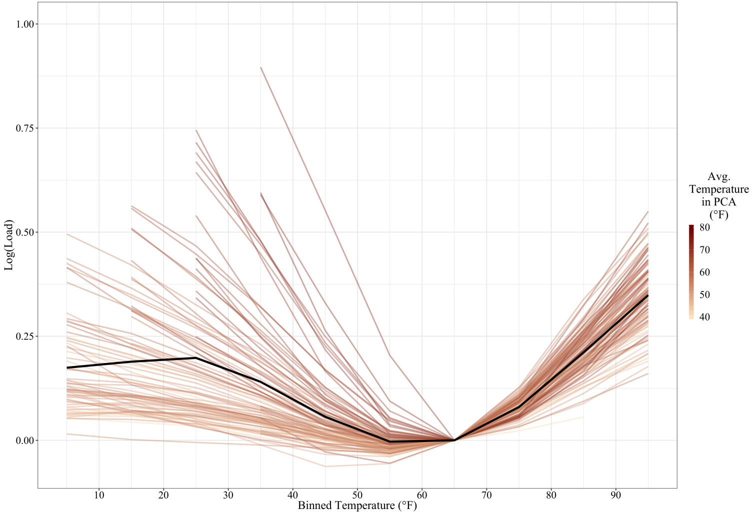
This Paper

- Demand Side:
  - Estimate temperature-load relationships in US PCAs
  - Estimate climate-load response *across* PCAs
    - Hsiang (2016): "time-series variation with stratification"
  - Predict demand under counterfactual climates
    - Aufhammer (2018) for residential CA
    - Carleton et al. (2018) for global mortality
    - Rivers & Shaffer (2019) for Canadian electricity
    - Heutel, Miller and Molitor (2018) for US mortality
- Supply Side:
  - Estimate temperature-capacity and temperature-heat rate relationships
  - Estimate dispatch rules for each PCA
- Put it all together:
  - Predict production costs using predicted demand and estimated dispatch

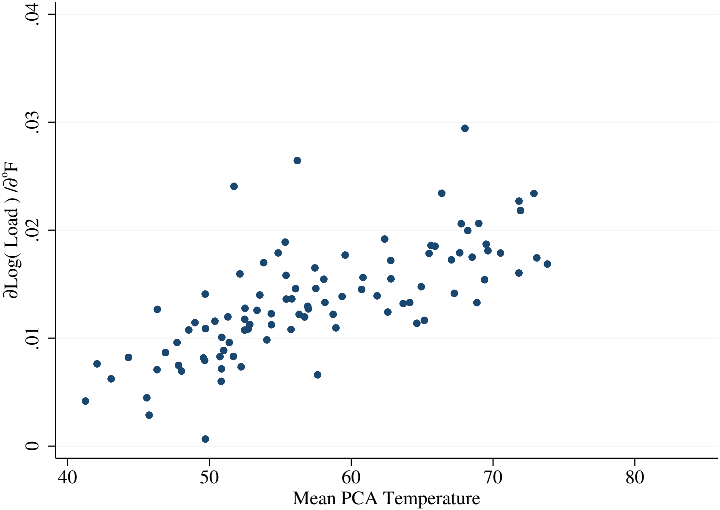
Temperature-Load Relationship:

- Hourly load 1999-2012 for 98 constant footprint PCAs
- Matched to counties
- PRISM daily weather scaled with NOAA hourly
- BLS economic data
- Downscaled CMIP5 RCP 4.5 and 8.5 scenarios 2070-2099.
- High frequency data for convexity

Estimated Relationship between $Log(Load)$ and Temperature by PCA



Temperature-Load Coefficients Across Climates: 90+



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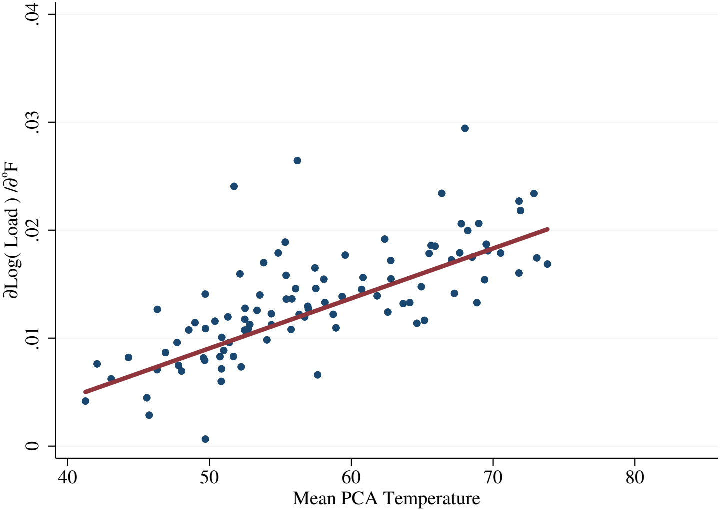
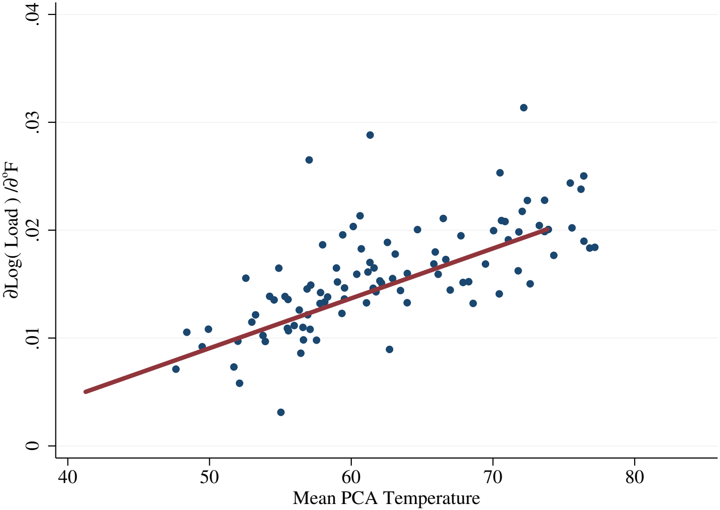
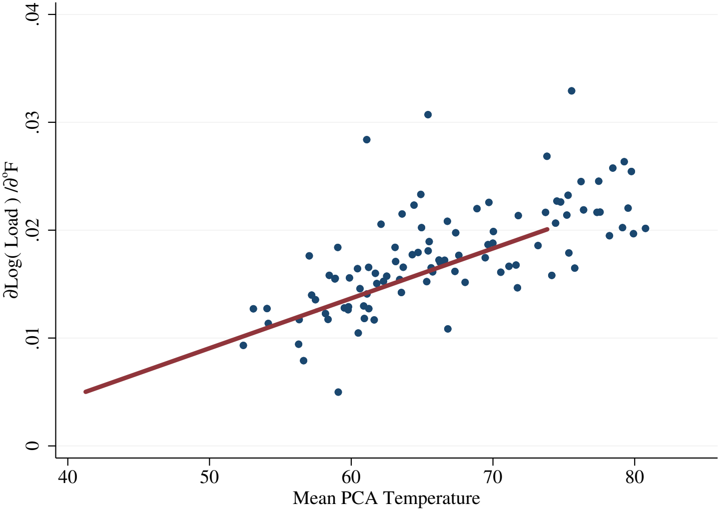


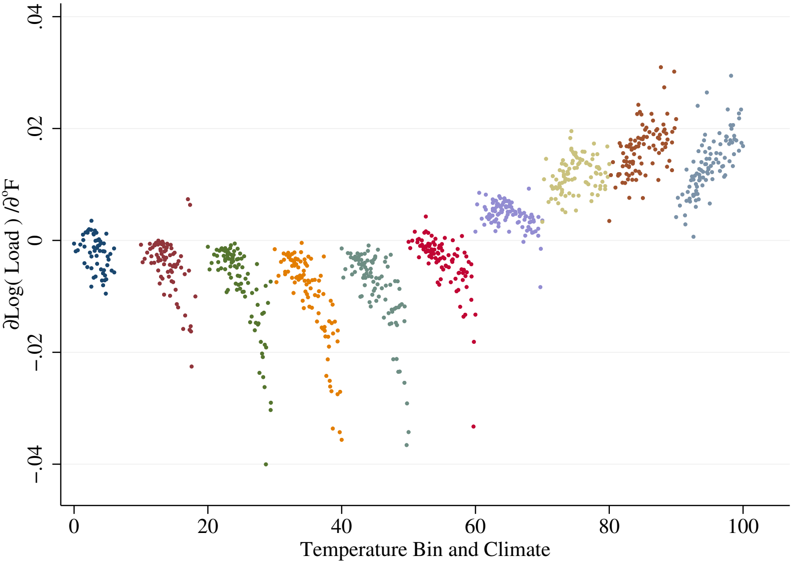
Temperature-Load Coefficients Across Climates: 90+ with RCP 4.5



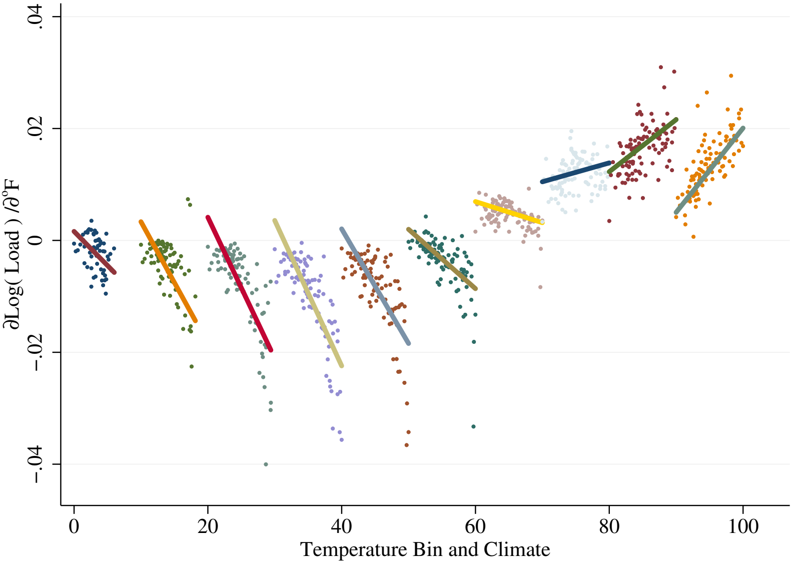
Temperature-Load Coefficients Across Climates: 90+ with RCP 8.5



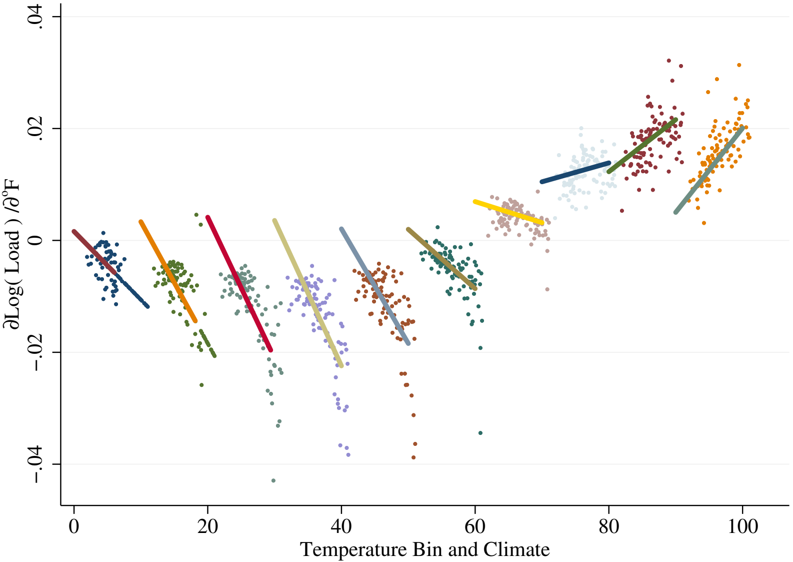
Temperature-Load Coefficients



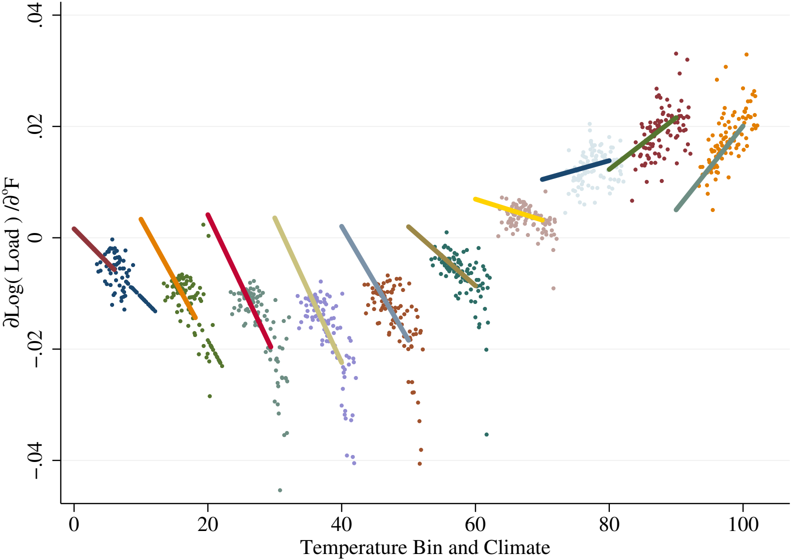
Temperature-Load Coefficients



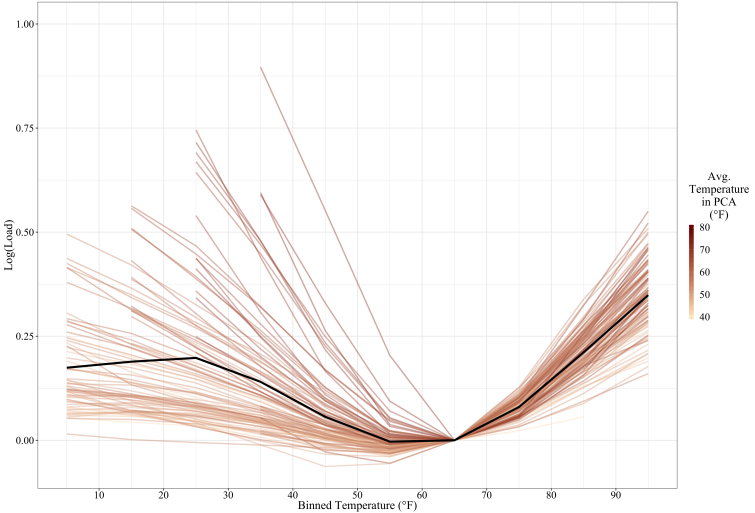
Temperature-Load Coefficients: RCP 4.5



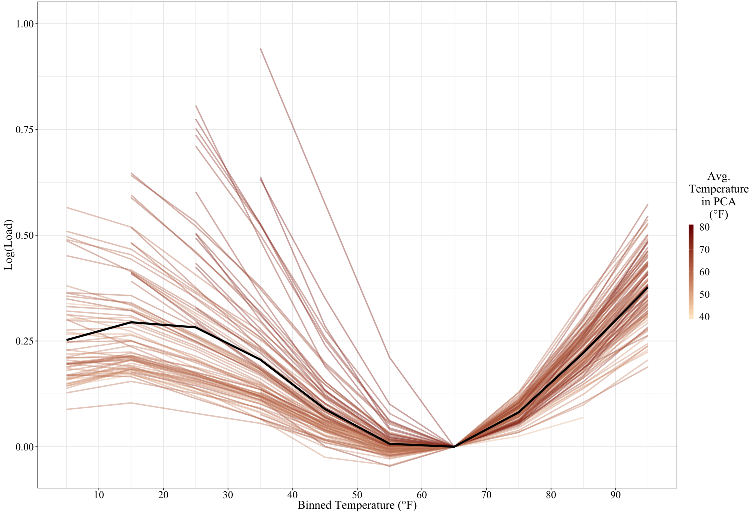
Temperature-Load Coefficients: RCP 8.5



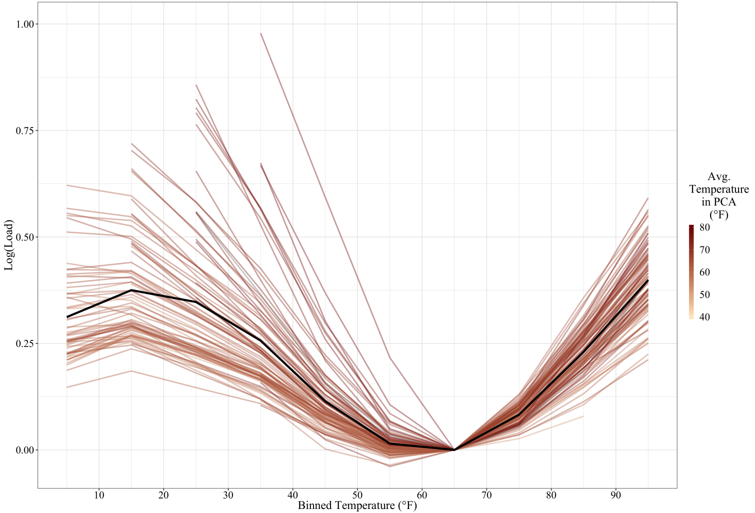
Estimated Relationship between $Log(Load)$ and Temperature by PCA: Unadjusted



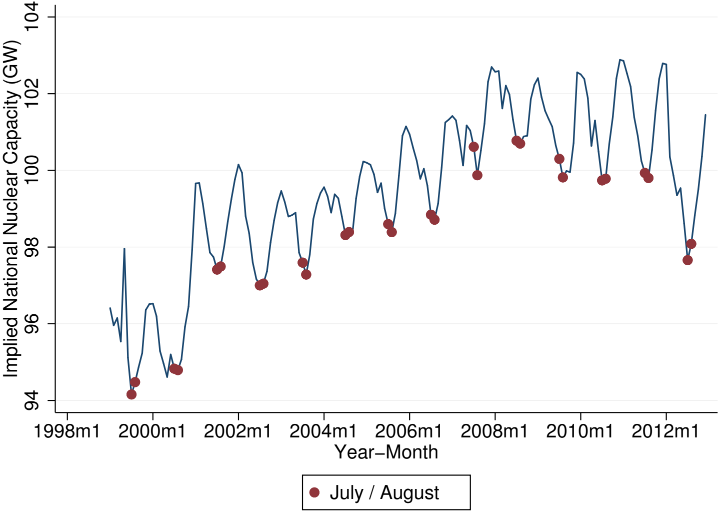
Estimated Relationship between $Log(Load)$ and Temperature by PCA: RCP 4.5-Adjusted



Estimated Relationship between $Log(Load)$ and Temperature by PCA: RCP 8.5-Adjusted



Temperature and Power Plant Productivity: Nuclear Capacity



Smart meters, electricity losses, and reliability: Evidence from an experiment in Kyrgyzstan

Robyn Meeks, Arstan Omuraliev, Ruslan Isaev, and Zhenxuan Wang

Duke University and Kyrgyz Research Institute for Energy and Economics

September 19, 2019

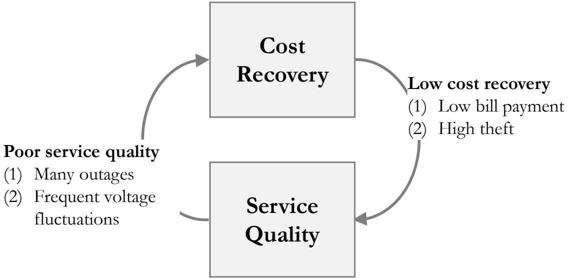
Poor quality electricity service and non-technical losses (including theft) are costly challenges in many countries.

- Non-technical losses (NTL) mean less money recovered by the electricity utility
  - Losses due to theft: estimated $25 billion per year globally (Depuru et al., 2010)
  - Results in lower investment in maintenance, upkeep, and replacing or updating of infrastructure components

Poor quality electricity service and non-technical losses (including theft) are costly challenges in many countries.

- Non-technical losses (NTL) mean less money recovered by the electricity utility
  - Losses due to theft: estimated $25 billion per year globally (Depuru et al., 2010)
  - Results in lower investment in maintenance, upkeep, and replacing or updating of infrastructure components
- Electricity service reliability is major concern in achieving economic benefits from grid (Pargal and Banerjee, 2014)
  - Unreliable electricity service impacts households (Chakravorty, Pelli, and Marchand, 2014) and firms (Allcott, Collard-Wexler, and OConnell, 2015)

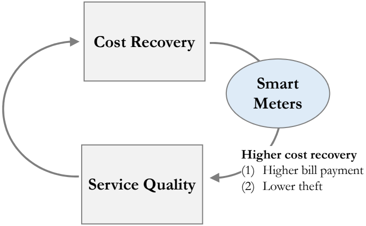
Poor infrastructure quality can be persistent, contributing to an infrastructure quality trap (McRae, 2015).



With these challenges in mind, utilities have been installing smart meters

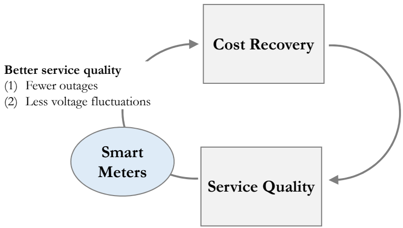
- Installed by utilities in both developed and developing countries for a variety of purposes, including improving grid reliability and reducing theft
- For example, the Canadian electricity utility, BCHydro, documents the installation of smart meter to deter theft on its website (www.bchydro.com)
- How could smart meters impact these outcomes?

Model A: Smart meters may improve cost recovery by reducing theft, non-payment *if utilities monitor*



- Transmits consumption data directly to utility → removes meter readers
- Measures electricity consumption every 15 minutes → identify losses
- Disconnects non-paying households remotely → reduces cost of enforcing payment

Model B: Smart meters may improve service quality if *consumers* monitor



- Detects and measure electricity outages $\rightarrow$ improving monitoring
- Disconnects households when voltage spikes/drops $\rightarrow$ (1) protecting appliances from damage (2) increase utility accountability

Can smart meters increase accountability to reduce theft or improve electricity service quality?

Through a randomized experiment in Kyrgyzstan, we test:

- Do smart meters impact billed electricity consumption?
- If so, why? Because of reduced theft or improved service quality?
- And what is the value of the improvement(s)?

Existing metering research

- Smart meters, research primarily in developed countries, used as vehicle for other interventions
  - e.g. time-varying prices or providing real-time electricity consumption information (e.g.: Wolak, 2011; Allcott, 2011; Jessoe & Rapson, 2014; Ito, Ida & Tanaka, 2015)
- Electricity metering interventions in developing countries have not focused on smart meters
  - McRae (2015) documents the impacts of moving from a fixed monthly fee to metered consumption on household welfare and utility revenue in Colombia
  - Jack and Smith (2019) measure impacts of introducing prepaid metering in South Africa

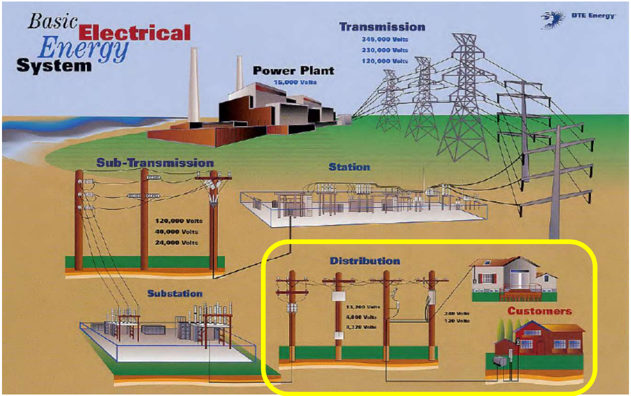
Background: Kyrgyzstan is a lower-middle income country in Central Asia

- Nearly 100% of population has access to electricity
- Reported distribution losses 15-18% (World Bank, 2017)
- In 2009-2012, distribution companies reported 2 outages/hour
- System has regular voltage and frequency fluctuations (World Bank, 2017) and per a 2013 survey:
    - $>$ 50% survey respondents reported problems with voltage (including low voltage and voltage fluctuations)
    - 18.9% of respondents reported damage to electrical appliances because of poor electricity quality

Partner with electricity utility operating in the Kyrgyz Republic and implement RCT in a small city

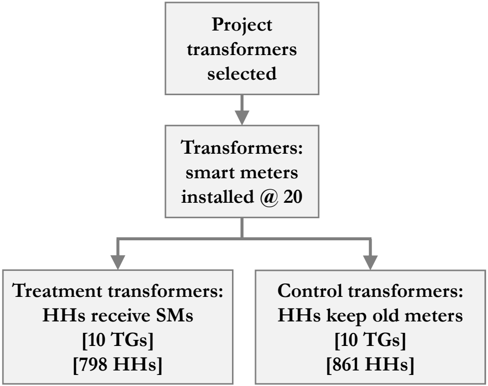
- Both electricity losses and quality of services are concerns for utility
- Focus on residential consumers, which include apartments and single-family homes
- Pre-intervention, house meters exist but are old and require human meter-reader

Intervention designed around distribution system



Source: DTE Energy.

Once transformers are selected for the project they are randomly assigned to treatment status



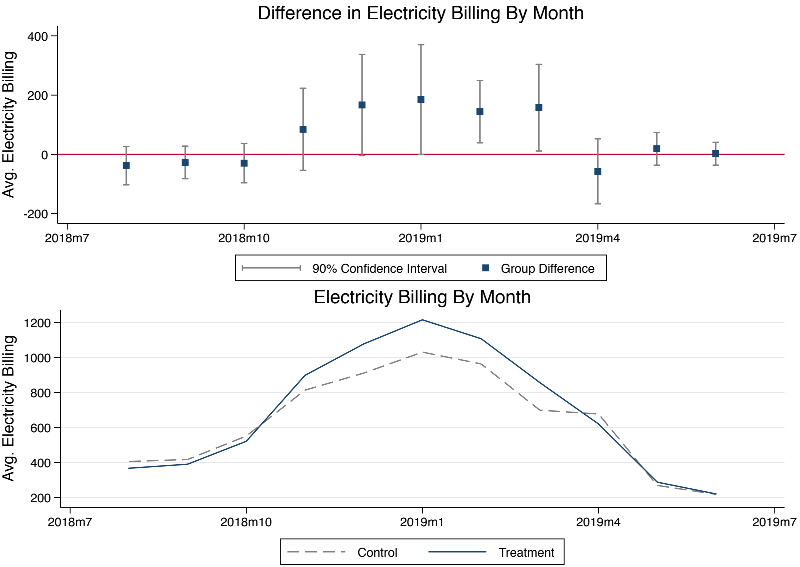
Transformer-level meters installed mid-2018

- Collect data in 15-minute increments
- Provide aggregate data on neighborhood consumption and alarms indicating problems

Household-level smart meters installed by September 2018

- Collect data in 15-minute increments
- Send data to aggregator at transformer and then uploaded to utility server

Event study analysis indicates an increase in winter billed electricity consumption in treated households



Billed electricity consumption increased by 44 kWh/month in winter and decreased by 32 kWh/month in summer

	(1) bill (kWh)	(2) bill (kWh)
Treat × Post	44.245*	-32.409**
	(22.566)	(14.977)
Post	-175.032***	-423.841***
	(34.100)	(30.444)
Constant	925.316***	660.652***
	(16.427)	(17.389)
Mean of Control Group	858.722	436.489
Observations	13,769	17,941
Number of Household	1,088	1,088
Season	Heating Season	Non-Heating Season

Evidence on the channels through which this occurs?

- Using the transformer-level alarms data
  - No evidence this occurred through reductions in theft
  - Is evidence that this occurred through improved electricity services: significantly fewer voltage fluctuations and power outages
- We can estimate the benefits of these electricity quality improvements: 6.50 USD per month during months of peak consumption
- Treatment households report spending more (14 USD in 3 months) on home appliances

Preliminary interpretation of findings

- There is no impact on electricity theft
  - would require the utility to monitor the smart meter data for indications of theft
  - utility does not appear to be monitoring
- But households with smart meters appear to be using as a tool to monitor the utility

Using Machine Learning to Target and Extrapolate

A Case Study of Household Energy Use

Christopher Knittel and Samuel Stolper

HEEP Workshop, September 19th, 2019

Machine learning to improve program evaluation

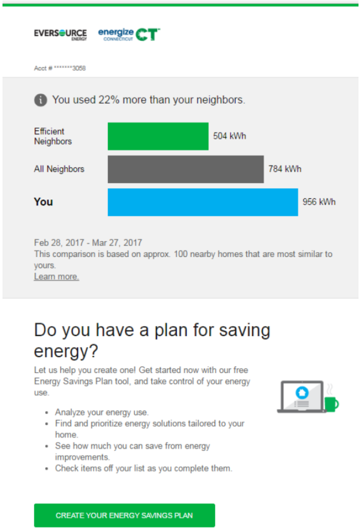
Understanding treatment effect heterogeneity facilitates improvements to program effectiveness

- Can selectively target those who respond "best"
- Can tailor treatment where it is not having the desired effect

Our aim: apply ML methods to the evaluation of a series of large-scale randomized experiments in household energy use

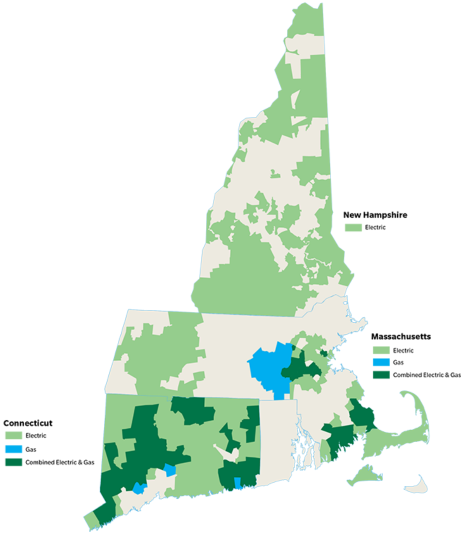
- The algorithm: "causal forests" (Athey, Tibshirani, and Wager 2018)
  - A tree-based ensemble method developed for treatment effect estimation
- The treatment: the "Home Energy Report" (HER)
  - A widely used nudge towards household energy efficiency (e.g., Allcott 2011)

The Home Energy Report



- The aim:
  - Nudge consumers to reduce usage
  - Increase customer satisfaction
- The format
  - Social comparison of usage
  - Ways to save

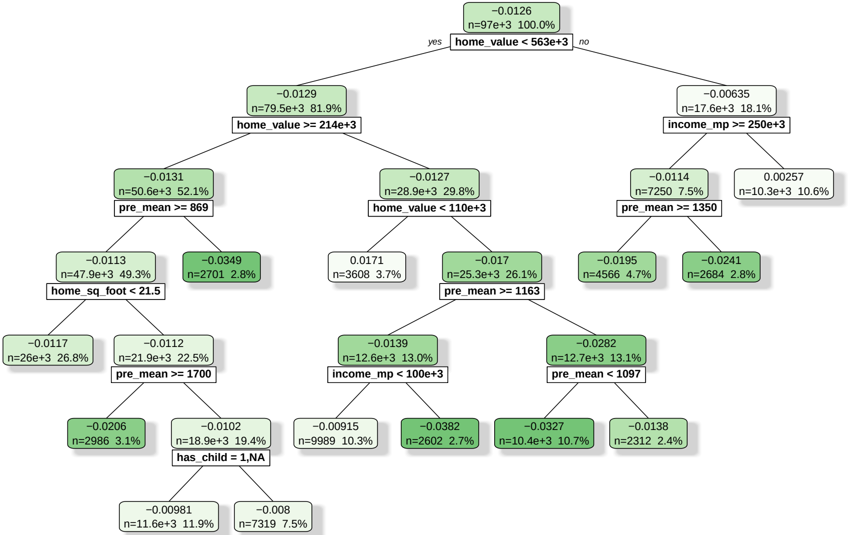
Geography and data



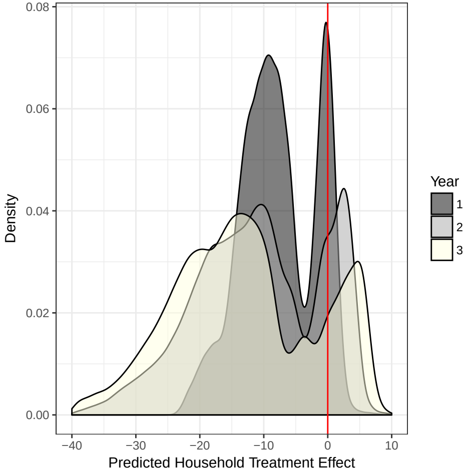
- 15 experimental waves of HER rollout
  - 900k households enrolled in an experiment
  - Monthly usage (kWh) from 2013-2018
    - 50m household-months
  - Household characteristics from Experian

Event study of pooled experimental waves (kWh)

A sample tree

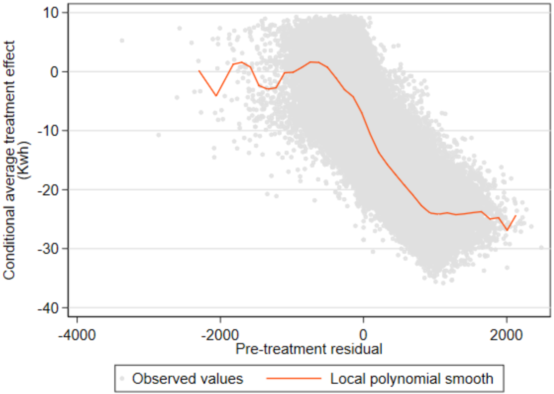


Causal forest household-level predictions



- Each plotted distribution is a specific post-year
  - At least two major “modes”
    - Those who respond in Year 1; those who don’t
  - Modes diverge over time
    - Some *in*creases in usage

The possibility of boomerang effects



- "Residual" indicates consumption *relative* to an average household with similar characteristics
  - This may be correlated with social comparison messaging

In summary

What we find:

1. The overall ATE is a -0.9% reduction in monthly consumption
    - Magnitude rises over time
2. The distribution of individual treatment effects ranges from -3% to +3.5%
    - Multiple “modes” are apparent
3. Pre-treatment consumption and home value are the strongest predictors
4. HERs may have a “boomerang effect”
5. The causal forest performs reasonably well out-of-sample
    - But performs less well when the “training set” and “test set” have little overlap

The Efficiency and Distributional Implications of Non-Price Rationing of Electricity in India

Kevin Rowe
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HEEP Conference
September 19, 2019

Targeted commodity subsidies and non-price rationing

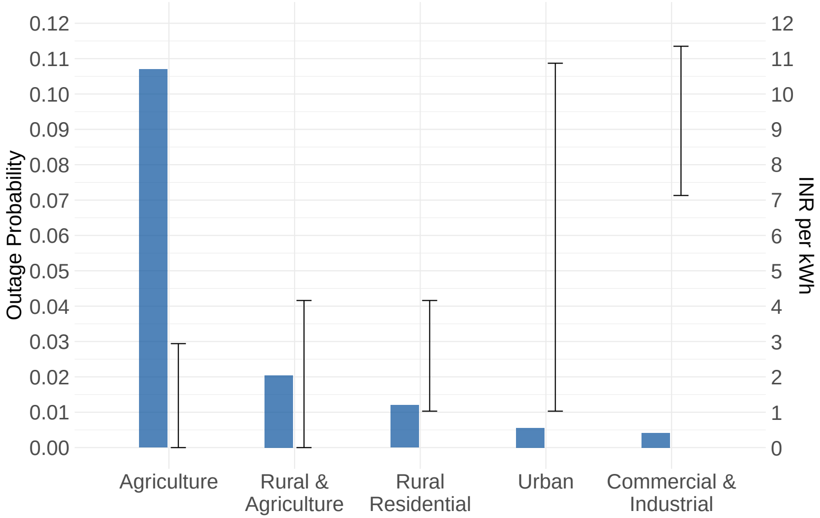
Negative commodity taxes a main mechanism for redistribution in many countries (Gadenne, 2018)

Non-price rationing often accompanies regulated prices

- Regulator sets prices $\rightarrow$ distribution company sets quantities

If the distribution company's revenue depends on the progressive price schedule, it may have an incentive to ration more subsidized markets more severely

Load Shedding Outages (bars) and Prices (ranges) by Customer Type, Maharashtra 2017



Research Question and Approach

What are the short-run welfare implications of targeted subsidies in retail electricity markets when they are accompanied by systematic non-price rationing?

1. Estimate demand for electricity across hours in the day by customer types (e.g., agriculture, residential, commercial and industrial) $\rightarrow$ characterize the welfare loss from outages
2. Estimate parameters of the state-owned electricity distribution company's objective function in rationing $\rightarrow$ surplus maximization vs. net revenue maximization
3. In counterfactuals, ask: whom would be better off under higher prices and higher reliability?

Outages on Marginal Cost of Wholesale Electricity

How responsive are the utility's load shedding decisions to its cost of wholesale electricity?

Similar to demand estimation: address simultaneity in determination of outages and costs with supply-shifting IV – **wind generation**

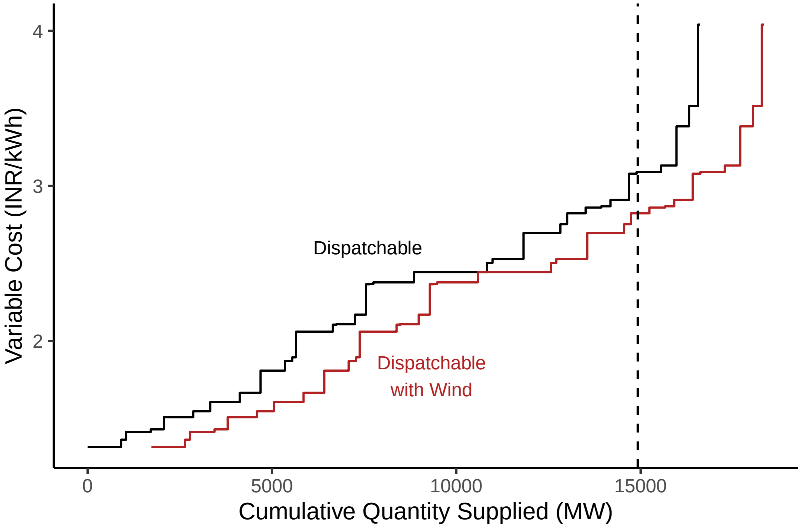
First stage:

$$MC_{d,h} = \alpha Wind_{d,h} + \beta X_{d,h} + \gamma_d + \gamma_h + \epsilon_{d,h}$$

Second Stage:

$$Out_{d,h} = \theta \hat{MC}_{d,h} + \delta X_{d,h} + \gamma_d + \gamma_h + \omega_{d,h}$$

MSEDCL's Supply Curve



Hour ending 18:00 on May 1, 2018

Outages on Marginal Cost of Wholesale Electricity

	Levels		*Elasticity*	
	First Stage MC (1)	IV Outages (2)	First Stage log MC (3)	IV log Outages (4)
Wind Generation (GW)	-0.212*** (0.0147)		-0.0632*** (0.00313)	
Marginal Cost (INR/kWh)		110.2*** (15.54)		
log Marginal Cost (INR/kWh)				0.440*** (0.137)
Load Served (GW)	0.218*** (0.00460)	-50.47*** (3.637)	0.0668*** (0.000978)	-0.104*** (0.00978)
Mumbai Demand (GW)	0.0804*** (0.0218)	98.98*** (4.994)	0.0111** (0.00464)	0.323*** (0.0129)
YMD FEs	✓	✓	✓	✓
Hour FEs	✓	✓	✓	✓
Mean of Outcome	3.203	372.5	1.141	5.637
Observations	16144	16144	16144	16138
First Stage F		207.7		408.2
R^2	0.759	0.829	0.839	0.951

Additional controls: Transmission congestion index, solar generation; * $p < .1$, ** $p < .05$, *** $p < .01$

Outages on Marginal Cost of Wholesale Electricity: Interpreting the Magnitudes

Effect on load shedding of a 1 SD increase in the cost of wholesale electricity:

+ about **86** additional **feeders** out
+ about **81,000** additional **connections** out
+ about **258,000** additional **people** (with residential or agricultural connections) out

Electricity Consumption Responses to Outages

How much consumption is lost for each hour of outage?

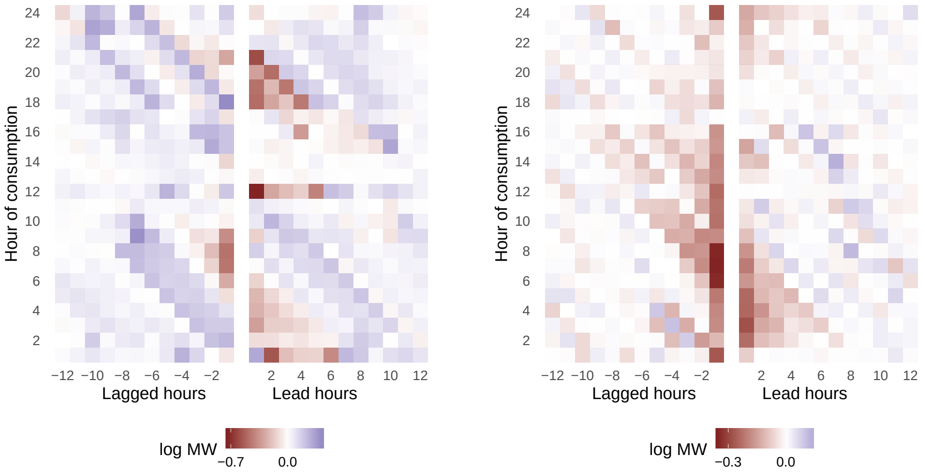
$$\log Load_{d,m} = \theta Out_{d,m} + g(W_{d,h}) + \gamma_m + \gamma_d + \epsilon_{d,m}$$

- Benchmark: one hour is .0417 of a day
- Effects conflate the timing of outages (peak vs. off-peak) with the degree of substitutability

	All (1)	All (2)	Agriculture (3)	Rural Mixed (4)	Rural Resi (5)	Urban (6)	C & I (7)
Hours Out	0.0195***	-0.0211***	-0.0168***	-0.0475***	-0.0440***	-0.0493***	-0.0811***
	(0.00283)	(0.00162)	(0.00165)	(0.00339)	(0.00300)	(0.00355)	(0.00465)
YMD FEs	✓	✓	✓	✓	✓	✓	✓
Feeder FEs	✓	✓	✓	✓	✓	✓	✓
HD Controls		✓	✓	✓	✓	✓	✓
Mean of log MW	2.149	2.141	2.049	1.973	1.789	2.724	2.020
Mean Hours Out	0.593	0.610	1.174	0.229	0.191	0.104	0.0764
Observations	587,501	528,851	236,800	36,926	76,873	111,252	65,191
Feeders	1762	1786	812	119	240	358	249
R^2	0.831						
Adjusted R^2	0.830						

* $p < .1$, ** $p < .05$, *** $p < .01$

Substitution Patterns: Agriculture (Left) and C&I (Right)



Summary of Preliminary Evidence

1. The distribution company's load shedding is highly responsive to regulated price incentives:
   - 1 SD increase in the cost of wholesale electricity $\rightarrow$ about 258,000 additional people facing outages
2. Strong relationship between the severity of rationing and the substitutability of demand in response to outages
   - Agriculture able to mitigate much of the effect of an outage through substitution, commercial and industrial consumers cannot
   - Consistent with efficient rationing

References

Gadenne, L. (2018). Can Rationing Increase Welfare? Theory and An Application to India's Ration Shop System. Centre for Economic Policy Research Discussion Paper DP13080.

U.S. Carbon Pricing and Coal Productivity

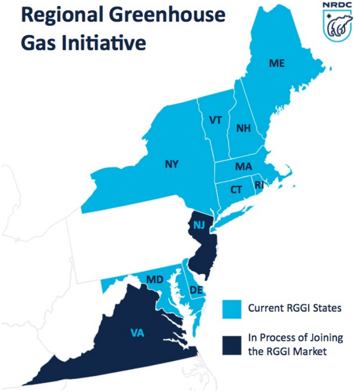
Megan R. Bailey

Harvard University

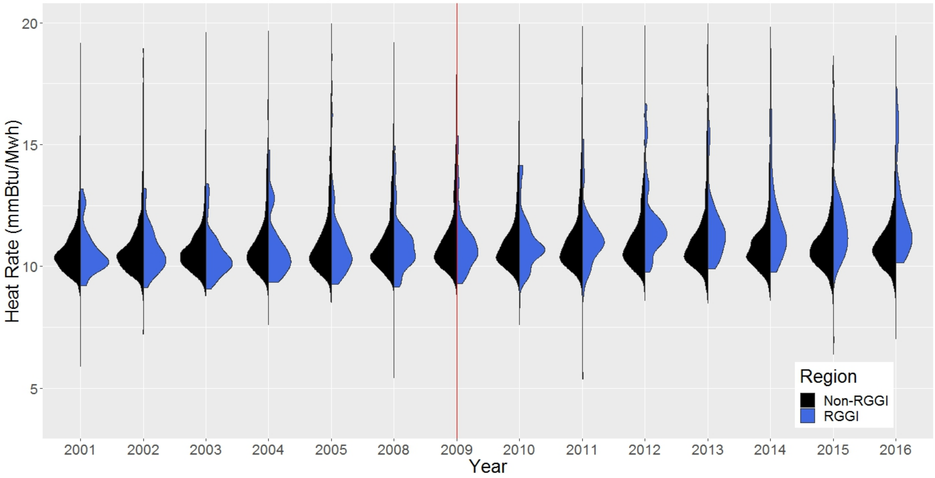
Sept 19, 2019

RGGI: An intro

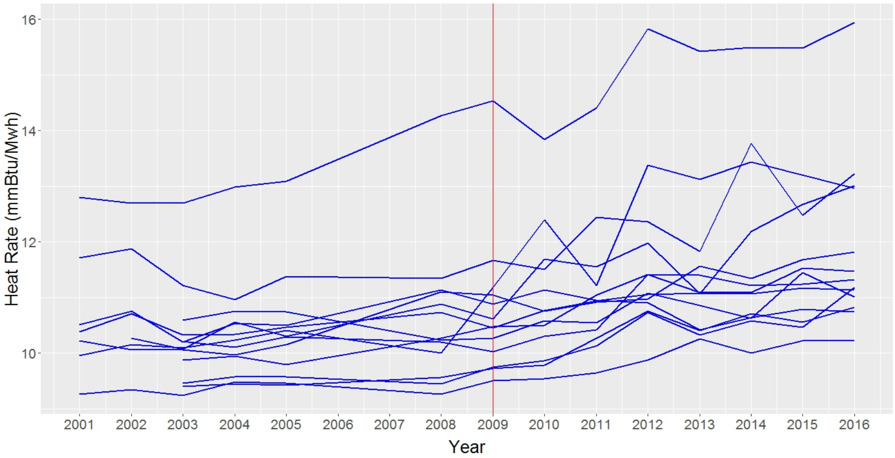
- Cap-and-trade program
  - CO_2 emissions from fossil power plants
- 2009: first compliance period started
- RGGI price has been 6-19% of coal & 2-8% of natural gas
- Induced innovation => increased efficiency



A regional divergence in heat rates of coal plants



Plant-level trends, RGGI survivors in 2016



Key phenomenon and questions

RGGI coal plants display

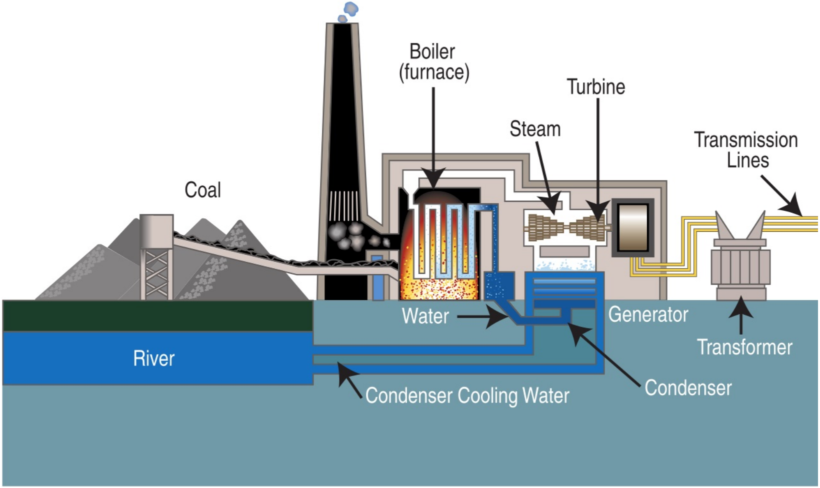
- 0.05% increase in net heat rates, post- vs. pre-RGGI. (diff-in-diff with plant and time fixed effects)
- 0.016% increase in net heat rates for every $1 increase in RGGI allowances (panel model with plant and time fixed effects)

Key questions

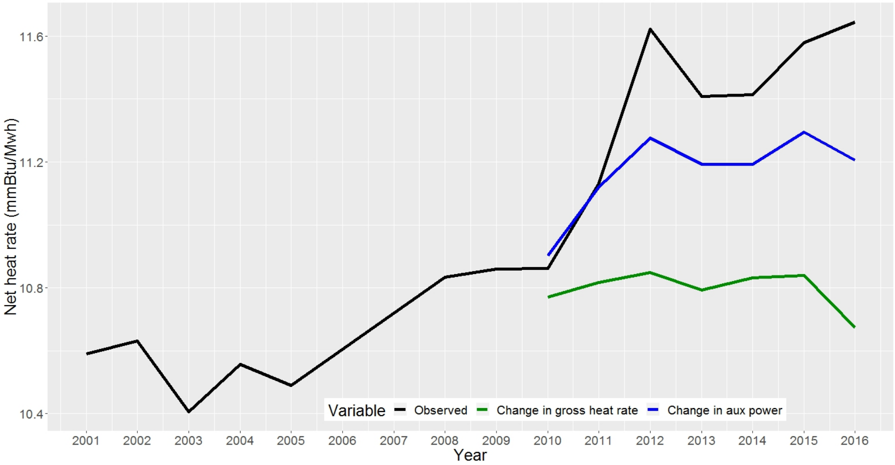
- Role of generation changes? (likely RGGI channel)
- Role of unannounced retirement, scrubber installation, etc.

Double-decomposition

Gross heat rate vs. auxiliary power consumption changes



Plant-level decomposition, RGGI plants



Thank you!

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Technical Progress in Wind Power

Thomas Covert [1] Richard Sweeney [2]

[1] University of Chicago Booth School of Business

[2] Boston College

September 2019

Motivation: Key questions about energy innovation

1. How much does technology improve as a result of policy?
   - Recent debate of role of RPS in cost declines

2. What's the *best* way to pull innovation with policy?
   - Green installations generate two externalities (today's abatement and tomorrow's innovation), policy separately should target both
   - Important forces: learning + spillovers

Motivation: Key questions about energy innovation

1. How much does technology improve as a result of policy?
    - Recent debate of role of RPS in cost declines
2. What's the *best* way to pull innovation with policy?
    - Green installations generate two externalities (today's abatement and tomorrow's innovation), policy separately should target both
    - Important forces: learning + spillovers

We study these in the wind power industry

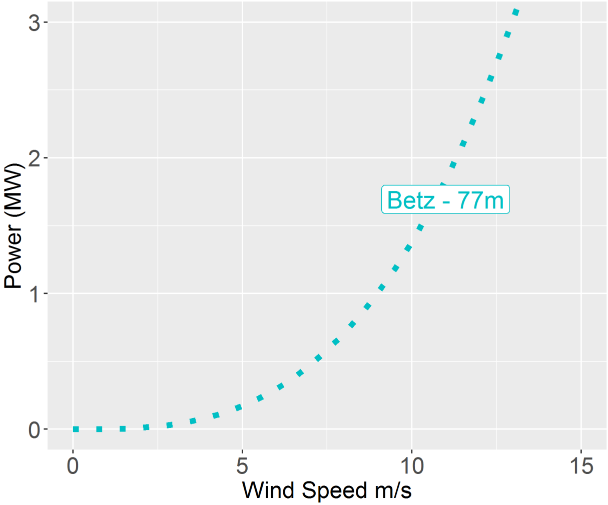
- 600 GW worldwide
- Technology "simple," solution "obvious"
- Great data + simple engineering

Wind basics: Max output from a turbine

Albert Betz (1919):

$$\text{Power} \quad Q = \left(\frac{16}{27}\right)\left(\frac{1}{2}\pi r^2\right) d v^3$$

- r is the radius (m)
- d is wind density
- v is velocity (m/s)



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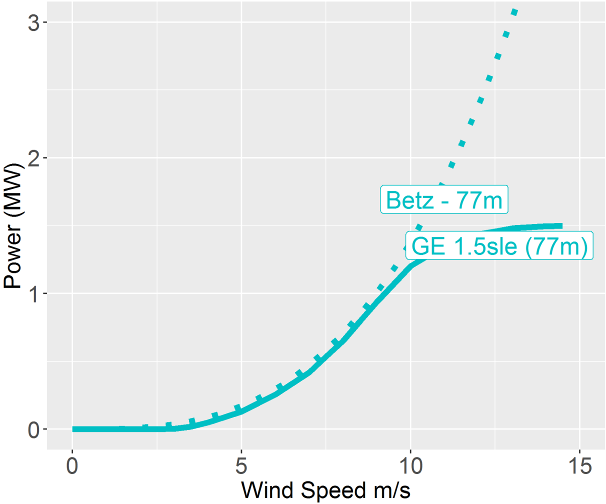
Actual turbine **power curves** lie below this.



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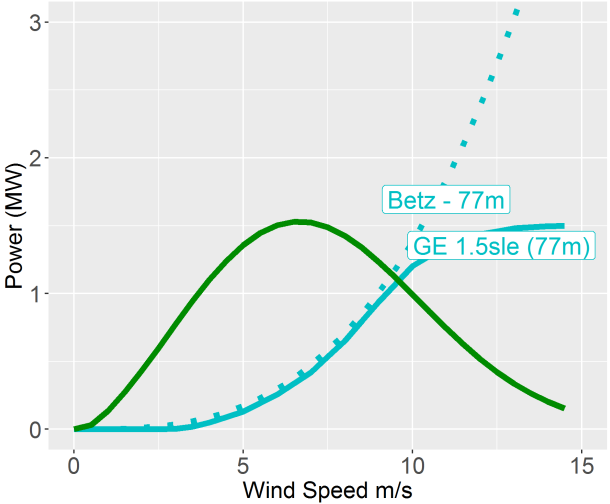

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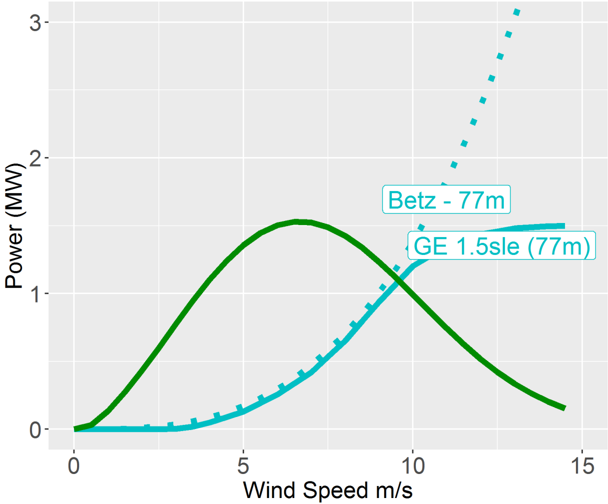
Power curve + Wind CDF = E[Output]



Simple physics suggest turbines should be large

Returns increasing in rotor length
(and site quality ...)

$$\partial Q / \partial r \propto 2 r v^3$$

This is where engineers started

- Vermont 1941: 1.25MW
- Denmark 1975: 1.5MW
- DOE 1970's: 1-2 MW

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(and site quality ...)

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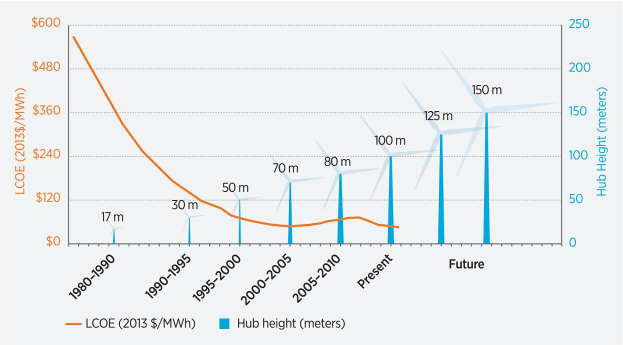
This is where engineers started

- Vermont 1941: 1.25MW
- Denmark 1975: 1.5MW
- DOE 1970's: 1-2 MW

But when industry went commercial, turbines were tiny

- Altamont Pass: 100kW

Scale-up of wind technology has supported cost reductions.



Note: LCOE is estimated in good to excellent wind resource sites (typically those with average wind speeds of 7.5 m/s or higher), excluding the federal production tax credit. Hub heights reflect typical turbine model size for the time period.

Figure ES.2-5. Wind technology scale-up trends and the levelized cost of electricity

Challenge: "square-cube" law

- As an object increases in size, surface area grows quadratically, but volume grows cubically (Galileo 1683).
- Optimal size determined by materials "cost of volume" c

$$
\begin{aligned}
\text{Max } \pi &= pr^2 v^3 - cr^3 \\
r^* &= (2pv^3)/(3c)
\end{aligned}
$$

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$$\begin{aligned} \text{Max } \pi &= pr^2v^3 - cr^3 \\ r^* &= (2pv^3)/(3c) \end{aligned}$$

Use this framework to recover the evolution of technology c for every firm

- data on over 25,000 wind farms worldwide
- know plant coordinates and exact turbine used
- detailed turbine database with over 1,600 turbines
- wind data from Vaisala (3Tier)

Intuition: If r^* increases (conditional on p and v), c must have fallen.

We then estimate a dynamic model which rationalizes technology evolution

Insights come from Stein ReStud 1997:

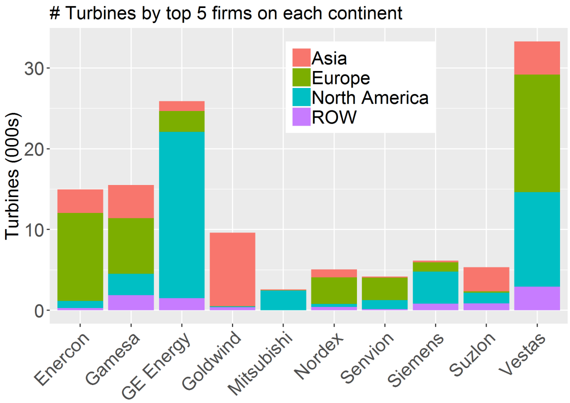
- if we see firms introduce a new tech, they abandon current learning
- if a firm pushes the frontier, that reduces the cost to other firms

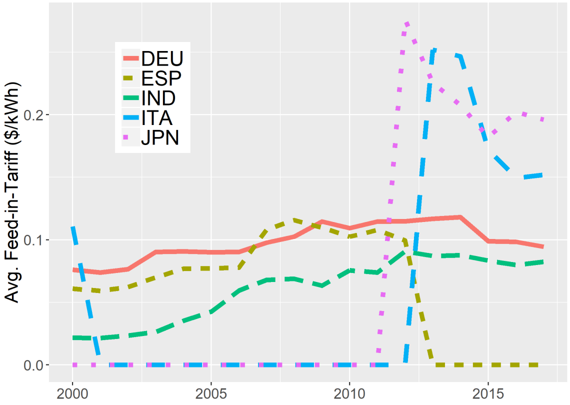
Estimation using Berry & Pakes 2000

- if we can compute the gradient of static profits with respect to turbine size, observed choices pin down unobserved investment cost function

We then estimate a dynamic model which rationalizes technology evolution

Identification: Home market bias + panel policy variation





What do we hope to get out of this?

Possible counterfactuals:

- policy increases earlier / later
- subsidies target adoption of frontier tech
- give Vestas the market (Schumpeter) vs increase competition (Arrow)
- remove home market bias?
- others?

We are also thinking about the developer side: returns from innovation increasing in site quality.

- Suggests scope for intertemporal misallocation

Backup Slides

Model: Ingredients for a project

- Wind farms have local power prices p and a wind speed v, so revenues from installing a turbine of size r will be $pv^3 r^2$
- Knowing p and v, each firm i receives a vintage-specific cost shock and bids in designs for *Mature* and *Frontier* projects:

$$r_i^M = \frac{2}{3} \frac{pv^3}{c_i^M \exp(\nu_i^M)}$$
$$r_i^F = \frac{2}{3} \frac{pv^3}{c_i^F \exp(\nu_i^F)}$$

  with associated prices f_i^M and f_i^F
- Developers choose among the $2N$ bids according to profit maximization + logit shocks.

Data

TheWindPower.net

- 24,227 wind farms worldwide (16,646 post 2000)
  - $\approx$ 80% know plant coordinates and exact turbine used
- Detailed turbine database with over 1,600 turbines

Wind data from Vaisala (3Tier)

- Monthly average speed, direction, temp, density
- Annual Weibull parameters

Currently cobbling together price information

- hundreds of press releases / public filings
- in US, have costs for about plants from regulatory filings and grants. SNL estimates for hundreds more.
- hopefully purchasing thousands of more observations from BNEF

Model: Ingredients for the firm

- Cost of manufacturing a turbine of size r for firms $i = 1...N$ is a function of two state variables c and x

$$C(r, c_i, x_i) = c_i r^3 + L(x_i)$$

  where $L(x) \geq 0$, $L'(x) < 0$, and $L''(x) > 0$ measures LBD

- $c \in \{\underline{c}, \underline{c} + \delta_c, ..., \bar{c} - \delta_c, \bar{c}\}$ is the cost of size at current tech level.
  - Firms can decrease c next period by paying an investment cost ϕ
  - ϕ depends on distance to industry frontier (spillovers)

- $x \in \{0, 1, ..., \bar{x}\}$ is the firm's "experience" level — $\log(\text{sales})$.
  - x evolves stochastically due to demand shocks.

- Firms have vintage specific states: *Frontier* (c_i^F, x_i^F) and *Mature* (c_i^M, x_i^M)

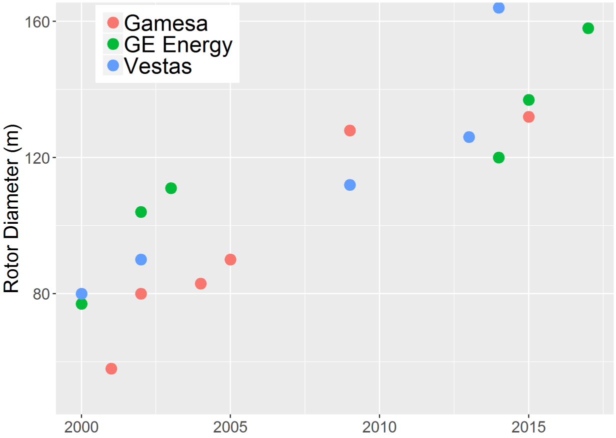
Model: Timing

In each period t, three things happen:

1. Firms decide whether to invest in upgrading their cost of volume c, and set pricing and sizing policies.
2. A set of projects $\{v_l, p_l\}_{l=1}^{W_t}$ is proposed. Each firm submits *Mature* and *Frontier* bids for each project, and the project developer choses the profit maximizing design, up to a logit shock.
3. Experience levels evolve as a result of realized sales. (If firm invests in c, previous mature *Frontier* is subsumed into *Mature*).

Estimation: Recover costs c_{it} offline

- Assume innovation has occurred when we see a firm expand it's r frontier.



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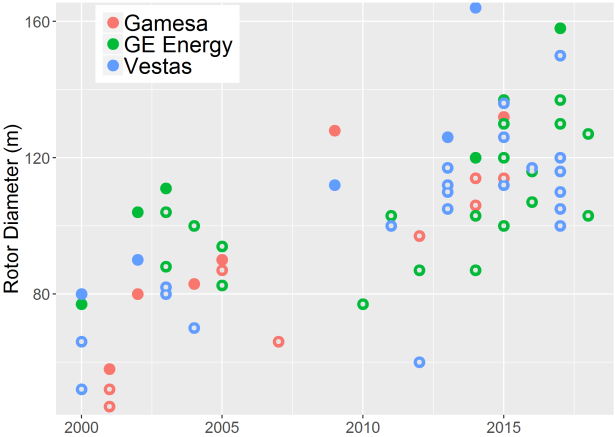
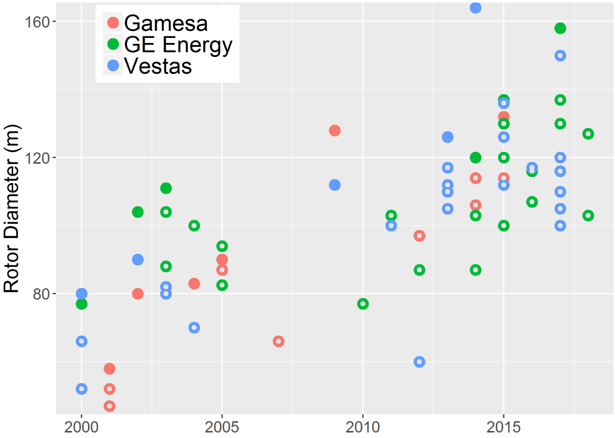
- Within that tech vintage, firms offer several models.



Estimation: Recover costs c_{it} offline

- Assume innovation has occurred when we see a firm expand it's *r* frontier.
- Within that tech vintage, firms offer several models.
- We assume that firms offer the *surplus* maximizing r^* within vintage to each site.
- This allows us to recover c for each vintage offline.
  - to incorporate discrete choice set, use logit + MLE



Recovering the dynamic terms

- Presence of $L(x)$ in cost function means firms have an incentive to *underprice* new turbines (to gain experience)
- If firms have "rational" expectations about future investment costs, the optimal price k should satisfy a FOC:

$$0 = \frac{d\Pr(\text{sale} \mid k)}{dk}\left(k - cr^3 - L(x)\right) + \Pr(\text{sale} \mid k) + \frac{d}{dk}\mathbb{E}\left[V(c', x')|c, x, k\right]$$

- Berry & Pakes (2000) insight: under a rational expectations assumption

$$\frac{d}{dk}\mathbb{E}\left[V(c', x')|c, x, k\right] = \mathbb{E}\left[V(c', x')\frac{d}{dk}\log f(c', x' \mid c, x, k)\right]$$

  where $f(c', x' \mid c, x, k)$ is the state transition density.
- Can reweight estimate of V to get expected gradient (magic)

Empirical implementation of dynamic estimator

- "Realized" cash flows are a function of realized investment and unobserved investment costs:

$$CF_{it}(L, \phi) = \sum_{j=1}^{N_{it}} \left(k_j - c_{it} r_j^3 - L(x_{it}) \right) + \mathcal{I}\left[\text{invest}\right]_{it} \phi(c_t^{max}))$$

- Observing prices/sizes of turbines sold + firm's decision to invest or not gives an empirical analogue to the "gradient of the continuation value"

$$\mathbb{E}\left[V(c_{it+1}, x_{it+1}) \frac{d}{d\mathbf{k}} \log f(c_{it+1}, x_{it+1} \mid c_{it}, x_{it}, \mathbf{k}_{it}) \right] =$$

$$\frac{d}{d\mathbf{k}} \log f(c_{it+1}, x_{it+1} \mid c_{it}, x_{it}, \mathbf{k}_{it}) \sum_{\tau=1}^{\infty} \delta^{t+\tau} CF_{it+\tau}(L, \phi)$$

HARVARD ENVIRONMENTAL ECONOMICS PROGRAM

Research Workshop
for
Pre-Doctoral Fellows and Alumni

Thursday-Friday, September 19 – 20, 2019
Harvard Kennedy School
Cambridge, Massachusetts