Policy Uncertainty in the Market for Coal Electricity: The Case of Air Toxics Standards

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Economic Consequences of Policy Uncertainty

- Uncertainty over government policy affects important and irreversible decisions such as technology adoption, entry, and exit.
- The process of forming and implementing policies often creates uncertainty.
  - In the U.S., new policies occur through legislation and/or regulations.
- Legislation is infrequent and often empowers agencies to make specific regulations.
  - This approach allows existing legislation to respond to new information.
  - However, developing regulations takes time, and regulations are subject to court challenges and executive branch changes.
- This system may lead to more responsive policies.
  - But uncertainty can both increase costs and delay policy objectives.

Costs of Policy Uncertainty Depend On:

1. The extent to which compliance requires irreversible decisions:
   - Making these decisions requires considering option value (Teisberg, 1993; Dixit and Pindyck, 1994).
   - Maintaining option value may increase compliance costs.
2. How maintaining option value changes externalities:
   - For instance, costs of policy uncertainty are affected by how uncertainty affects firm exit and adoption and how this affects externalities, such as pollution.
3. Whether the policy is eventually enforced:
   - Even discussion of a policy can lead to some irreversible decisions.

In many sectors, policy compliance requires costly and irreversible decisions.

- E.g., healthcare, telecommunications, and finance.
- We focus on the cost of uncertainty in environmental policy.

Goals of the Paper

1. Estimate beliefs about the likelihood of Mercury and Air Toxics Standard (MATS) enforcement.
   - MATS regulated emissions from electricity generation.
   - Model generators' exit and abatement technology adoption decisions.
2. Simulate how policy uncertainty affects counterfactual outcomes in the industry.
   - Evaluate how policy uncertainty affects pollution, exit, and compliance costs.

Accounting for option value requires estimating a dynamic equilibrium model:

- Novel way of estimating generators' beliefs about policy uncertainty.
- Dynamic equilibrium counterfactuals allow us to quantify the impacts of uncertainty.

Mercury and Air Toxics Standard (MATS)

- Coal-fired generators are the primary emitters of air toxics from electricity generation.
  - Air toxics cause cancer, birth defects, and other serious illnesses.
- Despite the dangers, federal regulation of air toxics has been recent and uncertain.
  - The EPA released the final MATS rule in 2012 with enforcement in 2016.
  - Regulation has been subject to substantial judicial and administrative review.
- While the federal government was formulating air toxics policy, some U.S. states mandated air toxics reductions for generators within their borders.
  - Either legislative or developed with input from power producers.
  - These policies were largely certain once announced.
- Can use these generators to identify extent of policy uncertainty in MATS.

Overview of Adoption and Exit Model

- We estimate a dynamic oligopoly model of coal generator actions from 2006-17.
  - Focus on coal independent power producers (IPPs), who face market incentives.
- Every year, generators subject to MATS:
  1. Form beliefs about the 2016 enforcement probability.
  2. Simultaneously decide whether to adopt abatement technology, exit, or continue.
  3. Earn operating profits by supplying electricity to hourly markets within the year.

Market Equilibrium

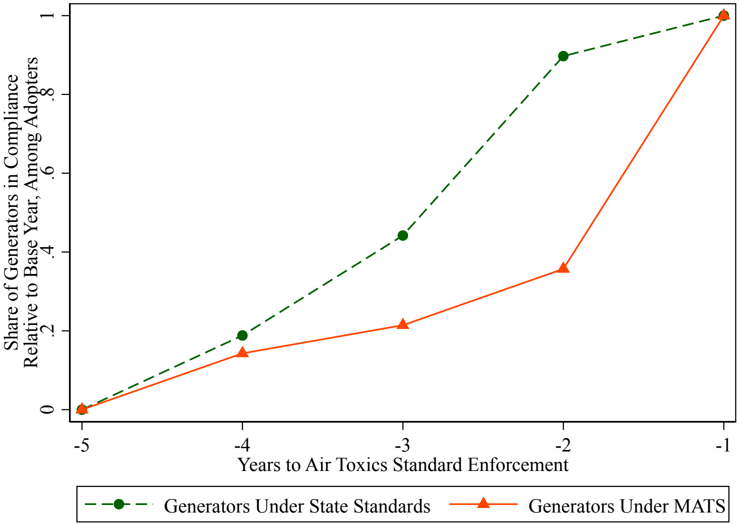
- Equilibrium effects are potentially important:
  - A generator's exit increases rivals' profits, decreasing further exit.
  - Generators may adopt abatement technology as commitment to not exiting (Riordan, 1992; Schmidt-Dengler, 2006).
- Generators compete in a Markov equilibrium.
  - Equilibrium concept builds on moment-based Markov equilibrium (MME):
    - In an MME, each player would either be a fringe or dominant player.
    - Players keep track of individual dominant player states and aggregate state.
  - In our approach, *all* generators know their actions affect the aggregate state.
    - But, they don't keep track of any individual generator states.
  - Aggregate states: coal capacity, technology adoption share, and fuel prices.
- Limitation: we do not model ownership linkages across generators.
  - States are relatively unconcentrated: generation HHI is 2,209 (1,659).

Identification of Generators' Beliefs

We use the difference between generators' responses to state air toxics standards and MATS to identify generators' perceived probability of enforcement.

- Might generally be difficult to separate MATS probability from exit scrap values.
- We leverage the assumption that generators subject to U.S. state policies face certain enforcement.
- Compare conditional exit rates between MATS-enforced and state-enforced generators.

Visual Identification of Perceived Enforcement Probabilities



Recovering Generators' Annual Profits

- Estimating the adoption and exit model requires recovering the relationship between profits and the underlying dynamic state.
- Annual profits are revenues from electricity sales net of three costs:
    1. Fuel costs: observed as fuel price times heat rate.
    2. Ramping costs: occur when generators adjust their production levels.
    3. Operations & maintenance (O&M) costs.
- Ramping costs in particular are important in our context.
    - These costs are substantial (Reguant, 2014, Linn and McCormack, 2019).
    - The fracking revolution has meant that coal generators cycle more, increasing ramping costs, and reducing generator profits.

Change in Ramping and Natural Gas Prices Over Time

Year	Hours at Max Generation Per Ramp	Natural Gas Price Over Coal Price
2006	27.99	4.62
2007	32.96	4.39
2008	30.42	4.82
2009	23.08	2.35
2010	26.70	2.27
2011	24.68	1.94
2012	20.73	1.32
2013	22.76	1.82
2014	24.41	2.28
2015	17.57	1.41
2016	17.17	1.35
2017	19.94	1.63

Note: Each observation in the second column pertains to one observed ramp to maximum generation. Each observation in the third column pertains to one observed generator-year.

Distribution

Estimating Ramping and O&M Costs

- We estimate ramping and O&M costs with new, tractable methods that incorporate dynamic linkages between hours.
- We develop a “conceptual experiment” that compares two sets of hours with similar future prices, but where generation varied in the previous hour.
  - We estimate ramping costs with a regression of chosen generation level on revenues, lagged generation, and controls for future value.
  - The difference in operating probabilities across these sets identifies ramping costs if controls sufficiently account for differences in continuation values.
- We estimate O&M costs with a related simple choice model.
- Limitation: costs estimated assuming generators are price-takers.
- We use generators’ observed actions and estimated costs to recover annual profits.

Relationship to Literature

This project builds three main literatures:

1. Measurement of economic and policy uncertainty:
   - Baker, Bloom, and Davis (2014), Handley and Li (2020), and Langer and Lemoine (2020) develop measures of uncertainty in different contexts.
   - E.g., Kellogg (2014), Dorsey (2019), Handley and Li (2020) examine the impact of uncertainty on economic outcomes.
   - We recover generator beliefs and perform counterfactual simulations.
2. Structural estimation of the electricity industry:
   - E.g., Fowlie (2010), Elliott (2022), Gowrisankaran, Langer, and Reguant (2022).
   - We develop a dynamic oligopoly model, and estimate ramping and O&M costs.
3. Dynamic Oligopoly Estimation with Approximations:
   - Extend MME (Ifrach and Weintraub, 2017) which builds on Oblivious Equilibrium.
   - Recent empirical applications of MME include Gerarden (2017), Vreugdenhil (2020), and Jeon (2022).

Outline of talk

Regulating Air Toxics

- The EPA regulates air toxics under the 1990 Clean Air Act Amendments (CAAA).
  - Initial rule for electricity announced in 2005 and judicially vacated in 2008.
  - Courts required a stricter standard for a wider set of pollutants.
- MATS has been subject to substantial uncertainty:
  - Final rule challenged up to the U.S. Supreme Court.
  - Executive branch changes alter administrative priorities.
- Despite this, MATS essentially in force starting in 2016.
  - Generators can use different technologies to comply with MATS.
- Beyond uncertainty, some differences between U.S. state regulations and MATS.
  - Compliance and enforcement sometimes less stringent than MATS.
  - U.S. states mostly covered mercury rather than all air toxics.
- Other pollution regulations allow for purchase of (relatively cheap) permits.

Data Sources

1. EPA's Continuous Emissions Monitoring System (CEMS):
   - Hourly heat input, generation, and SO_2 emitted for coal generators.
   - Fuel source by generator and year.
2. U.S. state air toxics standards announcements and enforcements.
3. Energy Information Administration (EIA) Form 423 data: fuel prices.
4. EIA Form 923 data: whether a facility is an independent power producer (IPP).
5. Wholesale electricity market price data for nodes in Eastern Interconnection.
6. Consumer price index to deflate prices.
7. Public Utility Data Liberation (PUDL) data: electricity load by state.
8. Weather data from PRISM.

State Policy Announcement and Enforcement Dates

State	Announced	Enforced
Connecticut	2003	2009
Massachusetts	2004	2009
Illinois	2006	2010
Delaware	2006	2010
Maryland	2006	2011
Minnesota	2006	2011
Wisconsin	2008	2016

Note: Collected from Federal Registry, state environmental agencies, and newspaper reports.

Main Analysis Samples

- Two main analysis data sets for IPP coal generators:
  1. Examine adoption/exit decisions using generator-year level data.
  2. Examine operations decisions using generator-hour level data.
- We analyze decisions at the "generator" level rather than the "plant" level.
  - Plants may have many generators w/ different characteristics.
  - Retirement/adoption decisions can be made independently.
- Sample covers IPP coal generators in the Eastern Interconnection form 2006-17.
- Key variable: timing of adoption of air toxic abatement technologies.
  - EPA determines MATS compliance, in part, by SO_2 rate below 0.2 lbs/MMBtu.
  - For most generators, we observed large SO_2 rate decline before MATS.
  - We infer compliance through SO_2 levels and declines.

Generator Level Descriptive Statistics by Regulatory Regime

	State Policy	MATS
Capacity (MW)	279.69 (213.78)	245.74 (282.60)
Heat Rate (MMBtu/MWh)	10.51 (2.25)	11.90 (4.64)
Coal Fuel Price ($/MMBtu)	1.70 (0.19)	2.13 (0.40)
Marginal Fuel Costs ($/MWh)	17.85 (4.44)	26.23 (13.94)
Generators	93	226
Generator-years	841	2040

Note: Authors' calculations based on analysis sample of IPP coal generators.

Counts of Generators Adopting Abatement Technology or Exiting

	State Policy			MATS		
Years to Enforcement	Adoptions	Exits	Share Complied	Adoptions	Exits	Share Complied
4	12	0	0.34	2	23	0.30
3	5	1	0.51	1	19	0.54
2	9	0	0.77	2	7	0.64
1	4	4	1.00	9	21	1.00
Total	30	11		14	84	

By calendar year

Annual Adoption/Exit Model

- Infinite-horizon dynamic equilibrium model of adoption, exit, and production.
- Model focuses on a market, which is a U.S. state.
- Each year, generators $j = 1, \ldots, J_t$ operate and earn profits Π_{jt}.
    - Each generator has time-invariant heat rate, $heat_j$, and capacity, K_j.
    - At year t, indicator for having installed abatement technology, $Tech_{jt}$.
- Generators compete in a dynamic oligopoly.
    - They also compete with gas, renewable, non-IPP coal, and other sources.
    - We treat other sources' decisions as exogenous, though state-contingent and time-varying.

Annual Model Timing and Payoffs

1. Policy environment updates.
   - In year t_0 the regulator announces an air toxics standard, τ_0 years in the future.
   - Before t_0, generators do not expect to be subject to any air toxics regulation.
   - At $\tau \leq \tau_0$ years from enforcement, generators perceive enforcement prob. P_τ.
     - At this time, they believe that they will continue to believe P_τ in the future.
2. Generators make adoption and exit decisions.
   - If they adopt, they pay an adoption cost $A - \sigma\varepsilon_{jat}$.
   - If they exit, they receive a scrap value $X + \sigma\varepsilon_{jxt}$.
   - Otherwise, they receive a continuation draw, $\sigma\varepsilon_{ict}$.
3. Generators compete in hourly electricity markets.
   - Use estimated costs and observed actions to calculate profit surface $\Pi(\Omega)$.
4. Adoption and exit decisions are implemented.
   - In final year before potential enforcement, regulator enforces with prob. P_1.

Bellman

Our Equilibrium Approach

- We use an approximate equilibrium method that extends MME.
  - In our approach, generators base decisions on a summary set of state variables.
- The generator's state includes its capacity, heat rate, and adoption status.
- Generators also keep track of a parsimonious subset of market characteristics:
  1. Share of IPP coal capacity that has adopted abatement technology.
  2. Coal capacity divided by 95^{th} percentile of load.
  3. Natural gas fuel price relative to coal price.
- Generators expect these variables to transition via AR(1) processes.
  - Generators know that their decisions affect adoption share and coal capacity.
  - Gas prices evolve exogenously and coal prices are assumed fixed.
- Equilibrium consists of AR(1) regression coefficients and generator strategies where:
  1. Strategies reflect individual dynamic optimization given AR(1) processes.
  2. Data simulated from these strategies yield these same AR(1) processes.

Model of Hourly Operations

- We recover $\Pi(\Omega)$ as the sum of hourly profits over the year $\Pi_{jt} = \sum_h \pi(\tilde{q}_{j,h-1}, \omega_{jh}, q_{jh})$.
- Within each year, generators choose hourly production q.
  - Trinomial choice: (1) off, (2) operating at minimum (LK), and (3) operating at K.
- State space:
  - $\tilde{q}$: last hour's generation.
  - ω: information that affects current and future profits, e.g., time of day, weather.
- Let $p(\omega, q)$ be the expected wholesale electricity price given ω.
- The generator bears O&M costs, om, and, if $q > \tilde{q}$, ramping costs $r_{\tilde{q}_h, q_h}$.
- Hourly Bellman equation is:

$$v(\tilde{q}, \omega) = \max_q \left\{ \pi(\tilde{q}, \omega, q) + \beta^{1/H} E[v(q, \omega')|\omega] \right\}$$

where

$$\pi(\tilde{q}, \omega, q) \equiv q \times [p(\omega, q) - heat \times f^C - om] - \mathbb{1}\{\tilde{q} < q\} r_{\tilde{q},q} + \sigma^g \varepsilon^g_q.$$

Estimation of Ramping Costs

- We recover annual profits by estimating ramping costs and the scale parameter σ^g from operating decisions.
- We estimate ramping costs with the following trinomial hourly specification:

$$u(q_h|\tilde{q}_h,\omega_h) = \overbrace{\frac{1}{\sigma^g}[q_h p_h]}^{\text{Revenues}} - \overbrace{\frac{1}{\sigma^g} r_{\tilde{q}_h,q_h} \mathbb{1}\{\tilde{q}_h < q_h\}}^{\text{Ramping cost term}} \underbrace{-\psi x(q_h,\omega_h)}_{\text{Other costs and relative continuation value}} + \varepsilon^g_{qh}.$$

- The key parameters from this model are $r_{\tilde{q}_h,q_h}$ and σ^g.
- Control for costs and relative continuation values, $x_h(q_h,\omega_h)$ with:
  - Quantity generated interacted with technology and fuel costs per MW.
  - Weather, hour of day, month, and current load, interacted with both indicators for the current generation level and time trends.

Identification of Ramping Costs

- We require three exclusion restrictions:
  1. Revenues don't enter into x_h.
  2. Lagged generation also does not enter into x_h.
  3. Units take wholesale electricity prices, p_h, as given.
- Hinges on ability of controls, x_h, to accurately capture relative state-contingent continuation values.
  - Would be inconsistent, e.g., if we overstate value from operating at maximum generation when lagged generation is maximum relative to minimum.
  - We provide empirical evidence on how our value relates to future prices.

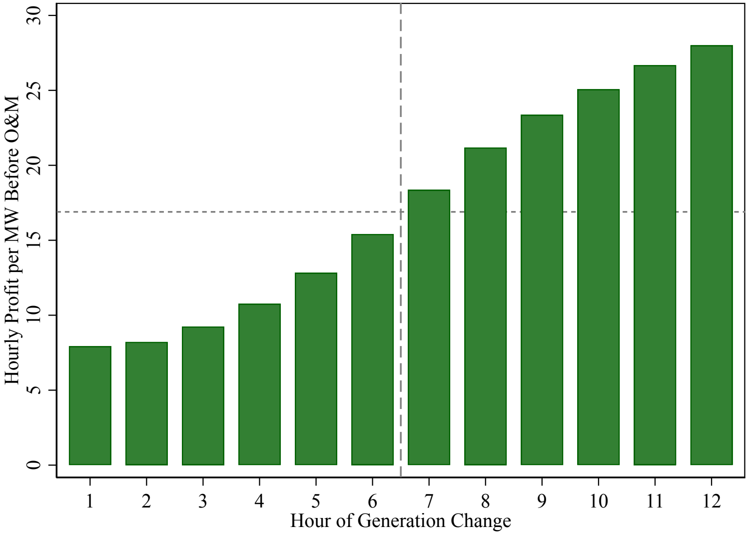
Estimation of O&M Costs

- We recover O&M costs from production decision within a set of hours with similar continuation values.
  - Consider a 12-hour window surrounding a ramp from min to max or reverse.
  - Estimate a 12-nomial choice of the hour to ramp or deramp.
- Assumption: generation change occurs sometime during window $\{\underline{h}, \dots, \underline{h}+11\}$
  - We then remove continuation value from decisions within this window:

$$\pi^w_{jh} = \sum_{\tilde{h}=h}^{\underline{h}+11} (p_{\tilde{h}} - heat_j \times f^C)(K_j - K_j L_j) - om \times (\underline{h} + 12 - h) \times (K_j - K_j L_j) + \sigma^w \varepsilon^w_{jh}.$$

- Estimation will make *om* fit the fact that the 7th hour is the first hour with extra operating profits enough to justify the ramp.
  - Intuition is flipped for deramps.

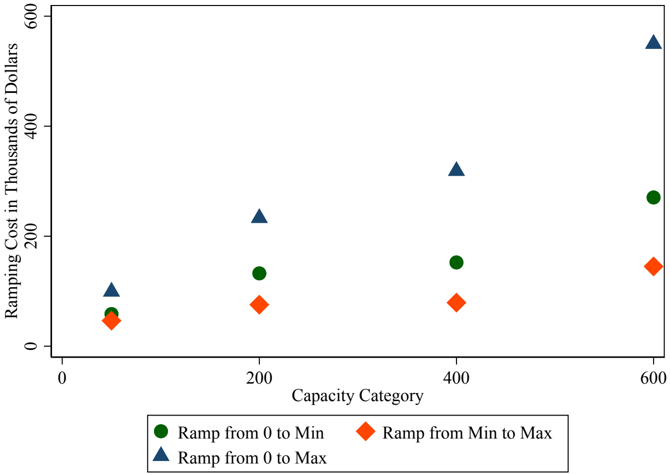
O&M Cost Identification



Estimation of Dynamic Parameters

- Parameters to estimate from adoption model:
  - Perceived probability of MATS enforcement by year, P_τ.
  - Cost of adoption, A, exit scrap value, X, and scale of uncertainty, σ.
  - Profits at each potential state come from our profit surface regression.
  - We allow A to vary across MATS and state policy generators.
- We use a nested fixed point maximum likelihood estimator.
  - Each generator in one year is an observation.
  - Likelihood has simple trinomial form, given equilibrium generator policies.
- Estimation algorithm:
  1. Search over structural parameters.
  2. Equilibrium: fixed point of transition regressions and generator optimization.
  3. Find parameter vector that maximizes simulated likelihood.
- We don't use CCP estimator since future data does not indicate expectations.

Ramping Cost Estimates



Note: Reported ramping costs are ratios of estimated ramping coefficient to operating revenue coefficient from separate regressions by capacity bin.

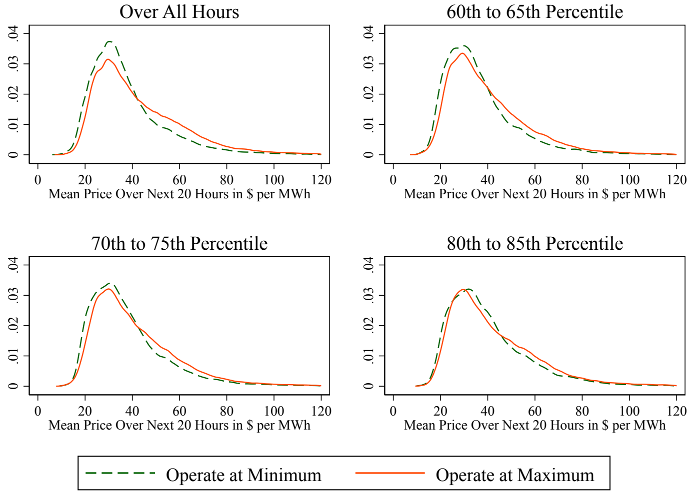
Ramping Cost Estimates: 100-300MW Capacity

	No Controls	With Controls	With Controls
Operating Rev. (Million $)	763.87*** (0.46)	76.47*** (0.84)	76.58*** (0.84)
Ramp 0 to Min	−9.03*** (0.01)	−10.13*** (0.01)	−5.21*** (0.18)
Ramp Min to Max	−6.06*** (0.00)	−5.77*** (0.00)	−2.83*** (0.19)
Ramp 0 to Max	−37.82*** (0.16)	−17.82*** (0.06)	−9.97*** (0.21)
Deramp Min to 0	–	–	−4.87*** (0.18)
Deramp Max to Min	–	–	−2.94*** (0.19)
Deramp Max to 0	–	–	−8.74*** (0.21)
N	28,686,219	28,686,219	28,686,219
Pseudo R^2	0.7612	0.8570	0.8571

Note: Regression controls include generation quantity, flexible time trend, and flexible function of fuel prices and coal capacity, all interacted with technology and fuel cost per MW, and weather, hour-of-day, month, and current load.

- Reguant (2014) estimates start-up costs of €15-20k for a 150MW coal plant.
- Kumar et al. (2012) suggest start-up costs of up to $500k for large coal plants.

Ramping Cost Controls Capture Future Value Reasonably Well



- Price densities plotted separately by minimum or maximum generation.
- The top left panel shows this for all hours.
- The other panels show hours where the difference in net value—ψx—from operating at maximum minus minimum generation is within quantiles.

O&M Cost Estimates

Benefit per Million Dollars of Variable Profit	10.55^{***} (0.45)
Cost per TW of Additional Production	-160.18^{***} (9.07)
Observations	384,672
Pseudo R^2	0.0043

Note: Multinomial logit regression of choice of number of hours produced within a 12 hour window surrounding each ramping event into or out of maximum generation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

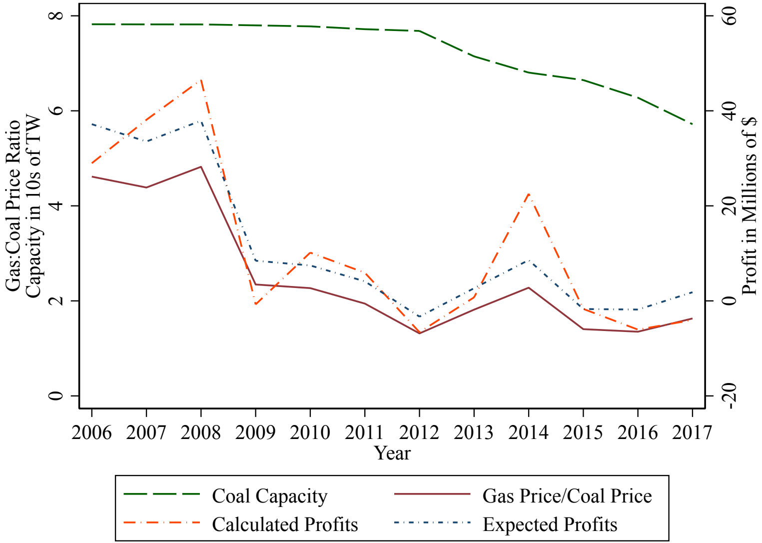
- Implies an operation and maintenance cost of $15.18/MW.
- EIA's National Energy Modeling System estimates are approximately $14/MWh.

Generators' Annual Profits and Pollution by State

	Annual Profit (millions of $)	Log Annual Pollution (lbs of SO_2)
Compliant		-1.285^{***} (0.054)
State Coal Share	-5.505^{***} (1.701)	0.335^{***} (0.064)
Gas to Coal Fuel Price Ratio	9.371^{***} (0.819)	0.798^{***} (0.042)
Interaction of Share and Price Ratio	2.681^{***} (0.773)	-0.182^{***} (0.064)
State Coal Fuel Price ($)	16.231^{***} (1.230)	-0.728^{***} (0.182)
Heat Rate (MMBtu/MW)	-0.648^{***} (0.133)	1.278^{***} (0.244)
Capacity (MW)	0.052^{***} (0.004)	0.985^{***} (0.046)
Constant	-55.418^{***} (4.109)	7.847^{***} (0.809)
Observations	3035	2819
R^2	0.4778	0.9938

Note: Regression of calculated profits and log pollution from observed data on dynamic model states. Independent variables in log pollution regression are also logged.

Profits, Fuel Prices, and Capacity



Adoption Cost, Exit Value, and Belief Estimation Results

	Base Specification	Same Adoption Cost State vs. MATS
Predicted Enforcement Probabilities:		
Probability 2012	1.000^{***} (0.061)	0.999^{***} (0.080)
Probability 2013	0.699^{***} (0.120)	0.525^{***} (0.159)
Probability 2014	0.433^{***} (0.109)	0.306^{**} (0.139)
Probability 2015	0.999^{***} (0.107)	0.997^{***} (0.103)
Generator Costs:		
Adoption Cost (million \$)	150.9^{**} (75.1)	413.9^{***} (41.8)
Extra MATS Adoption Cost (million \$)	398.7^{***} (72.1)	–
Exit Scrap Value (million \$)	-196.4^{***} (37.4)	-196.8^{***} (42.6)
$1/\sigma$ (million \$)	63.6^{***} (5.7)	63.4^{***} (6.5)
Simulated Log Likelihood	-628.34	-637.88

Note: Structural parameter estimates from nested-fixed point estimation.

Counterfactual Results

	Data	Estimated Model	Prob $= 0.7827$ All Years	Uncertainty Resolved 2012	No Exit Cost
Adoption Costs (Bill. \$)					
Exit Costs (Bill. \$)					
Total Profits (Bill. \$)					
Pollution (Mill. lbs. SO_2)		867.52			
Number of Generators:					
2012	191	191.0			
2013	168	175.9			
2014	149	163.0			
2015	142	152.5			
2016	121	129.5			
Count Adopting	14	14.5			

- Estimated model fits the data reasonably well.

Counterfactual Results

	Data	Estimated Model	Prob $= 0.7827$ All Years	Uncertainty Resolved 2012	No Exit Cost
Adoption Costs (Bill. \$)		7.30			
Exit Costs (Bill. \$)		19.24			
Total Profits (Bill. \$)		46.74			
Pollution (Mill. lbs. SO_2)		867.52			
Number of Generators:					
2012	191	191.0			
2013	168	175.9			
2014	149	163.0			
2015	142	152.5			
2016	121	129.5			
Count Adopting	14	14.5			

- Adoption and exit costs are substantial relative to 30-year profits.
- EPA estimated ex ante \$9.6 billion in compliance costs.

Counterfactual Results

	Data	Estimated Model	Prob $= 0.7827$ All Years	Uncertainty Resolved 2012	No Exit Cost
Adoption Costs (Bill. \$)		7.30	6.99		
Exit Costs (Bill. \$)		19.24	19.15		
Total Profits (Bill. \$)		46.74	47.73		
Pollution (Mill. lbs. SO_2)		867.52	881.30		
Number of Generators:					
2012	191	191.0	191.0		
2013	168	175.9	176.5		
2014	149	163.0	163.1		
2015	142	152.5	150.7		
2016	121	129.5	131.0		
Count Adopting	14	14.5	13.7		

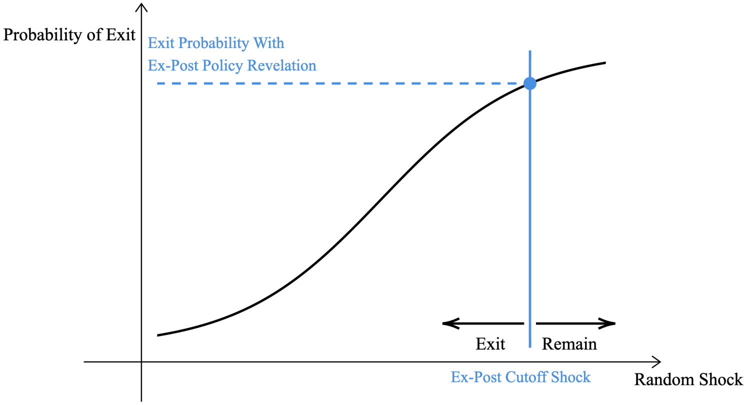
- To understand uncertainty, start with average probability in all years.

Counterfactual Results

	Data	Estimated Model	Prob = 0.7827 All Years	Uncertainty Resolved 2012	No Exit Cost
Adoption Costs (Bill. $)		7.30	6.99	6.53	
Exit Costs (Bill. $)		19.24	19.15	18.74	
Total Profits (Bill. $)		46.74	47.73	48.66	
Pollution (Mill. lbs. SO_2)		867.52	881.30	946.50	
Number of Generators:					
2012	191	191.0	191.0	191.0	
2013	168	175.9	176.5	176.8	
2014	149	163.0	163.1	163.6	
2015	142	152.5	150.7	151.4	
2016	121	129.5	131.0	135.0	
Count Adopting	14	14.5	13.7	12.85	

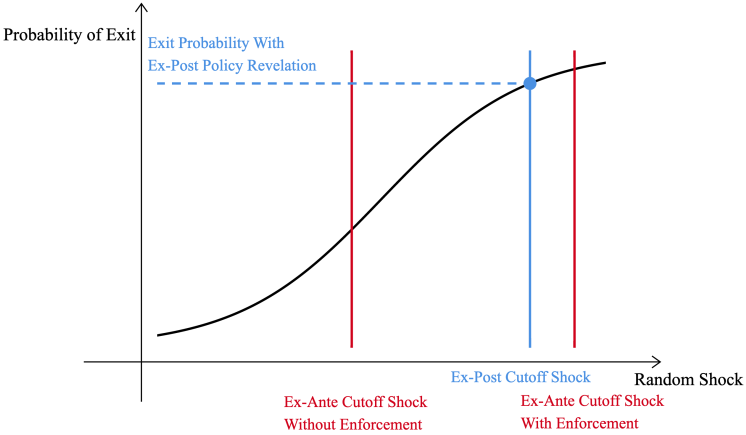
- Eliminating uncertainty saves $930 mil., but increases pollution $809 – $2,206 mil.
- Increases 2016 generators by 3.1% and pollution by 7.4%.

Why Does Resolving Uncertainty Early Decrease Exit?



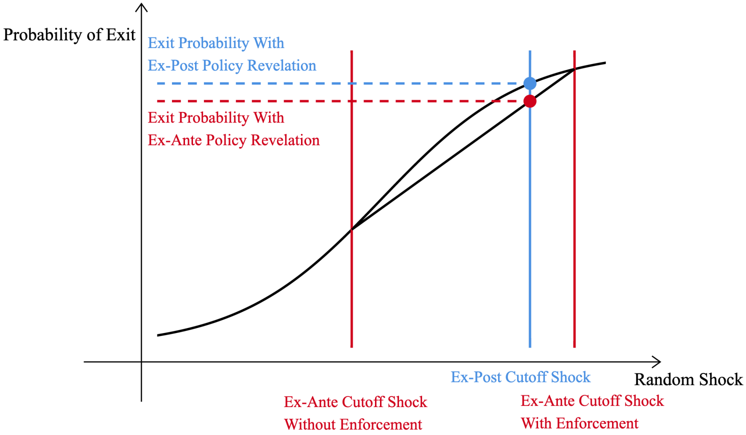
- Conceptual CDF of a generator's shocks from 2012-16 that affect exit.
- Blue vertical line indicates minimum shock for generator to remain.
- Blue horizontal dashed line indicates probability of exit.

Why Does Resolving Uncertainty Early Decrease Exit?



- With early uncertainty resolution, MATS is enforced with probability 0.7827.
- This leads to red vertical lines, which vary based on the enforcement decision.
- We placed red lines so blue line is 78.27% of way to enforcement line.
- Without enforcement, generators exit less often.

Why Does Resolving Uncertainty Early Decrease Exit?



- Counterfactuals show lower exit probability with ex-ante uncertainty resolution (replicated here).
- Blue line must be on the concave part of CDF, where generators are likely to exit.
- Low natural gas prices meant that many coal generators were very likely to exit.
- In other contexts, ex-ante resolution could *increase* exit.

$\Rightarrow$ Early uncertainty resolution attenuates extreme outcomes.

Counterfactual Results

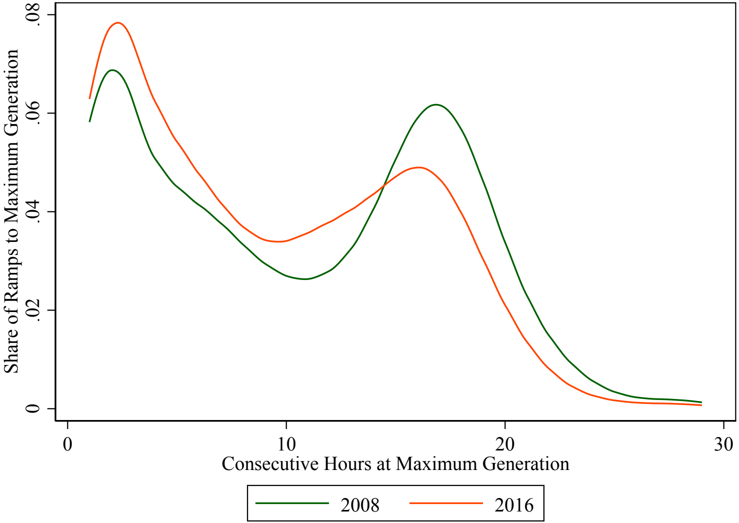
	Data	Estimated Model	Prob = 0.7827 All Years	Uncertainty Resolved 2012	No Exit Cost
Adoption Costs (Bill. \$)		7.30	6.99	6.53	5.10
Exit Costs (Bill. \$)		19.24	19.15	18.74	0.00
Total Profits (Bill. \$)		46.74	47.73	48.66	69.90
Pollution (Mill. lbs. SO_2)		867.52	881.30	946.50	740.91
Number of Generators:					
2012	191	191.0	191.0	191.0	191.0
2013	168	175.9	176.5	176.8	169.4
2014	149	163.0	163.1	163.6	151.6
2015	142	152.5	150.7	151.4	137.1
2016	121	129.5	131.0	135.0	111.0
Count Adopting	14	14.5	13.7	12.85	10.1

- Exit subsidies reduce the number of coal generators by 15.1% in 4 years.
- Requires a large transfer from government to generators.

Conclusion

- We estimate the extent and impact of policy uncertainty for MATS.
  - We recover the 2012-15 expected probabilities of 2016 MATS enforcement.
  - Develop a dynamic oligopoly framework to estimate adoption and exit.
  - Provide new approaches to estimating ramping and O&M costs.
- Main findings:
  1. Substantial uncertainty surrounding MATS enforcement in 2013 and 2014.
  2. Eliminating uncertainty increases generator expected profits by $930 million.
  3. It *increases* pollution by allowing generators to better time market uncertainty.
  4. Subsidizing exit costs would cause more generator exit than MATS.
- We expect that resolving policy uncertainty will generally raise profits.
  - In our case, it also leads to more pollution.

Distribution of Consecutive Hours at Maximum Generation



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Counts of Generators Adopting Abatement Technology or Exiting

Year	State Policy		MATS	
	Adoptions	Exits	Adoptions	Exits
2006	6	0	26	2
2007	4	1	24	9
2008	1	0	32	1
2009	13	5	22	2
2010	1	7	0	15
2011	0	10	2	6
2012	0	6	2	23
2013	0	1	1	19
2014	0	2	2	7
2015	0	3	9	21
2016	0	11	0	14
2017	0	0	0	0
Total	25	46	120	119

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Dynamic Optimization

- Let $V(\Omega, Tech, \tau', \vec{\varepsilon})$ denote the generator's value function.
- With beliefs P_τ, one year before potential enforcement, $V(\Omega, 0, 1, \vec{\varepsilon})$ for a generator that hasn't adopted is the maximum over:
  1. Continue without adopting:
  $$\Pi(\Omega) + P_\tau X + (1 - P_\tau)\beta E[V(\Omega', 0, 0, \vec{\varepsilon'})|\Omega, \text{No Standard}] + \sigma\varepsilon_c$$
  2. Adopt:
  $$\Pi(\Omega) - A + \beta\{P_\tau E[V(\Omega', 1, 0, \vec{\varepsilon'})|\Omega, \text{Standard}] + (1 - P_\tau)E[V(\Omega', 1, 0, \vec{\varepsilon'})|\Omega, \text{No Standard}]\} + \sigma\varepsilon_a$$
  3. Exit:
  $$\Pi(\Omega) + X + \sigma\varepsilon_x.$$
- In earlier years, P_τ doesn't enter the choice in the current year except through expectations of future values.

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