Escalation of Scrutiny: The Gains from Dynamic Enforcement of Environmental Regulations

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Motivation

- Governments spend billions on environmental enforcement.
  - Plants also spend substantial time and money on compliance.

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  - Plant investment costs may be heterogeneous.

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- The design of effective enforcement is complicated:
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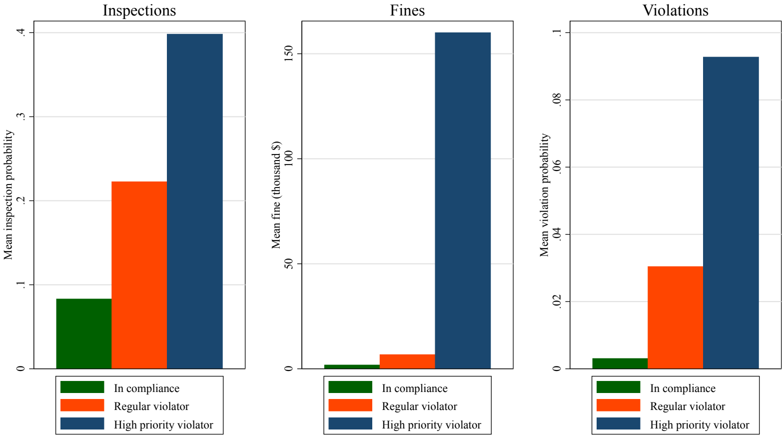
  - Investment in pollution abatement is costly and takes time.
  - Penalties are limited by bankruptcy and political pressure.
  - Plant investment costs may be heterogeneous.
- These complications have led to *dynamic regulation* where repeat offenders are punished more severely than one-time offenders.
  - In enforcing the Clean Air Act and Amendments, the U.S. EPA designates repeat offenders as *high priority violators* (HPVs).

Regulatory Actions by Lagged Plant Status



Note: Authors' calculations for plants covered by Clean Air Act, 2007-13.

- HPVs face more inspections, higher fines, and more violations.

Goals of this Paper

1. Estimate the cost to plants of compliance with the EPA's current dynamic enforcement approach.
2. Simulate the value of alternative enforcement regimes in affecting pollution and ensuring compliance.

Our Approach

- Develop and estimate a dynamic game between a plant and a regulator enforcing environmental laws.
  - Recover regulator's conditional choice probabilities (CCPs).
  - Estimate random coefficient model of plants' costs.
- Use the structural model to simulate counterfactuals that change the non-linearity of fines and plants' cost of regulation.
  - Counterfactuals focus on optimal dynamic plant behavior, not dynamic equilibrium.

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- Use the structural model to simulate counterfactuals that change the non-linearity of fines and plants' cost of regulation.
  - Counterfactuals focus on optimal dynamic plant behavior, not dynamic equilibrium.
- Why a dynamic model?
  - Previous empirical research largely focused on documenting the response of plants, not estimating the costs of compliance.
  - Estimating costs requires accounting for how investment decreases future penalties and moves plants between regulatory states.
  - Requires a model that formally accounts for dynamic, optimizing behavior of plants.

Relation to the Literature

1. Empirical studies of dynamic enforcement.
   - Landsberger and Meilijson, 1982; Earnhart, 2004; Eckert, 2004; Shimshack and Ward, 2005; Ko et al., 2010; Shinkuma and Shunsuke, 2012; Telle, 2013; Blondiau et al., 2015; Evans, 2017; Blundell, 2017.
2. Structural evaluations of environmental regulatory policy.
   - Timmins, 2002; Ryan, 2012; Lim and Yurukoglu, 2015; Fowlie et al., 2016; Duflo et al. 2018; Houde, 2018; Kang and Silveira 2018.
   - Most closely related to Duflo et al. 2018; Kang and Silveira 2018.
3. Dynamic discrete choice models with random coefficients.
   - Arcidiacono and Miller 2011; Fox et al, 2011; Gowrisankaran and Rysman 2012; Fox et al., 2016; Nevo, Turner, and Williams, 2016; Connault, 2017.
   - Our fixed grid model is similar to the Fox/Nevo et al. approaches.

Regulatory Setting

- The Clean Air Act and Amendments (CAAA) are enforced by the EPA using a system of inspections, violations, fines, and classification into different regulatory states.
  - Being in violator status subjects a plant to additional inspections, which might uncover additional violations and yield greater fines.
- Plants in that are substantially or persistently out of compliance may be designated high priority violators.
  - HPVs face increased scrutiny from federal, state, and potentially local authorities.
- Much of the enforcement activity occurs at the state and regional level.
  - Regional EPA offices oversee states and incorporate different regional preferences in enforcement: provide identifying variation.

Data Sources

Our study primarily uses two CAAA monitoring and enforcement databases:

1. Environmental Compliance History Online (ECHO) database.
    - EPA Actions: inspections, violations, and fines.
    - Investments inferred from permits and resolution codes.
    - Historical compliance: regular and high priority violator.
2. National Emissions Inventory (NEI) database.
    - Data are every 3 years.
    - Only used to understand pollution effects of counterfactual policies.

We create a quarterly unbalanced panel from Q1:2007 to Q3:2013.

- Period of consistent policy and record-keeping.
- Unit of observation is the plant-quarter.
- We keep seven industrial sectors with high pollution levels.

Summary Statistics on Estimation Sample

Status:	Compliance	Regular violator	HPV
Regulator actions:			
Inspection (%)	7.87	22.45	39.71
Fine amount (thousands of $)	1.58	14.03	154.74
	(60.85)	(190.59)	(645.19)
$\mathbb{1}\{\text{Fine} > 0\}$ (%)	0.16	2.92	13.39
Regulatory outcomes:			
Violation (%)	0.29	3.08	9.29
Entrance into HPV status (%)	0.12	1.54	0.00
Plant actions:			
Investment (%)	0.00	4.58	17.21
Plant / quarter observations	2,823,738	79,310	41,109

Note: authors' calculations based on estimation sample. Regulatory actions and outcomes are based on lagged status. Plant actions are based on current status.

Summary Statistics on Criteria Air Pollutants

Table: Summary Statistics on Criteria Air Pollutants

Industrial sector	Observations in analysis data	Mean level in compliance	Mean level as regular violator	Mean level as HPV
Mining & extraction	758,792	138.0	383.8	1,117.0
Manufacturing: wood/petro/pharma	679,137	289.3	782.5	2,483.2
Manufacturing: metal	568,682	101.7	176.4	1,240.0
Transportation	166,202	190.7	202.5	207.5
Manufacturing: food/textiles	147,433	117.3	393.1	338.7
Educational services	147,161	67.3	169.8	186.3
Utilities	120,536	1,885.0	5,242.3	12,546.5

Note: table reports summary statistics on total criteria air pollutant levels in tons for plant / quarter observations in our analysis data, matched to the NEI data based on EPA region, industrial sector, and compliance, regular violator, or HPV status.

What Underlies Our Structural Model?

- For our model, we need to define a tractable regulatory state.
- We show results from reduced-form analysis that motivates how our state space reflects:
  1. Investments.
  2. Violations.
  3. Industry and EPA region.
  4. Heterogeneity.
- Already made case for HPV status affecting regulatory actions.

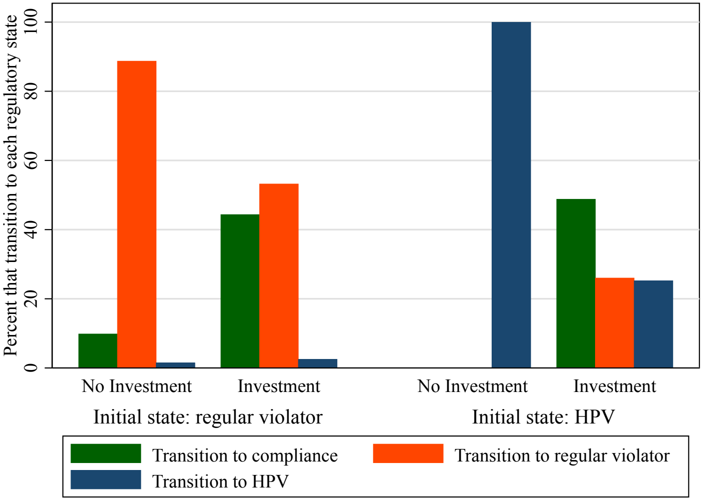
Investments and Resolution of Violations

Dependent variable: return to compliance		
Current investment	-0.117^{***}	(0.002)
One quarter lag of investment	0.381^{***}	(0.006)
Two quarters lag of investment	0.082^{***}	(0.006)
Three quarters lag of investment	-0.012^{**}	(0.005)
Four quarters lag of investment	-0.051^{***}	(0.005)
Number of observations	120,419	

Note: regressions include fixed effects for 2-digit NAICS industrial sector and EPA region. Regression uses the estimation sample restricted to plants not in compliance in the previous quarter. Standard errors, which are clustered at the plant level, are in parentheses. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

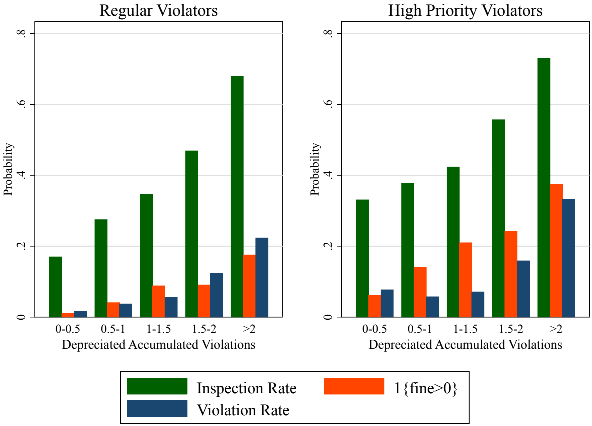
- We allow for two lags of investment to affect transitions.
- Timing assumption: investment occurs at end of period.

Effect of Investment on Regulatory State



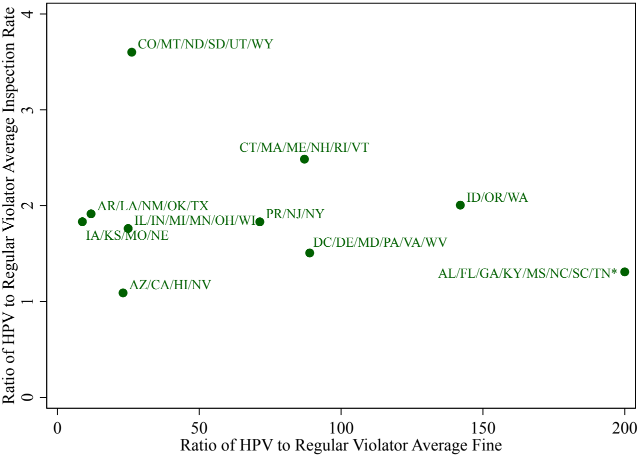
- Investment predicts return to compliance but only stochastically.

Depreciated Accumulated Violations



- Defined as sum of the discounted violations, from the previous quarter back to the quarter the plant most recently left compliance.
- Use 10% quarterly discount factor here.
- Very predictive of regulatory actions and outcomes.

Heterogeneity in Regulatory Actions: EPA Regions



- Variation across EPA regions in effect of regulatory status on inspections and fines.

Serial Correlation In Investment

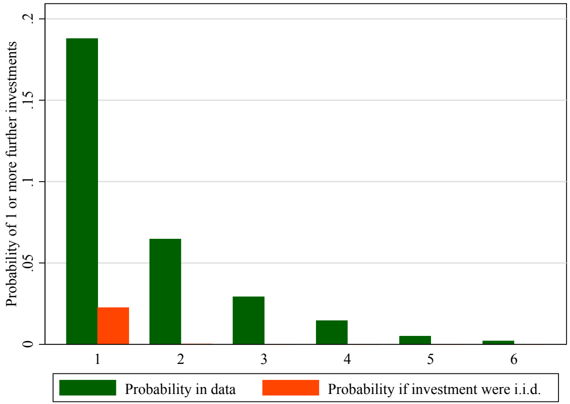


Figure: Further Investments After Initial Investment

- Strong serial correlation suggests heterogeneity in costs.
- One set of moments tries to match this serial correlation.

Overview of Model

- Discrete-time two-player dynamic game with discount factor β.
  - Data reflect the Markov Perfect Equilibrium of the game.
- Each (quarter) period t, the plant starts with some regulatory state Ω_t.
- Timing each period is as follows:
  1. The regulator chooses whether to inspect, $Ins(\Omega)$.
     - Inspection probability $\mathcal{I}(\Omega)$.
  2. Regulator obtains a signal e (based on inspection and state).
     - Signal indicates whether a violation $Vio(\Omega, e)$ should be issued.
     - Signal also indicates transition to $\Omega' \equiv T(\Omega, e)$.
     - Regulator assesses fines with policy $Fine(\Omega, e)$.
  3. The plant chooses whether to invest, using Ω'.
     - Investment helps return plant to compliance in next two periods.
     - Idiosyncratic logit shocks to costs of investment/not investment.

Assumption on State Evolution

Assumption

The environmental compliance signal at time t, e_t, is a function only of the regulatory state Ω_t, inspection decision Ins_t, and regulator CCPs $\mathcal{I}$.

- Rules out the possibility that an investment that is not in the regulatory state could change the compliance signal.
  - e.g. investment more than two periods ago.

Plant's Utility and Investment

- Flow (dis)utility of plant from regulatory actions is:

$$U(\Omega, e) = \theta^I Ins(\Omega) + \theta^V Vio(\Omega, e) + \theta^F Fine(\Omega, e) + \theta^H HPV(T(\Omega, e)).$$

  where $\theta^I, \theta^F, \theta^V, \theta^H$ are parameters.

- If Ω' indicates non-compliance, plant chooses whether to invest, $X = 1$, or not, $X = 0$.
  - Flow (dis)utility from action X at this point is: $X\theta^X + \varepsilon_X$.
- Plants in compliance obtain only ε_0 at this point.
- The (fixed) structural parameters for any plant are $\theta \equiv (\theta^I, \theta^F, \theta^V, \theta^H, \theta^X)$.
  - We model random coefficients: θ can vary across plants.
  - Regulator cannot condition its monitoring and enforcement on θ.

Estimation Overview

- We estimate regulator's policy as conditional choice probabilities (CCP).
- Model 1: Quasi-maximum likelihood with one θ value.
- Model 2: GMM with random coefficients over fixed grid of θs.
  - Assumes that θ takes one of a finite number of values, $(\theta_1, \ldots, \theta_J)$.
    - Large number of grid points, J=10,001.
  - Each plant i gets a draw from the distribution of potential θ values.
  - Point of estimation is to recover η_j, $\forall j$, population prevalence of θ_j.
  - GMM estimator takes form:

$$G_k(\eta) = m_k^d - \sum_{j=1}^{J} \eta_j m_k(\theta_j)$$

  where m_d^k are moments in data and $m_k(\theta_j)$ are moments predicted by model with parameters θ_j.

Details for Random Coefficients Model

Assumption

The data reflect plants at the steady state distribution of variable states, Ω'^{1} (e.g. compliance status), conditional on fixed states, Ω'^{2} (e.g. industry).

- We use the following $m_k(\theta_j)$ for moments:
  1. Long-run probability of state Ω'^{1}.
  2. Long-run probability of state Ω'^{1} times investment.
  3. Long-run probability of state Ω'^{1} times investment times sum of investments in next six quarters (as in Figure).
- Two step estimator where moments are weighted by $\hat{Var}(G(\eta))^{-1}$.

Identification

Homogeneous cost model:

- Differences in regulatory actions that the plant could expect from investing vs not investing
- Useful variation across region and industrial sector.

Random coefficients model:

- The spread of plants across regulatory states in equilibrium.
- The level of within plant correlation in investment over time.

Coefficient Estimates

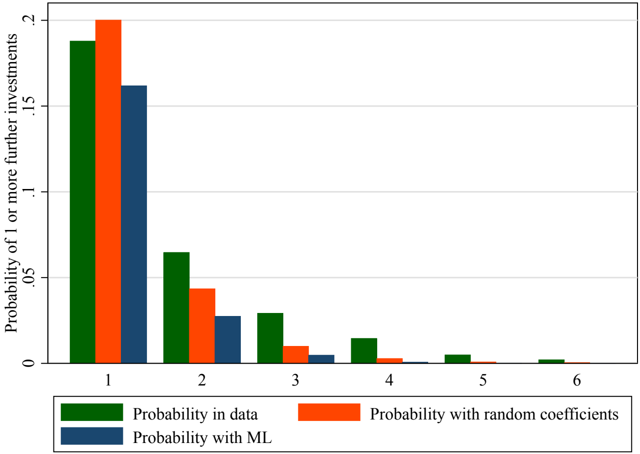
	QML estimates	GMM random coefficient estimates (1)	(2)	(3)	(4)	(5)
Investment utility (θ^X)	-2.95^{***} (0.04)	-2.95	-1.40	-2.19	-0.56	0.55
Inspection utility (θ^I)	-0.02 (0.05)	-0.02	0.48	0.42	-0.74	0.51
Violation utility (θ^V)	-0.30 (0.24)	-0.30	-0.10	1.03	2.13	-1.78
Fine utility (million \$, θ^F)	-0.11^{***} (0.03)	-0.11	-0.21	-0.32	-0.19	-0.03
HPV status utility (θ^H)	-0.05^{**} (0.02)	-0.05	-0.22	-0.14	0.03	-0.11
Weight on param. vector	1	0.42	0.33	0.18	0.04	0.03

Note: standard errors for maximum likelihood estimates, which are bootstrapped with resampling at the plant level, are in parentheses. For GMM estimates, we report weights on all types j with probability $\eta_j > 0.001$.

- Investment, fines, and HPV status are costly for most plants.
- Heterogeneity in ratio of investment costs to fine costs.
  - 42%: \$26 million, 51% ≈\$7 million.

Random Coefficients Generate a Better Fit to the Data

Figure: Further Investments After Initial Investment, in Steady State



Counterfactuals

- How would long-run averages of plant actions and outcomes and air pollution change if:
    1. Non-linearity of fines changed.
    2. Plants' utility from regulatory actions changed.
- Limitations of counterfactuals:
    - Policy rules on inspections, violations, and transitions are unchanged.
        - Following Assumption 1, the same distribution of signals, e, will occur.
    - Consistent with plant optimization but not necessarily with an equilibrium of the dynamic game.
- We only present counterfactuals with GMM estimates here.

Counterfactuals: Changing Fine Structure

Using GMM random coefficient estimates:

	Baseline	Same fines for all violators	HPV fines halved	HPV fines doubled
Compliance (%)	95.07 (0.07)			
Regular violator (%)	3.59 (0.07)			
HPV (%)	1.34 (0.04)			
Inspection rate (%)	9.19 (0.05)			
Mean fines (1000$)	16.23 (2.08)			
Mean CAP (tons)	294.4 (1.6)			
Mean pollution cost (1000$)	2,579 (11.5)			

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

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	Baseline	Same fines for all violators	HPV fines halved	HPV fines doubled
Compliance (%)	95.07 (0.07)			
Regular violator (%)	3.59 (0.07)			
HPV (%)	1.34 (0.04)			
Inspection rate (%)	9.19 (0.05)			
Mean fines (1000$)	16.23 (2.08)	16.23 (2.08)		
Mean CAP (tons)	294.4 (1.6)			
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Counterfactuals: Changing Fine Structure

Using GMM random coefficient estimates:

	Baseline	Same fines for all violators	HPV fines halved	HPV fines doubled
Compliance (%)	95.07 (0.07)	87.14 (3.24)		
Regular violator (%)	3.59 (0.07)	3.31 (0.11)		
HPV (%)	1.34 (0.04)	9.55 (3.32)		
Inspection rate (%)	9.19 (0.05)			
Mean fines (1000$)	16.23 (2.08)	16.23 (2.08)		
Mean CAP (tons)	294.4 (1.6)			
Mean pollution cost (1000$)	2,579 (11.5)			

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

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	Baseline	Same fines for all violators	HPV fines halved	HPV fines doubled
Compliance (%)	95.07 (0.07)	87.14 (3.24)		
Regular violator (%)	3.59 (0.07)	3.31 (0.11)		
HPV (%)	1.34 (0.04)	9.55 (3.32)		
Inspection rate (%)	9.19 (0.05)	12.76 (1.49)		
Mean fines (1000$)	16.23 (2.08)	16.23 (2.08)		
Mean CAP (tons)	294.4 (1.6)			
Mean pollution cost (1000$)	2,579 (11.5)			

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

Counterfactuals: Changing Fine Structure

Using GMM random coefficient estimates:

	Baseline	Same fines for all violators	HPV fines halved	HPV fines doubled
Compliance (%)	95.07 (0.07)	87.14 (3.24)		
Regular violator (%)	3.59 (0.07)	3.31 (0.11)		
HPV (%)	1.34 (0.04)	9.55 (3.32)		
Inspection rate (%)	9.19 (0.05)	12.76 (1.49)		
Mean fines (1000$)	16.23 (2.08)	16.23 (2.08)		
Mean CAP (tons)	294.4 (1.6)	463.8 (67.2)		
Mean pollution cost (1000$)	2,579 (11.5)	3,751 (454.9)		

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

Counterfactuals: Changing Fine Structure

Using GMM random coefficient estimates:

	Baseline	Same fines for all violators	HPV fines halved	HPV fines doubled
Compliance (%)	95.07 (0.07)	87.14 (3.24)	94.16 (0.20)	95.40 (0.10)
Regular violator (%)	3.59 (0.07)	3.31 (0.11)	3.58 (0.07)	3.58 (0.07)
HPV (%)	1.34 (0.04)	9.55 (3.32)	2.26 (0.20)	1.01 (0.07)
Inspection rate (%)	9.19 (0.05)	12.76 (1.49)	9.55 (0.11)	9.09 (0.05)
Mean fines (1000$)	16.23 (2.08)	16.23 (2.08)	16.74 (2.52)	23.50 (6.09)
Mean CAP (tons)	294.4 (1.6)	463.8 (67.2)	321.4 (7.0)	285.5 (1.3)
Mean pollution cost (1000$)	2,579 (11.5)	3,751 (454.9)	2,756 (44.5)	2,520 (10.2)

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

Counterfactuals: Changing Plants' Cost Structure

Using GMM random coefficient estimates:

	Baseline	No enforce/ HPV cost	No HPV cost	HPV Cost doubled
Compliance (%)	95.07 (0.07)			
Regular violator (%)	3.59 (0.07)			
HPV (%)	1.34 (0.04)			
Inspection rate (%)	9.19 (0.05)			
Mean fines (1000$)	16.23 (2.08)			
Mean CAP (tons)	294.4 (1.6)			
Mean pollution cost (1000$)	2,579 (11.5)			

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Counterfactuals: Changing Plants' Cost Structure

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	Baseline	No enforce/ HPV cost	No HPV cost	HPV Cost doubled
Compliance (%)	95.07 (0.07)	94.50 (0.39)		
Regular violator (%)	3.59 (0.07)	3.53 (0.08)		
HPV (%)	1.34 (0.04)	1.97 (0.39)		
Inspection rate (%)	9.19 (0.05)	9.38 (0.16)		
Mean fines (1000$)	16.23 (2.08)	24.09 (15.89)		
Mean CAP (tons)	294.4 (1.6)	308.7 (6.7)		
Mean pollution cost (1000$)	2,579 (11.5)	2,670 (50.8)		

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

Counterfactuals: Changing Plants' Cost Structure

Using GMM random coefficient estimates:

	Baseline	No enforce/ HPV cost	No HPV cost	HPV Cost doubled
Compliance (%)	95.07 (0.07)	94.50 (0.39)	92.16 (1.44)	
Regular violator (%)	3.59 (0.07)	3.53 (0.08)	3.56 (0.08)	
HPV (%)	1.34 (0.04)	1.97 (0.39)	4.28 (1.48)	
Inspection rate (%)	9.19 (0.05)	9.38 (0.16)	10.25 (0.61)	
Mean fines (1000$)	16.23 (2.08)	24.09 (15.89)	35.35 (10.30)	
Mean CAP (tons)	294.4 (1.6)	308.7 (6.7)	366.7 (30.4)	
Mean pollution cost (1000$)	2,579 (11.5)	2,670 (50.8)	2,972 (168.0)	

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

Counterfactuals: Changing Plants' Cost Structure

Using GMM random coefficient estimates:

	Baseline	No enforce/ HPV cost	No HPV cost	HPV Cost doubled
Compliance (%)	95.07 (0.07)	94.50 (0.39)	92.16 (1.44)	95.31 (0.18)
Regular violator (%)	3.59 (0.07)	3.53 (0.08)	3.56 (0.08)	3.59 (0.07)
HPV (%)	1.34 (0.04)	1.97 (0.39)	4.28 (1.48)	1.10 (0.16)
Inspection rate (%)	9.19 (0.05)	9.38 (0.16)	10.25 (0.61)	9.12 (0.06)
Mean fines (1000$)	16.23 (2.08)	24.09 (15.89)	35.35 (10.30)	14.34 (3.18)
Mean CAP (tons)	294.4 (1.6)	308.7 (6.7)	366.7 (30.4)	287.0 (2.4)
Mean pollution cost (1000$)	2,579 (11.5)	2,670 (50.8)	2,972 (168.0)	2,531 (15.6)

Note: all statistics report the weighted average of the long-run equilibrium mean, weighting with the number of plants by industry and region in our data. CAP are criteria air pollutants. Pollution cost only includes the cost of NO_X, SO_2, $PM_{2.5}$, and VOCs.

Conclusion

- CAAA regulators utilize dynamic enforcement with inspections, violations, and fines.
- Dynamic enforcement increases compliance through plant investment in environmental remediation.
- Effects are large, particularly in random coefficients model:
  - Linear fines would result in $>$6X increase in high priority violators.
  - Criteria air pollutants would rise 58%.
- We provide a structural framework for evaluating dynamic enforcement in alternative contexts beyond CAAA regulation.
- Extend fixed grid approach for estimating random coefficients.