Low-Carbon Investment Incentives and Climate Policy

Sarah Armitage, Nathan Miller, Matthew Osborne, Gretchen Sileo

December 9, 2023

Motivation: Spurring Technology Adoption in Concentrated Industries

- Common features in many areas of industrial decarbonization:
  - Concentrated industries
  - Commodity products
  - Important role of incumbents
  - Lumpy investments in technology adoption

- How to spur technology adoption efficiently in this context?

(Source: Wikipedia)

Empirical Setting: Cement Production

The Washington Post
Democracy Dies in Darkness

CLIMATE SOLUTIONS

Cement emits as much CO2 as India. Why is it so hard to fix?

The cement industry is responsible for 8 percent of global carbon emissions – triple the emissions of the aviation industry

By Shannon Osaka

June 27, 2023 at 6:30 a.m. EDT

Empirical Setting: Cement Production

- After water, concrete is the most widely used substance in the world.
- Cement is responsible for 8% of global $\mathrm{CO_2}$ emissions. (1 ton of cement $\rightarrow$ 1 ton of $\mathrm{CO_2}$)
- Technological transformation in last 40 years: adoption of fuel-efficient precalciner kilns.
- Regional cement markets arise from high transport costs & limited storability.

Source: Wikipedia

Research Questions

1. How does market structure influence the effectiveness of technology adoption subsidies?
2. How might subsidies have affected the historical transition path for precalciner adoption in Portland cement?
3. How might alternative subsidies affect the transition path for future cement decarbonization technologies?

Related Literature

Technology Adoption and Market Power

Gilbert & Harris (1984); Riordan (1992); Igami & Yang (2016); Fang & Yang (2022); Schmidt-Dengler (2023)

Externalities and Market Power

Millimet, Roy, & Sengupta (2009); Fowlie, Reguant, & Ryan (2016); Leslie (2018); Preonas (2023)

Design of Second-Best Policy Instruments

Newell, Pizer, & Raimi (2019); De Groote & Verboven (2019); Langer & Lemoine (2022)

Economics of Cement Production

Ryan (2012); Fowlie, Reguant, & Ryan (2016); Macher, Miller, & Osborne (2017); Miller, Osborne, Sheu, & Sileo (2023); Glenk, Kelnhofer, Meier, & Reichelstein (2023)

Dynamic Structural Modeling

Rust (1997); Benkard, Bajari, and Levin (2007); Weintraub, Benkard, and Van Roy (2008); Qi (2013); Seiler (2013); Ifrach and Weintraub (2016); Gowrisankaran, Langer, and Zhang (2023)

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Economic Theory: Market Power and Technology Adoption

Why might subsidies for technology adoption operate differently in concentrated markets?

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Why might subsidies for technology adoption operate differently in concentrated markets?

1. Firms may not internalize inframarginal consumer benefits from adopting.
2. Firms may adopt to preempt rivals.
3. Conditional on adopting, firms may still underproduce.

Economic Theory

Simple model:

- Two firms that can produce with $TC_i = cq_i + \frac{1}{2}q_i^2$ or with $TC_i' = c'q_i + \frac{1}{2}q_i^2 + F$ ("new technology"), where $c' < c$ and F is a one-time sunk cost

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- Demand is $P = a - Q$ where $Q = q_1 + q_2$; firms compete in quantities

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1. Wedge between firm adoption of technology and social planner adoption:

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1. Wedge between firm adoption of technology and social planner adoption:

$$\overbrace{\frac{3}{2}\left[\frac{1}{16}\left((a-c')^2-(a-c)^2\right)\right]}^{}_{\text{Firm chooses not to adopt}} < \underbrace{F < \frac{5}{2}\left[\frac{1}{16}\left((a-c')^2-(a-c)^2\right)\right]}_{\text{Social planner chooses to adopt}}$$

Economic Theory

Simple model:

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- Demand is $P = a - Q$ where $Q = q_1 + q_2$; firms compete in quantities

3. Wedge between firm and social planner output conditional on adoption:

$$\underbrace{\frac{1}{4}(c - c')}_{\text{Firm's } \Delta q \text{ from adoption}} < \underbrace{\frac{1}{3}(c - c')}_{\text{Planner's } \Delta q \text{ from adoption}}$$

Economic Theory

Simple model:

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- Demand is $P = a - Q$ where $Q = q_1 + q_2$; firms compete in quantities

2. Additional firm adoption benefits from preempting rivals:

$$\text{Prob}(\text{firm 2 adopt}|\text{firm 1 adopted}) < \text{Prob}(\text{firm 2 adopt}|\text{firm 1 did not adopt})$$

(Assume sequential decision-making and $F_i \sim G(\theta)$)

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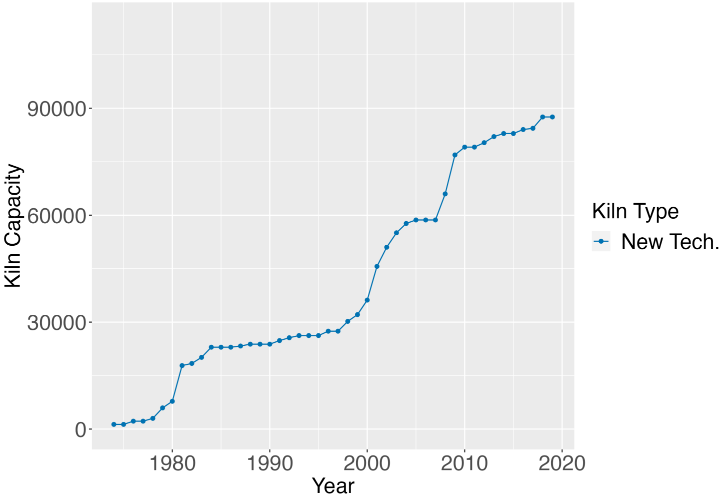
Cement Market: Precalciner Kilns

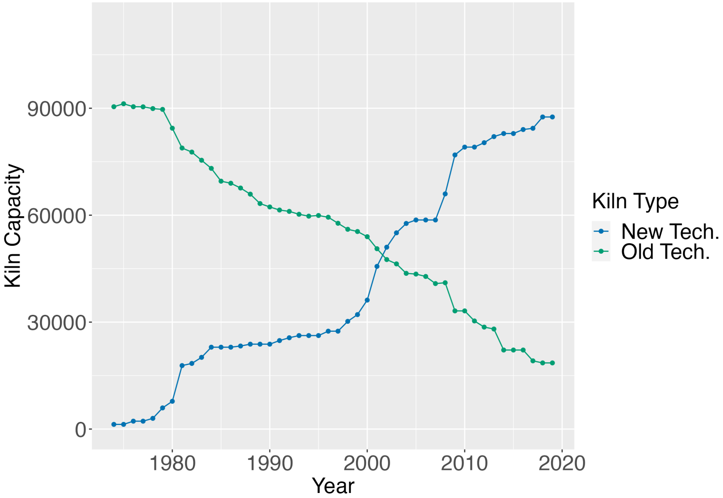
- Precalciner kilns improve fuel efficiency (by 25-35%), relax capacity constraints
- Design and installation costs are high
- Adoption occurred over 40+ years, unevenly across the U.S.
- Macher, Miller, Osborne (2021): Adoption more likely with higher fuel costs, stronger local demand, higher capacity utilization, fewer nearby competitors

Cement Precalcincer (Source: Cement Production)

Cement Market: Precalciner Adoption



Cement Market: Precalciner Adoption & Old Kiln Retirement



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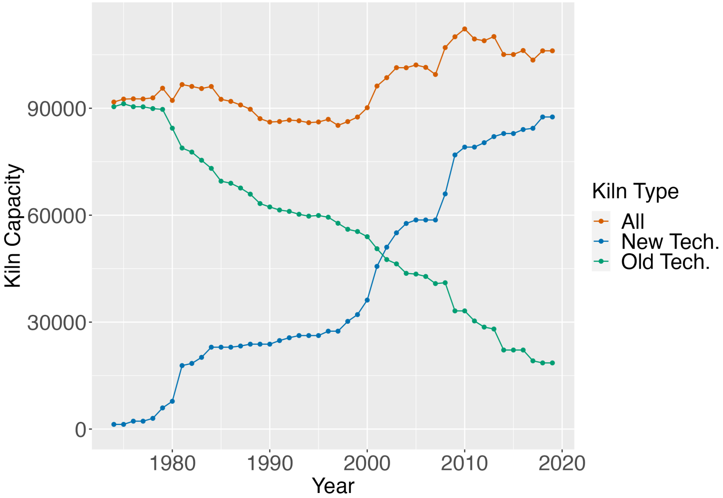
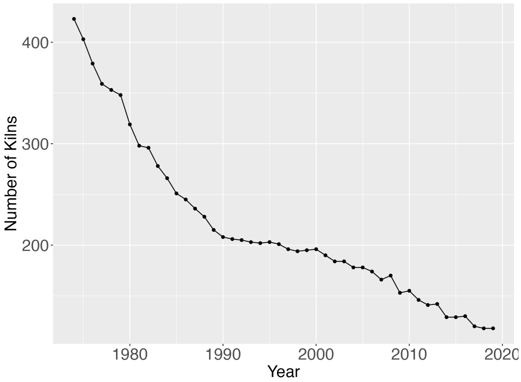
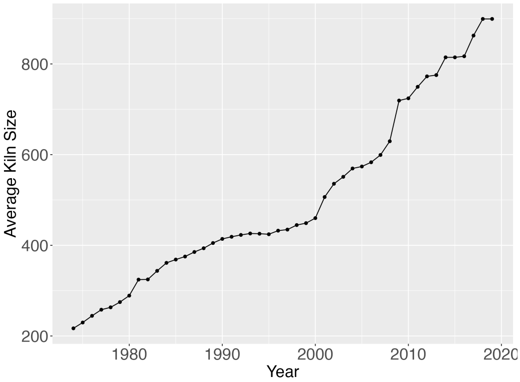


Cement Market: Changing Kiln Numbers and Capacity



(a) Number of Kilns



(b) Kiln Size

Cement Market: Decarbonization Pathways

- Cement decarbonization is particularly challenging: process emissions (approx. 60%) as well as combustion emissions (approx. 40%)
- Like precalciners, many decarbonization pathways entail large lumpy investments (Glenk et al., 2023)
- Unlike precalciners, most decarbonization pathways would not be realized without policy

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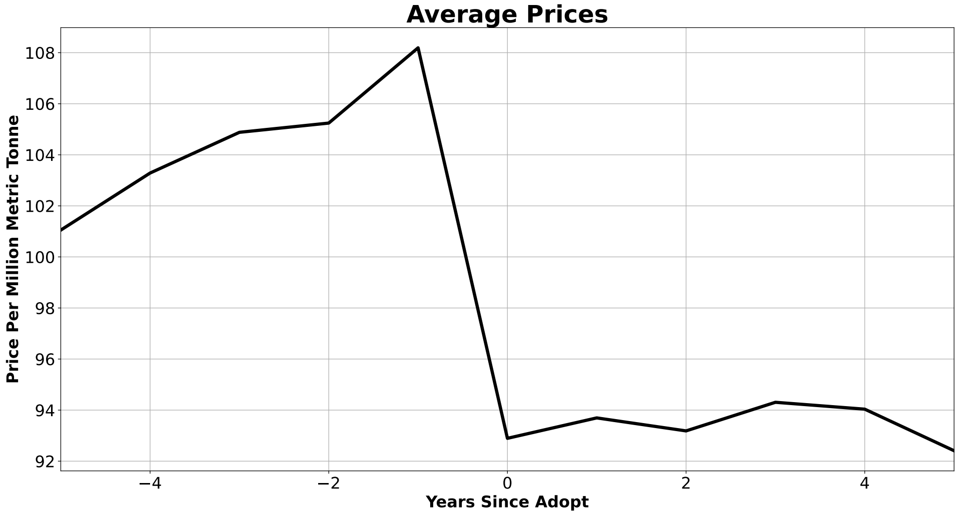
Cement Market: Impact of Precalciner Adoption



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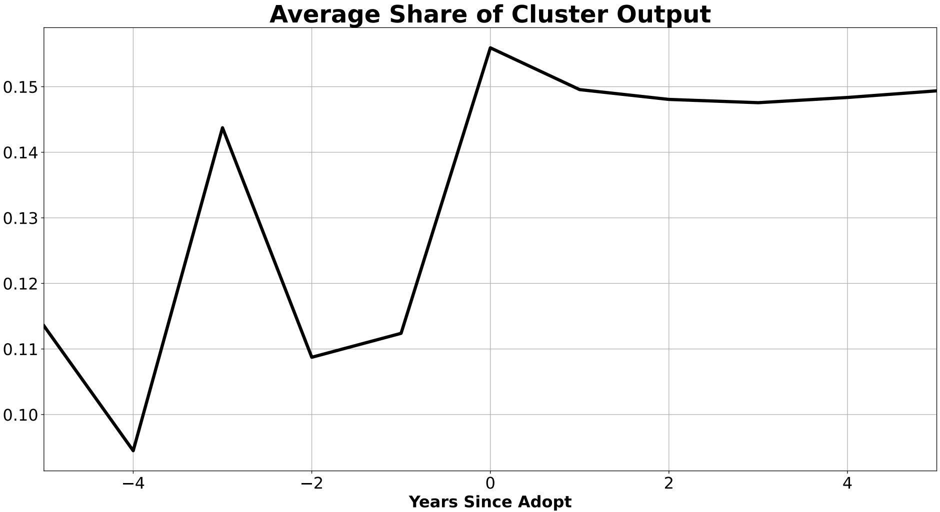

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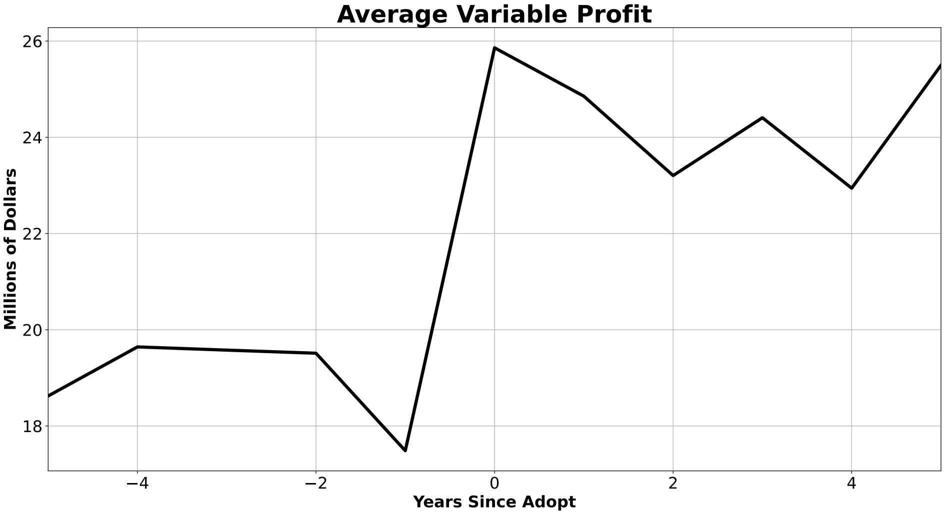

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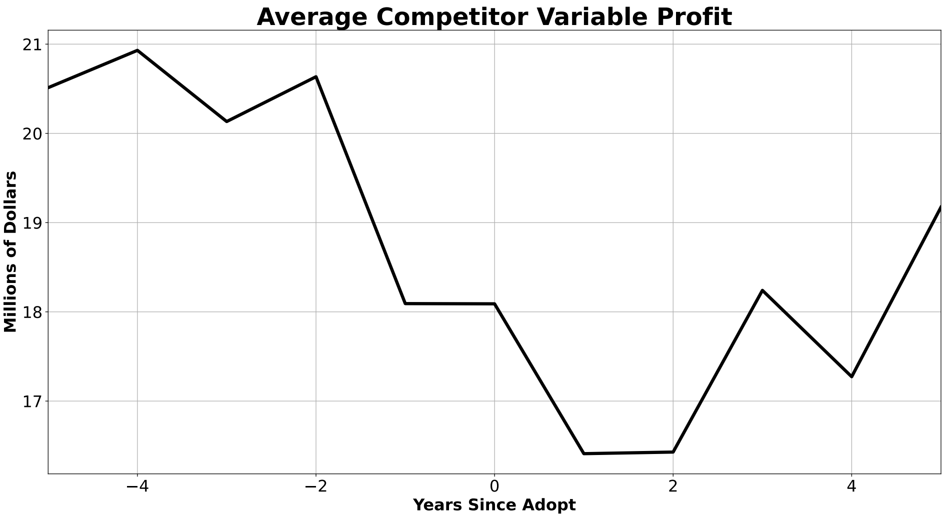

Cement Market: Impact of Precalciner Adoption

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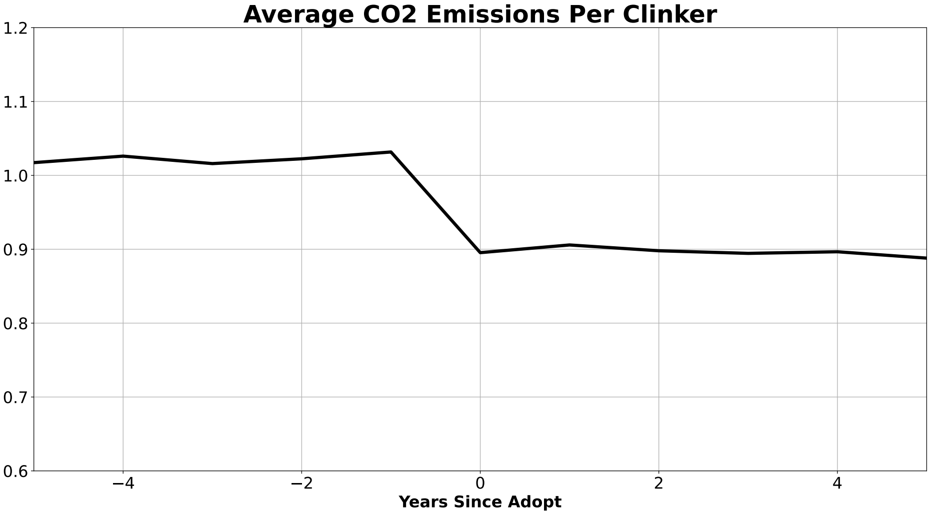

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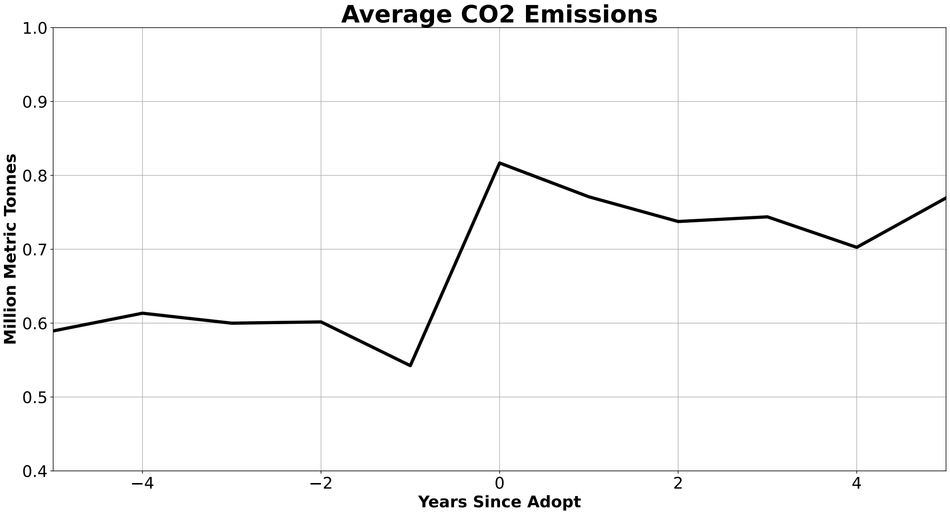

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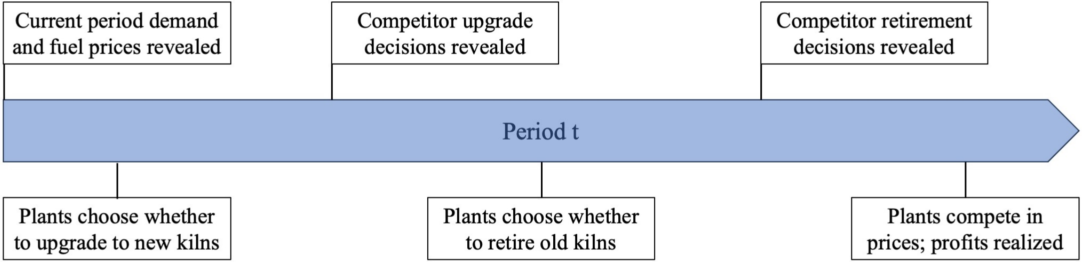
Dynamic Structural Model

- Dynamic structural model of technology transition in US cement
- In each period, cement plants decide whether to **upgrade** with new technology kilns and/or **retire** old technology kilns
- Inputs into plant-level upgrade and retirement decisions:
  - Old and new technology capacity at plant
  - Old and new technology capacity at other plants owned by same firm and competitor plants
  - Market demand (construction)
  - Fuel prices
- Dynamic parameters of interest: **upgrade cost** and **decommissioning cost**

Dynamic Structural Model

Timeline of Plant Decision-Making:



Dynamic Structural Model

Discounted sum of profits for plant i in market m:

$$\max_{\{u_{imt}, r_{imt}\}_{t=0}^{\infty}} \mathrm{E}[\sum_{t=0}^{\infty} \beta^t(-\text{upgrade cost}(u_{imt}) + \epsilon_{imt}^{upgrade}(u_{imt}) - \text{decommission cost}(r_{imt}) + \epsilon_{imt}^{retire}(r_{imt}) + \text{flow profit}(\mathbf{x_{mt}}, \mathbf{z_{mt}}))|\mathbf{x_{mt}}, \mathbf{z_{mt}}, \epsilon_{\mathbf{mt}}]$$

where u_{imt} and r_{imt}: upgrade and retire decisions

$\epsilon_{\mathbf{mt}}$: upgrade and retire shocks (i.i.d. Type I EV)

$\mathbf{x_{mt}}$: endogenous state variables (old and new tech capacities)

$\mathbf{z_{mt}}$: exogenous state variables (demand, fuel prices)

Cement Data

- Regional prices, production, consumption, imports, and transportation methods from USGS Minerals Yearbook and California Letter
- Plant locations, owners, primary fuels, kiln technologies, and kiln capacities from Portland Cement Association Plant Information Summary
- State-level fuel prices from US EIA
- Construction employment from US Census Bureau
- Engineering estimates of fixed and variable costs for cement decarbonization technologies from Glenk et al. (2023)

Summary Statistics

Variable	Mean	Median	Std. Dev.
Plant New Tech. Boilerplate Capacity	436	0	667
Plant Old Tech. Boilerplate Capacity	468	454	433
Competitor New Tech.	8437	5853	9331
Competitor Old Tech.	12634	8691	11620
Own Plant New Tech.	701	0	1274
Own Plant Old Tech.	820	424	1103
Share of Demand 300mi from Port	0.78	0.94	0.30
Market Size	44965	28603	34844
Coal Price ($/tonne)	2.86	2.80	0.80

Boilerplate capacity and market size in 1000s of metric tonnes.

Dynamic Structural Model: Estimation Overview

- Follow two-step estimator of Benkard, Bajari, and Levin (2007), adapted for multi-stage decision (Seiler, 2013)

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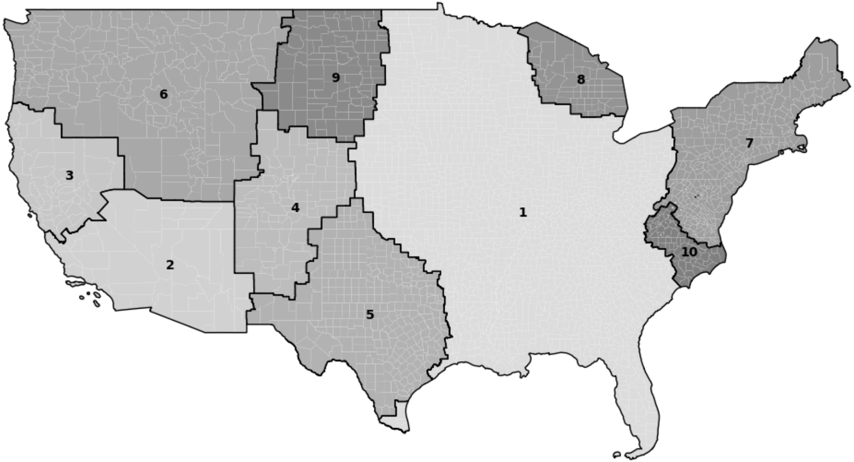
Dynamic Structural Model: Clusters

Clustering algorithm from Atalay et al. (2023)



Dynamic Structural Model: Cluster-Level Summary Statistics

	1980			2019		
	HHI	Number of Firms	Precalciner Capacity Share	HHI	Number of Firms	Precalciner Capacity Share
Cluster 1	512	27	4.76 %	1,136	13	78.73%
Cluster 2	2,563	6	7.50%	2,062	7	100.00%
Cluster 3	3,083	4	0.00%	6,916	2	80.87%
Cluster 4	4,489	3	22.50%	2,795	4	76.51%
Cluster 5	1,235	12	23.22%	1,818	8	96.49%
Cluster 6	2,549	6	0.00%	5,793	3	84.02%
Cluster 7	900	13	0.00%	2,489	5	67.91%
Cluster 8	5,396	6	19.25%	7,158	4	66.47%
Cluster 9	10,000	1	0.00%	10,000	1	100.00%
Cluster 10	5,320	2	0.00%	10,000	1	100.00%

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"Highly concentrated": HHI $>$ 2500; "moderately concentrated": 2500 $\geq$ HHI $>$ 1500; "unconcentrated": HHI $\geq$ 1500

Dynamic Structural Model: Static Profits

- Plant-level profits estimated in Miller et al. (2023):

$$\pi_{it} = \sum_{n \in M} \bar{p}_{int}(\tilde{\mathbf{x}}_{\mathbf{mt}}, \tilde{\mathbf{z}}_{\mathbf{mt}}) q_{int}(\tilde{\mathbf{x}}_{\mathbf{mt}}, \tilde{\mathbf{z}}_{\mathbf{mt}}) - \int_0^{Q_{it}} c_{it}(Q, \tilde{\mathbf{x}}_{\mathbf{imt}}, \tilde{\mathbf{z}}_{\mathbf{mt}}) dQ$$

- Plants allocate production across kilns to minimize cost, given different kiln efficiencies and convex marginal costs.
- Utility from a plant's cement depends on transportation disutility (overland or by Mississippi barge), importer/domestic supplier status, and time trend.
- Price determined through second-score auction.

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- Utility from a plant's cement depends on transportation disutility (overland or by Mississippi barge), importer/domestic supplier status, and time trend.
- Price determined through second-score auction.
- For computational reasons, dynamic model uses prediction of equilibrium profits.

Dynamic Structural Model: Static Profits

	Est. Plant Profit
Plant New Tech. BP	10.733*** (2.271)
Plant Old Tech. BP	5.868** (2.981)
Competitor New BP	−0.559*** (0.119)
Competitor Old BP	−0.659*** (0.078)
Own Firm New BP	−0.652*** (0.250)
Own Firm Old BP	−0.300* (0.154)
Market Size	0.340*** (0.042)
Coal Price	−3,371.628*** (994.390)
Constant	21,102.500*** (4,135.337)

Note: *p<0.1; **p<0.05; ***p<0.01.
SEs clustered at regional level.
Boilerplate capacity & market size in 1000s of tonnes.

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SEs clustered at regional level.
Boilerplate capacity & market size in 1000s of tonnes.

xgboost non-linear prediction model:

- Test/train sampled at plant-year level: "adjusted-R^2" = 0.89
- Test/train sampled at plant level: "adjusted-R^2" = 0.44

Dynamic Structural Model: Estimation Step 1

Key assumptions in Step 1: recovering policy functions:

- Plants can upgrade 0 or 1 kiln per period (100% of observed upgrades)
- Plants can retire 0, 1, 2 3, or 4 kilns per period (97.2% of observed retirements)
- For now, focus only on upgrades by incumbents, with no new entry (79% of observed precalciner kiln arrivals)

- Plants make upgrade decisions, then retirement decisions.

- Plants consider aggregate competitor capacity, not capacity of individual competitors (Weintraub, Benkard, Van Roy, 2008; Qi, 2013; Ifrach and Weintraub, 2016; Gowrisankaran, Langer, Zhang, 2023).

Dynamic Estimation: Upgrade Policy Function

	Logit Model	Logit Model
Plant New Tech. BP	-1.690^{***} (0.409)	-1.918^{***} (0.428)
Plant Old Tech. BP	-0.161 (0.459)	-0.156 (0.459)
Competitor BP	-0.079^{***} (0.018)	
Competitor New BP		-0.043^{**} (0.021)
Competitor Old BP		-0.103^{***} (0.023)
Own Firm BP	-0.206^{***} (0.072)	
Own Firm New BP		-0.252^{***} (0.061)
Own Firm Old BP		-0.234 (0.147)
Market Demand	0.033^{***} (0.007)	0.034^{***} (0.009)
Coal Price	0.523^{**} (0.237)	0.420^{*} (0.253)
Constant	-4.992^{***} (0.517)	-4.628^{***} (0.564)
Observations	4,347	4,347
Log Likelihood	-282.755	-279.957
Akaike Inf. Crit.	579.510	577.914

Note: *p<0.1; **p<0.05; ***p<0.01. SE's clustered at market level. BP in million tonnes.

Dynamic Estimation: Retire Policy Function

	Ordered Logit Model	Ordered Logit Model
Plant New Tech. BP	0.439 [0.277, 0.601]	
Plant Old Tech. BP	−0.337 [−0.675, −0.079]	
Competitor BP	0.351 [−0.221, 0.923]	0.251 [0.058, 0.539]
Own Firm New BP	0.250 [0.02, 0.48]	
Own Firm Old BP	0.256 [−0.028, 0.540]	
Plant + Own Firm New BP		0.382 [0.310, 0.467]
Plant + Own Firm Old BP		0.090 [−0.034, 0.219]
Market Demand	−0.477 [−1.123, 0.169]	−0.423 [−0.755, −0.181]
Coal Price	0.220 [−0.064, 0.504]	0.219 [0.087, 0.331]
Observations	3,028	3,028
Log Likelihood	−1252.804	−1306.958

Note: We report bounds on the parameter estimates at the 5th and 95th percentiles. SE's calculated using bootstrapping. BP in 1000s of tons.

Dynamic Structural Model: Estimation Step 2

Key assumptions in Step 2: recovering dynamic parameters of interest:

- Estimated policy functions are expected profit maximizing:

$$V(\text{est. policy func.}) \geq V(\text{perturbed policy func.})$$

- Objective function minimizes deviations from profit maximizing behavior:

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{k=1}^{N_I} \min\{\hat{V}_k(\boldsymbol{\theta}) - \hat{V}'_k(\boldsymbol{\theta}), 0\}^2$$

- Use 500 draws of shocks; 500 policy function perturbations; 20 cluster draws (corresponding to 250+ plants).

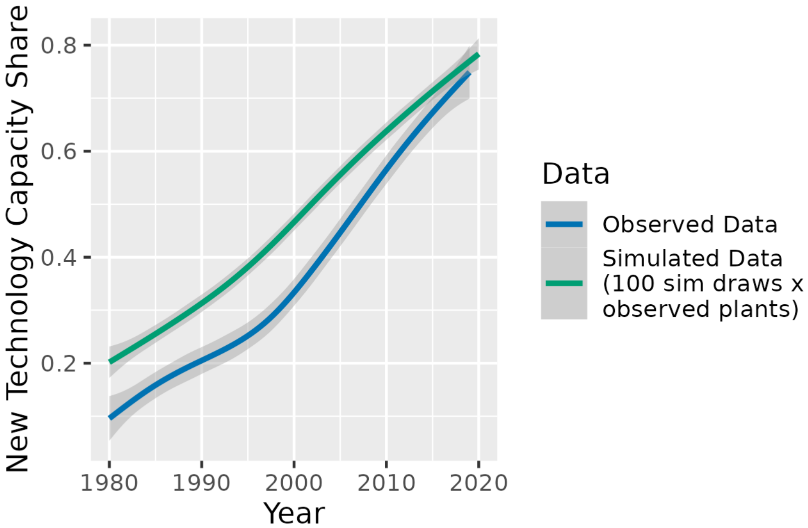
Dynamic Model: Preliminary Estimation Results

Estimated average per-kiln upgrade cost: **\$662 million** (2010\$)

- Compare to best available public estimates: approx. \$800 million, using data from European cement association & environmental group

Estimated average per-kiln decommissioning cost: **\$183 million** (2010\$)

Dynamic Estimation: Preliminary Estimation Results



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Counterfactual Simulations: Questions

1. How does the effectiveness & efficiency of technology adoption subsidies vary with market structure?
2. What are the implications for subsidy design? (e.g., increasing vs decreasing subsidy schedules)

Counterfactual Simulations: Implementation

- Further assume for tractability: all old and new kilns have same capacity (respectively)

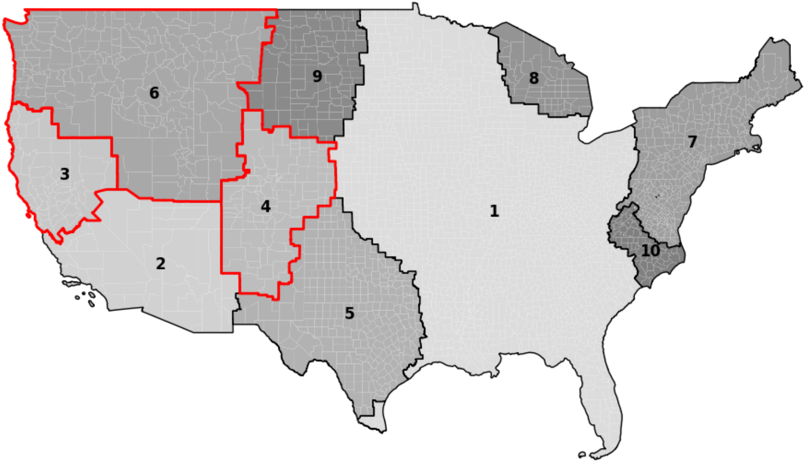
Counterfactual Simulations: Implementation

- Further assume for tractability: all old and new kilns have same capacity (respectively)
- Assume *approximate belief oblivious equilibrium* (Gowrisankaran, Langer, Zhang, 2023)
- Estimate (zero-inflated) Poisson process for evolution of competitor capacity, conditioning on whether plant has old/new capacity
- Inner loop: recover value function conditional on states (successive approximations)
  Outer loop: recover Poisson process

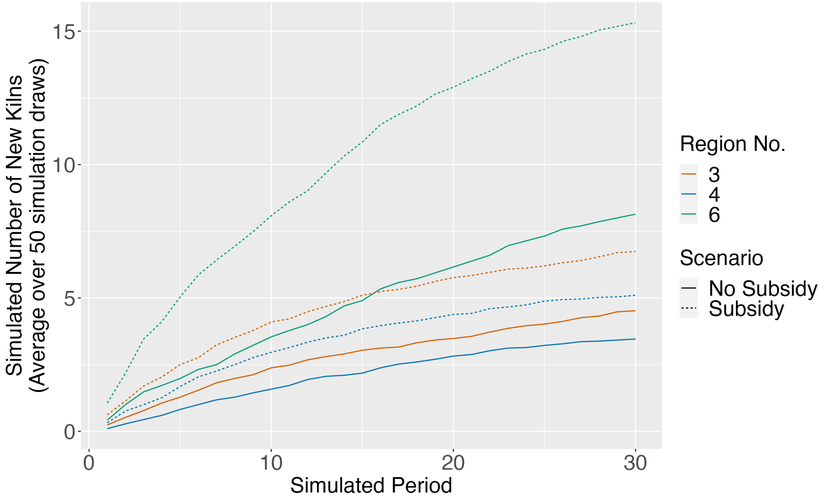
Counterfactual Simulations: Implementation

- Further assume for tractability: all old and new kilns have same capacity (respectively)
- Assume *approximate belief oblivious equilibrium* (Gowrisankaran, Langer, Zhang, 2023)
- Estimate (zero-inflated) Poisson process for evolution of competitor capacity, conditioning on whether plant has old/new capacity
- Inner loop: recover value function conditional on states (successive approximations)
  Outer loop: recover Poisson process
- Investment subsidy: average entry costs are 70% of estimated amount

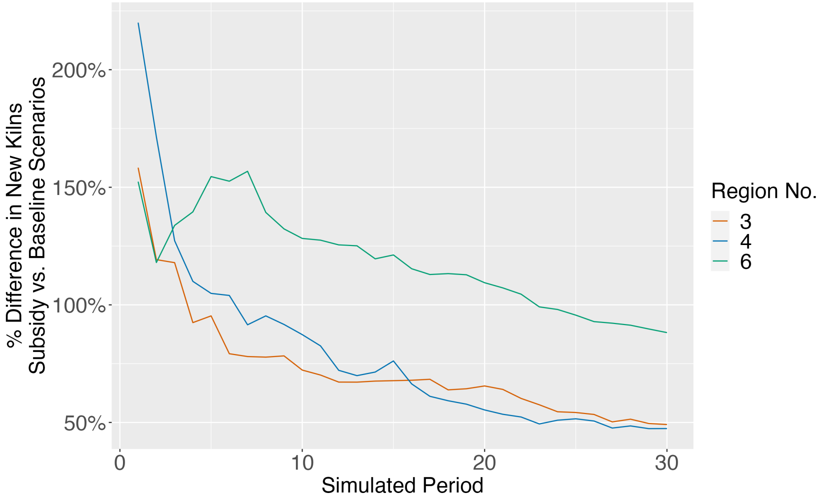
Counterfactual Simulations: Preliminary Results



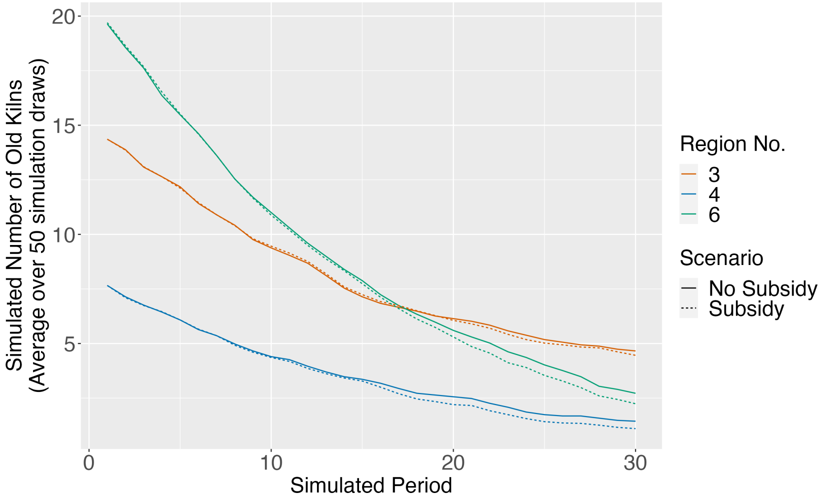
Counterfactual Simulations: Preliminary Results



Counterfactual Simulations: Preliminary Results



Counterfactual Simulations: Preliminary Results



Model Refinements

Further refinements to dynamic model planned:

- Further stress testing of structural model: alternative estimation methods, alternative policy functional forms, alternative decision timing assumptions, etc.
- Explore heterogeneity in upgrade and decommissioning costs
- Explore new plant entry
- Explore variation in policy design

Conclusion

- Subsidies for technology adoption interact with tendencies to under- or over-invest in concentrated industries, which includes many industrial sectors.
- Precalciner kiln adoption in the cement industry provides opportunity to study lumpy investments by incumbents in a new technology.
- Structural dynamic model underway will shed light on alternative subsidy designs.

Thank you! Comments welcome: `armitage@bu.edu`

Dynamic Model: Upgrade Policy Function

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	(1)	(2)	(3)
Plant New Tech. BP	-1.837^{***} (0.522)	-1.841^{***} (0.531)	-2.245^{***} (0.570)
Plant Old Tech. BP	-0.161 (0.382)	-0.070 (0.381)	-0.472 (0.502)
Competitor New BP	-0.031 (0.030)	-0.044 (0.032)	-0.103 (0.101)
Competitor Old BP	-0.076^{***} (0.029)	-0.106^{***} (0.033)	-0.162 (0.135)
Own Firm New BP		-0.249 (0.157)	-0.275 (0.181)
Own Firm Old BP		-0.245 (0.175)	-0.258 (0.225)
Market Demand	0.019^{*} (0.011)	0.037^{***} (0.014)	0.034^{**} (0.017)
Coal Price	0.315 (0.221)	0.435^{**} (0.222)	0.622^{**} (0.258)
Import Exposure		-0.552 (0.459)	
Cluster FE	No	No	Yes
Observations	4,347	4,347	4,347
Log Likelihood	-283.282	-279.258	-274.326
Akaike Inf. Crit.	580.563	578.515	584.651

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Cement Market: Impact of Precalciner Adoption

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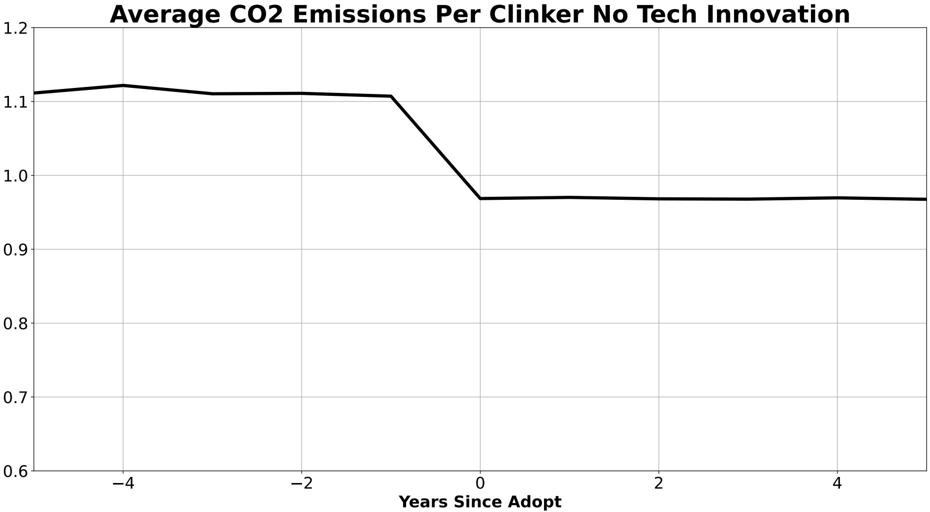

Cement Market: Impact of Precalciner Adoption

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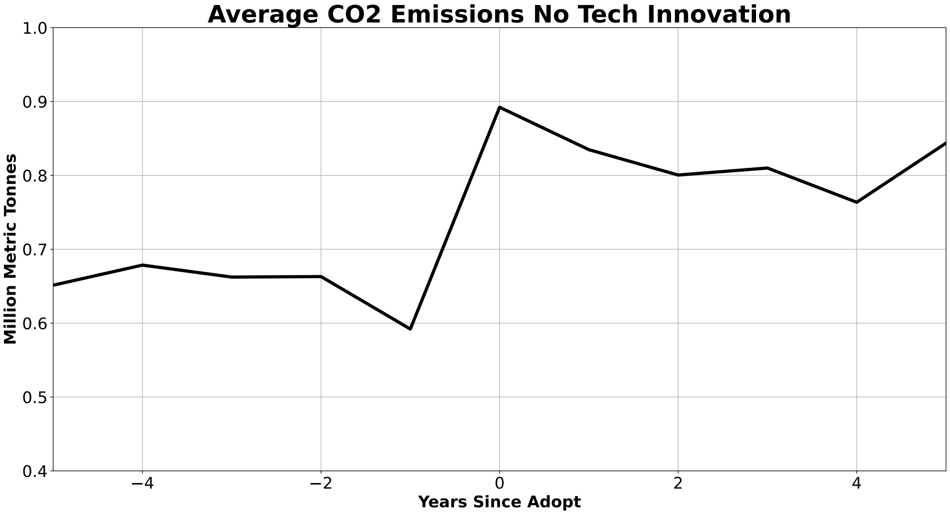

Dynamic Structural Model: Static Profits

	Est. Plant Profit
Plant New Tech. BP	10.733^{***} (0.295)
Plant Old Tech. BP	5.868^{***} (0.435)
Competitor New BP	-0.559^{***} (0.031)
Competitor Old BP	-0.659^{***} (0.029)
Own Firm New BP	-0.652^{***} (0.140)
Own Firm Old BP	-0.300^{*} (0.161)
Market Demand	0.340^{***} (0.013)
Coal Price	$-3{,}371.628^{***}$ (250.642)
Constant	$21{,}102.500^{***}$ (766.168)
Observations	4,285
Adjusted R^2	0.411
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

xgboost non-linear prediction model:

- Test/train sampled at plant-year level: "adjusted-R^2" $= 0.89$
- Test/train sampled at plant level: "adjusted-R^2" $= 0.44$

Dynamic Estimation: Upgrade Policy Function

Alternative Models

	Logit Model	Logit Model
Plant New Tech. BP	-1.690^{***} (0.509)	-1.918^{***} (0.527)
Plant Old Tech. BP	-0.161 (0.375)	-0.156 (0.374)
Competitor BP	-0.079^{***} (0.029)	
Competitor New BP		-0.043 (0.032)
Competitor Old BP		-0.103^{***} (0.033)
Own Firm BP	-0.206^{**} (0.103)	
Own Firm New BP		-0.252 (0.157)
Own Firm Old BP		-0.234 (0.175)
Market Demand	0.033^{**} (0.013)	0.034^{**} (0.013)
Coal Price	0.523^{**} (0.225)	0.420^{*} (0.224)
Constant	-4.992^{***} (0.730)	-4.628^{***} (0.718)
Observations	4,347	4,347
Log Likelihood	-282.755	-279.957
Akaike Inf. Crit.	579.510	577.914

Note: *p<0.1; **p<0.05; ***p<0.01. BP in 1000s of tons.