Balancing Production and Carbon Emissions with Fuel Substitution

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November 27, 2023

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Key issue: fossil fuel combustion in production

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  - Reduction in emissions
    (Andresson 2019; Ahmadi and Yamazaki 2020; Alpino, Citino and Frigo 2023)
  - Cost pass-through and reduction in production
    (Gittens 2019; Ganapati, Shapiro and Walker 2020; Fontagné, Martin and Orefice 2023)

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- Important: growth concerns can explains lack of carbon tax in India (Jack 2017)

How cost-effective are leading carbon policies at reducing emissions? Are there winners and losers?

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2. Heterogeneity across firms' ability to convert fuels to energy ▸ Examples

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I estimate model with rich panel of Indian manufacturing establishments (2009-2016)

- Key challenge: multidimensional unobserved heterogeneity (fuel productivity)
- Tractable estimation in four stages (Ganapati, Shapiro and Walker 2020; Grieco, Li and Zhang 2016; Zhang 2019; Arcidiacono and Jones 2003)

Quantify trade-off of policies: carbon tax on fossil fuels, cleaner fuel subsidy

How do Firms Respond to Increase in Fuel Cost?

1. Intensive margin: flexible fuel substitution within fuel set
2. Extensive margin: costly switching between fuel sets across periods
3. Scale: pass-through to consumers and reduce output

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Role of heterogeneity in fuel productivity: use more of most productive fuels

1. High fuel productivity, less willing to substitute: higher $\uparrow$ marginal cost, higher pass-through (more exposed)
2. Output reallocates towards less exposed plants who become more competitive

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Reallocation of output consistent with empirical literature (Alpino, Citino and Frigo 2023, Dussaux 2021, Najjar and Cherniwchan 2023)

Literature and Contribution

1. Fuel substitution in manufacturing (Hyland and Haller 2018, Wang and Lin 2017, Stern 2012, Ma et al. 2008, Pindyck 1979, Fuss 1977)
   - Novel channels capturing firms' response to changes in fuel cost Details
     1.1 Inter-temporal switching between fuel sets
     1.2 Heterogeneity fuel productivity

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3. Production function estimation (Olley and Pakes 1996; Blundell and Bond, 2000; Levinsohn and Petrin 2003; Ackerberg, Caves and Frazer 2015; Grieco, Li and Zhang 2016; Zhang 2019; Gandhi, Navarro and Rivers, 2020; Demirer, 2020)
   - 4-stages estimation technique can be applied to other settings

Data: Indian Survey of Industries (ASI) 2009-2016

- Annual panel of Indian manufacturing establishments
- Establishment-level data on prices and quantities for all inputs and outputs
- **Energy inputs: Coal, Oil, Electricity and Natural Gas**
  - Price and quantities: heating potential in mmBtu
  - Emissions (schedule 1 and 2): One mmBtu of each fuel releases some amount of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O)
    - I convert these three pollutants to carbon dioxide equivalent (CO_{2e}) using the Global Warming Potential method (GWP).

Today: Steel

- Highly polluting industry (70% of fuel usage in coal): scope for reducing emissions

Plants Producing Steel use Different Fuel Sets and Often Switch

Percentage (%) of establishments in different fuel sets

	Steel
Oil, Electricity	51.3
Oil, Electricity, Coal	19.3
Oil, Electricity, Gas	10.8
Oil, Electricity, Coal, Gas	7.4
Other	11.1

Significant proportion of plants add or drop a fuel at least once

	Adds New Fuel	Drop Existing Fuel	Both Add and Drop
Yes (%)	39.4	39.6	26.0

▸ Switching by year ▸ Switching by Fuel ▸ Number of Fuels and Productivity

Model

Production Model

1. Outer Production (plant i at time t):

$$Y_{it} = z_{it}\left[\left(\alpha_K\big(\underbrace{K_{it}}_{\text{Capital}}\big)^{\frac{\sigma-1}{\sigma}} + \alpha_L\big(\underbrace{L_{it}}_{\text{Labor}}\big)^{\frac{\sigma-1}{\sigma}} + \alpha_M\big(\underbrace{M_{it}}_{\text{Materials}}\big)^{\frac{\sigma-1}{\sigma}} + \alpha_E\big(\underbrace{E_{it}}_{\text{Energy -- Unobserved}}\big)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\right]^{\eta}$$

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2. Inner Energy Production given a fuel set $\mathcal{F}_{it}$

$$E_{it} = \left(\sum_{f\in\mathcal{F}_{it}} (\psi_{fit} e_{fit})^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}} \qquad \mathcal{F}_{it} \subseteq \{\text{Oil, Elec, Gas, Coal}\}$$

Key innovation:

1. plant-by-year productivity ψ_{fit}: different incentives to substitute across firms
2. More substitution possibilities when $\mathcal{F}_{it}$ is larger (option value)

Production Decisions: (1) Within-Period (Static Profits)

Maximize profits taking input prices & productivities (s_{it}) and fuel set $\mathcal{F}_{it}$ as given

$$\pi(s_{it}, \mathcal{F}_{it}) = \max_{M_{it}, L_{it}, \{e_{fit}\}_{f \in \mathcal{F}_{it}}} \left\{ P_{it}(Y_{it})Y_{it} - w_t L_{it} - p_{mit} M_{it} - \sum_{f \in \mathcal{F}_{it}} p_{fit} e_{fit} \right\}$$

- Technological constraint Y_{it}
- Demand constraint $P_{it}(Y_{it})$ (monopolistic competition with demand elasticity ρ)

▸ two-stages ▸ energy price

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Can be separated in two optimization problems (leverage for estimation)

1. Minimize cost to produce energy with fuels $\rightarrow$ endogenous price of energy $p_{E_{it}}$
2. Maximize profits using energy as an input

▸ two-stages ▸ energy price

Production Decisions: (2) Inter-temporal Fuel Set Choices

$$V(\mathbf{s}_{it}, \mathcal{F}_{it}) = \max_{\mathcal{F}'} \Big\{ \underbrace{\pi(\mathbf{s}_{it}, \mathcal{F}_{it})}_{\text{period profits}} - \underbrace{\mathcal{K}(\mathcal{F}' \mid \mathcal{F}_{it}, s_{it}) + \sigma_\epsilon \epsilon_{\mathcal{F}' it}}_{\text{fixed switching costs}} + \underbrace{\beta\, \mathbb{E}[V(\mathbf{s}_{it+1}, \mathcal{F}') \mid s_{it}]}_{\text{continuation value}} \Big\}$$

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1. Plants face price & productivity (s_{it}) uncertainty

$$\mathbb{E}(\ln s_{it+1} \mid \mathcal{I}_{it}) = (1-\rho_s)(\mu_0^s + \mu_t^s + \mu_i^s) + \rho_s \ln s_{it}$$

- States s_{it}: fuel prices and productivity ($\{p_{fit}, \psi_{fit}\}_{f\in\mathbb{F}}$), material prices ($p_{mit}$), productivity ($z_{it}$), location and year.

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2. Fixed cost to add fuel and salvage value from dropping fuel
   - Vary with productivity z_{it} and access to natural gas pipeline network

Identification/Estimation

Identification and Estimation in **Four Separate Stages**

Goal: Recover everything (demand and production parameters, fuel productivity, switching costs)

1. Demand estimation: shift-share instrument exploiting shocks to fuel prices (Ganapati, Shapiro and Walker 2020)
2. Outer production function: I allow for unobserved quantity E_{it} and price $p_{E_{it}}$ of energy (Grieco, Li and Zhang 2019)
3. Energy production function: Fuel productivity ψ_{fit} for fuels that plants are using (Zhang 2019)
4. Inter-temporal switching: Distribution of fuel productivity for fuels that plants are not using jointly with switching costs (Arcidiacono and Jones 2003)

Stage 1: Demand Estimation (ρ)

Plant i in year t

$$\ln Y_{it} = \Lambda_t - \rho \ln P_{it} + \epsilon_{it}$$

- Due to simultaneity, I create a shift-share instrument for output prices that affects marginal cost following Ganapati et al. (2020)

$$z_{rt} = \Big[\overline{p}_{-r,t,f} * \sigma_{r,2008,f}\Big], \quad f \in \{\text{coal, gas, oil}\}$$

1. **Shift** $\overline{p}_{-r,t,f}$: average price of fuel f in year t across all but own state
2. **Share** $\sigma_{r,2008,f}$: pre-sample share of fuel f used to generate electricity in state r

▸ Output price ▸ Results & Robustness

Stage 2: Outer Production Function

$$Y_{it} = z_{it}\left[\left(\alpha_K (K_{it})^{\frac{\sigma-1}{\sigma}} + \alpha_L (L_{it})^{\frac{\sigma-1}{\sigma}} + \alpha_M (M_{it})^{\frac{\sigma-1}{\sigma}} + \alpha_E (\underbrace{E_{it}}_{\text{Energy - unobserved}})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\right]^{\eta}$$

Issues:

1. One of the input is unobserved E_{it}
2. Productivity z_{it} is correlated with input choices (bias parameter estimates)

Stage 2: Outer Production Function

- FOC of energy/labor: $\underbrace{E_{it}}_{\text{Profit-max quantity of energy}} = \left(\frac{\alpha_L}{\alpha_E}\underbrace{\frac{S_{Eit}}{S_{Lit}}}_{\text{Relative input spending}}\right)^{\frac{\sigma}{\sigma-1}} \times \underbrace{L_{it}}_{\text{Quantity of labor}}$

- FOC labor: $z_{it} = f(L_{it}, S_{L_{it}}, K_{it}, S_{E_{it}}, S_{M_{it}}; \theta)$

Consistency with demand

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Substitute E_{it} and z_{it} into revenue to get estimating equation (Grieco, Li and Zhang 2016)

$$\ln R_{it} = \underbrace{\ln \frac{\rho}{\rho - 1}}_{\text{demand elasticity: known}} + \ln \frac{1}{\eta} + \ln \left(S_{Lit}\left(1 + \frac{\alpha_k}{\alpha_L}\left(\frac{K_{it}}{L_{it}}\right)^{\frac{\sigma-1}{\sigma}}\right) + S_{Mit} + S_{Eit} \right) + \underbrace{u_{it}}_{\text{Measurement error}}$$

▸ Consistency with demand

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Normalization

Consistency with demand

Stage 3: Energy Production Function (Now that $\hat{E}_{it}$ is Observed)

1. Normalize fuel productivity relative to electricity

$$\hat{E}_{it} = \Big(\sum_{f \in \mathcal{F}_{it}} \left(\psi_{fit} e_{fit} \right)^{\frac{\lambda-1}{\lambda}} \Big)^{\frac{\lambda}{\lambda-1}}$$

$$= \psi_{eit} \Big(\sum_{f \in \mathcal{F}_{it}} \left(\tilde{\psi}_{fit} e_{fit} \right)^{\frac{\lambda-1}{\lambda}} \Big)^{\frac{\lambda}{\lambda-1}} \quad \text{where} \quad \tilde{\psi}_{fit} \equiv \underbrace{\psi_{fit}/\psi_{eit}}_{\text{Relative fuel productivity}}$$

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2. Exploit FOC of cost-minimization to produce energy

$$\underbrace{\tilde{\psi}_{fit}}_{\text{Relative fuel productivity}} \quad s.t. \quad \underbrace{\frac{p_{fit}}{p_{eit}}}_{\text{Relative fuel prices}} = \underbrace{\tilde{\psi}_{fit}^{\frac{\lambda-1}{\lambda}} \left(\frac{e_{eit}}{e_{fit}} \right)^{\frac{1}{\lambda}}}_{\text{Relative fuel Marginal Products}}$$

Stage 3: Energy Production Function (Now that $\hat{E}_{it}$ is Observed)

Substitute relative fuel productivity into energy production function (similar to Zhang 2019)

$$\underbrace{\ln \frac{E_{it}}{e_{eit}}}_{\text{value-added of electricity}} = \underbrace{\ln \psi_{eit}}_{\text{Electricity productivity}} + \underbrace{\frac{\lambda}{\lambda - 1} \ln \left(\sum_{f \in \mathcal{F}_{it}} \frac{s_{fit}}{s_{eit}} \right)}_{\text{Relative spending on other fuels}}$$

- Only one unobservable left ($\ln \psi_{eit}$): **can use standard methods**
  - AR(1) for $\ln \psi_{eit}$ (Gandhi, Navarro and Rivers 2020) and lagged fuel prices as instruments
  - Estimating equation is canonical linear dynamic panel (Blundell and Bond 1998)

Estimating eq

Production Function Estimation Results

Production Function Parameters		Average Revenue Elasticities	
Returns to scale $\hat{\eta}$	1.19 [1.18,1.20]	Labor	0.030 [0.03,0.032]
Outer substitution elasticity $\hat{\sigma}$	**1.87** [0.9,2.85]	Capital	0.016 [0.01,0.024]
Fuel substitution elasticity $\hat{\lambda}$	**2.22** [1.5,3.25]	Materials	0.745 [0.74,0.75]
Demand Elasticity $\hat{\rho}$	4.20 [2.79,5.68]	Energy	**0.12** [0.113,0.12]
"Effective" returns to scale	0.91 [0.89,0.91]		

1. Fuels are more substitutable among each others than energy with other inputs
2. Elasticity of energy larger than labor and capital: Energy matters for steel

Stage 4: Dynamic Discrete Choice

$$V(\mathbf{s}_{it}, \mathcal{F}_{it}) = \max_{\mathcal{F}'} \Big\{ \underbrace{\pi(\mathbf{s}_{it}, \mathcal{F}_{it})}_{\text{period profits}} - \underbrace{\mathcal{K}(\mathcal{F}' \mid \mathcal{F}_{it}, s_{it}; \theta) + \sigma_\epsilon \epsilon_{\mathcal{F}' it}}_{\text{fixed switching costs}} + \underbrace{\beta\, \mathbb{E}[V(\mathbf{s}_{it+1}, \mathcal{F}') \mid s_{it}]}_{\text{continuation value}} \Big\}$$

▸ switching cost matrix ▸ assumptions states

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Fixed switching cost function $\mathcal{K}(\mathcal{F}' \mid \mathcal{F}_{it}, s_{it}; \theta)$

- Add gas: $\kappa_g + \kappa \ln z_{it} + \lambda_g \mathbb{I}(\text{no pipeline})$
- Drop gas: $\gamma_g + \gamma \ln z_{it}$
- Add coal: $\kappa_c + \kappa \ln z_{it}$
- Drop coal: $\gamma_c + \gamma \ln z_{it}$

switching cost matrix | assumptions states

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Uncertainty over future states s_{it+1}. plants forecast using AR(1) with correlated shocks (Farmer and Akiro Toda, 2017)

- Fuel productivity over prices $\psi_{fit}/p_{fit} \quad \forall f \in \mathbb{F}$
- Price of intermediate materias p_{mit}
- Hicks-neutral productivity z_{it}

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$\epsilon_{\mathcal{F}'it}$: Type-1 extreme value shock to choice-specific switching cost

- Choice probabilities take logit form

$$\frac{e^{\left(v_{\mathcal{F}'}(s_{it}, \mathcal{F}_{it}; \theta)\right)}}{\sum_{\mathcal{F} \in \mathbb{F}} e^{\left(v_{\mathcal{F}}(s_{it}, \mathcal{F}_{it}; \theta)\right)}}$$

- To estimate switching costs, need to solve the model under all possible fuel sets

How to predict fuel productivity for fuels that plants have never used?

switching cost matrix
assumptions states

Fuel Productivity for Fuels that Plants have Never Used

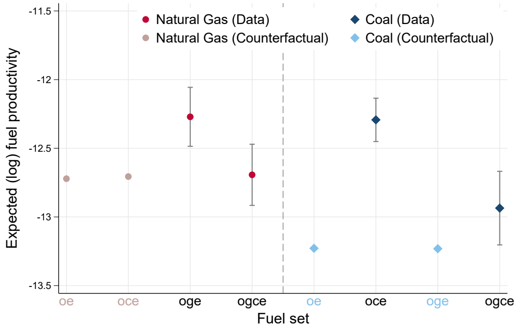
Assumption: plant systematic differences in fuel productivity (comparative advantage):
$\mu_i^f \quad \forall f \in \mathbb{F}$

- Plants know about μ_i^f which guides their fuel set choices
- Researcher doesn't observe μ_i^f (similar to Roy model)
- Treat comparative advantage as unobserved types in dynamic discrete choice model
- Estimate distribution of unobserved typs jointly with switching costs in full info likelihood following Arcidiacono and Jones (2003)
    - Expectation-Maximum algorithm where you recursively iterate between distribution of switching costs and distribution of unobserved types

▸ Details E-M

Distribution of Expected Fuel Productivity (Gas and Coal)

$\mathbb{E}(\psi_{fit} \mid \mathcal{F}) \ \forall \mathcal{F} \subseteq \mathbb{F}$



1. Plants who do not use coal would be 60% less productive at it
2. Plants who do not use gas would be 20% less productive at it

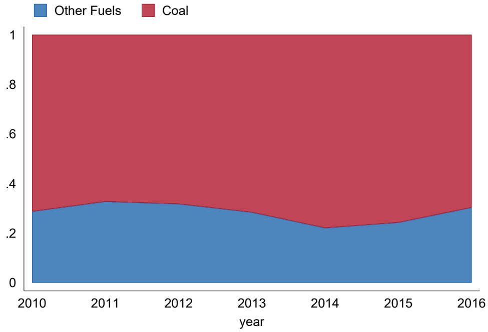
▸ Contribution to energy price

Fixed Switching Costs

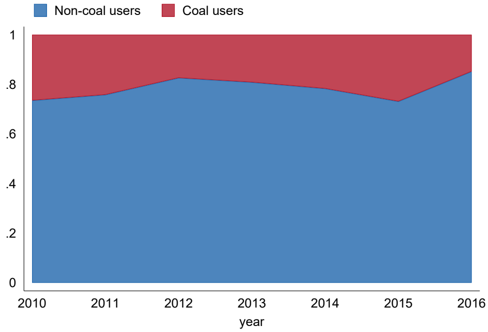
		Fixed Costs (Million USD)	Salvage Values (Million USD)
Natural Gas	*Pipeline Access*	28.83	15.12
	No Pipeline Access	40.46	
Coal		28.82	8.33
Total Factor Productivity (100 % increase)		0.82	0.25
Observations		2,393	

- Fixed costs economically significant: for gas, 6x median and 2x average revenues.
- Fixed costs are 2-3 times larger than salvage values
- Gas fixed costs 50% larger for plans without access to pipeline

Concentration of Energy in high Coal Productivity, low TFP Plants



Yearly Aggregate Fuel Quantities (mmBtu)



Yearly Aggregate Output

Results Provide Evidence for Technology Lock-in

Combining the two previous results points towards technology lock-in, especially for large coal users located in *Steel Belt*

- No access to natural gas pipeline (fixed costs averaging $40 Million USD)
- Too productive at coal relative to other fuels to justify dropping it
- Would not be productive enough overall and at natural gas to justify adoption

Map

Model Fit – Distribution of Fuel Sets

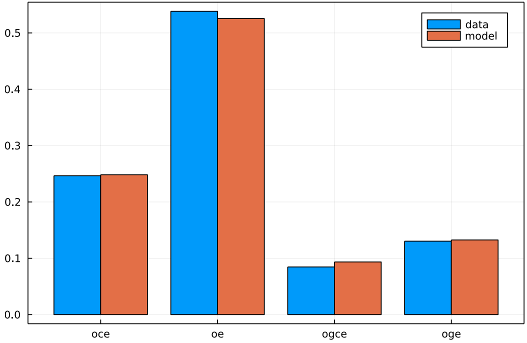
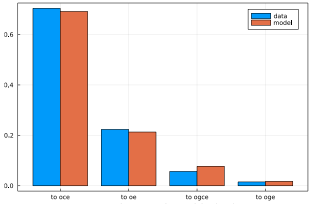


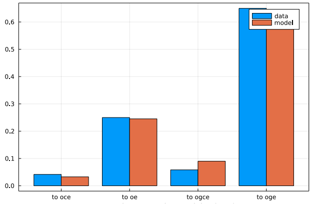
Figure: Unconditional distribution of fuel sets, model vs. data $(N = 2,393)$

▸ tfp ▸ fuel expenditures

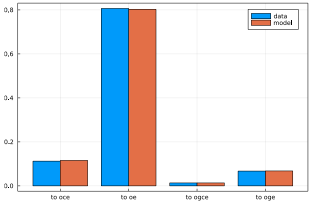
Model Fit – Fuel Set Transitions



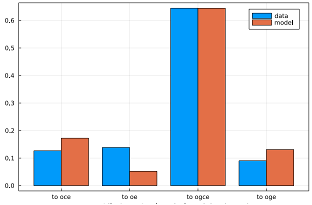
From Oil,Coal,Electricity (OCE) – $N = 572$



From Oil, Gas, Electricity (OGE) – $N = 280$



From Oil, Electricity (OE) – $N = 1,342$



From Oil, Gas, Coal, Electricity (OGCE) – $N = 199$

Policy

Policy Counterfactuals: **Carbon Tax**

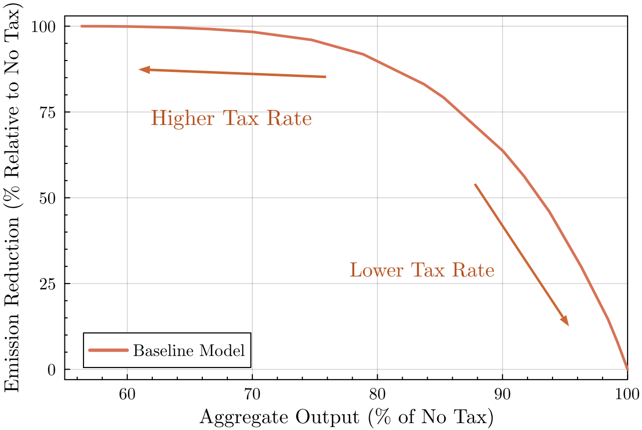
- Per-unit fuel tax where relative tax rate proportional to fuel's emission intensity.
- Trace out trade-off between output and emission reduction for various tax **levels**
- I simulate the economy with and without the tax for 40 years and compare net present value of outcomes along entire path

$$\mathbb{E}(X(\tau)) \approx \frac{1}{S}\frac{1}{40}\sum_{s=1}^{S}\sum_{t=0}^{40}\beta^t X_{ts}(\tau)$$

$X = \{$aggregate output, aggregate emissions$\}$

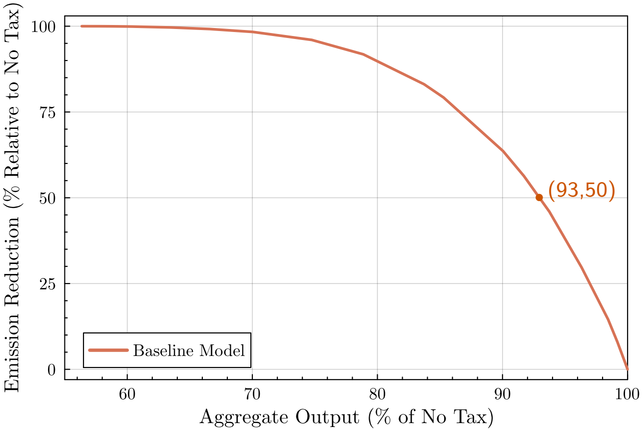
Fuel	Average Price (Rupees)	Emission Factor (Kg CO_{2e}/mmBtu)
Coal	262	100
Oil	665	82
Electricity	1,681	65
Natural Gas	1,307	60

Policy Results - Greater Emission Reduction than Production Loss



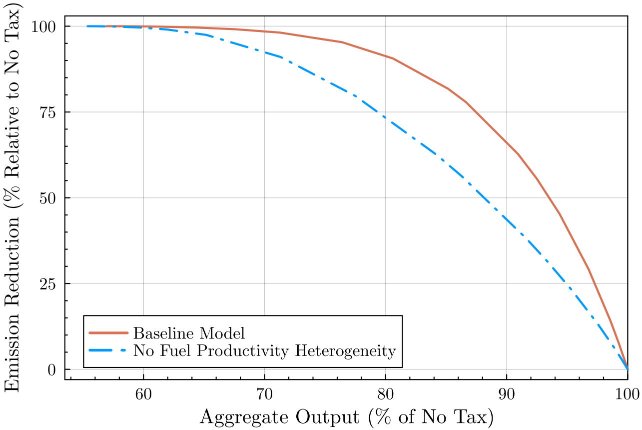
- Production frontier between output and emission reduction
- Each point on graph correspond to different **levels** of tax
- Increasing marginal cost of reducing emissions
  (Fowlie, Reguant and Ryan 2016)

Policy Results - Greater Emission Reduction than Production Loss



- For 50% reduction in emissions, produce 93% of output
- Full Model: $\frac{\%\Delta Emission}{\%\Delta Output} = 7.14$

Policy Results - Greater Emission Reduction than Production Loss

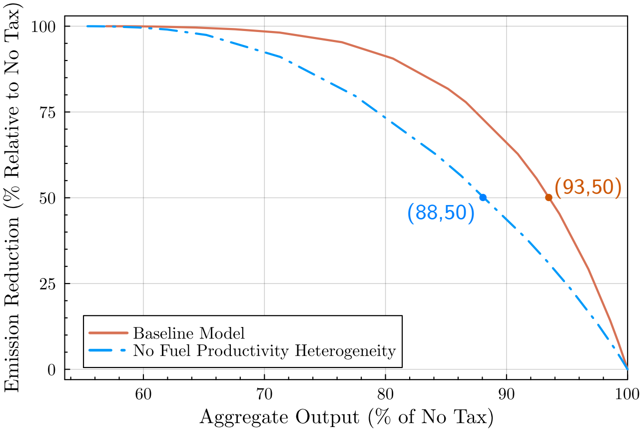


Economy with no fuel productivity heterogeneity

- Energy production with average fuel productivity β_f
- Similar to Hawkins-Pierot and Wagner (2022)

$$E_{it} = \psi_{Eit} \left(\sum_{f \in \mathcal{F}_{it}} \beta_f e_{fit}^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}$$

Policy Results - Greater Emission Reduction than Production Loss



- Full Model: $\frac{\%\Delta Emission}{\%\Delta Output} = 7.14$
- No Fuel Productivity: $\frac{\%\Delta Emission}{\%\Delta Output} = 4.16$

Policy Results - Why Heterogeneity in Fuel Productivity Matters

- Carbon tax raises price of coal and oil relative to electricity and gas
- **Envelope theorem**: elasticity of energy price with respect to relative fuel prices increasing in relative fuel productivity
  - Counter-intuitive
- Plants relatively more productive at coal (big polluters)

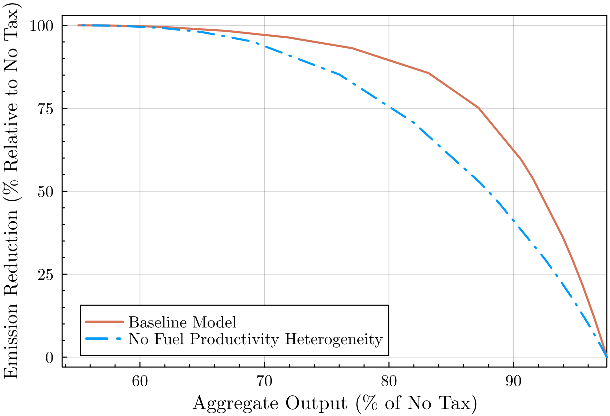
Details elasticity

Policy Results - Why Heterogeneity in Fuel Productivity Matters

- Carbon tax raises price of coal and oil relative to electricity and gas
- **Envelope theorem**: elasticity of energy price with respect to relative fuel prices increasing in relative fuel productivity
  - Counter-intuitive
- Plants relatively more productive at coal (big polluters)
  1. Higher elasticity (more exposed to tax)
  2. Higher increase in marginal cost
  3. Higher pass-through of tax to output price
- Reallocation of demand shifts industry output from high to low elasticity plants: benefits cleaner plants at expense of dirty plants

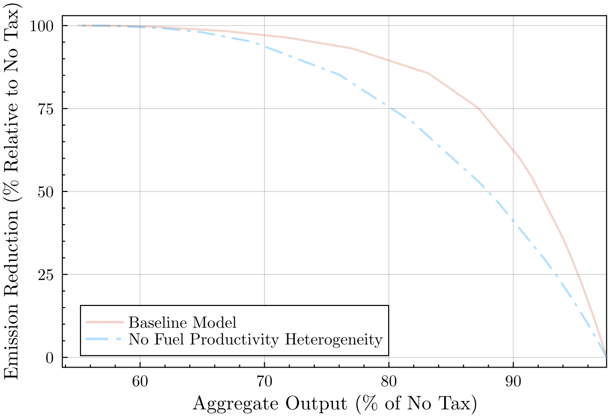
▸ Details elasticity

Policy Results – Extent of Reallocation Depends on Demand Elasticity (ρ)



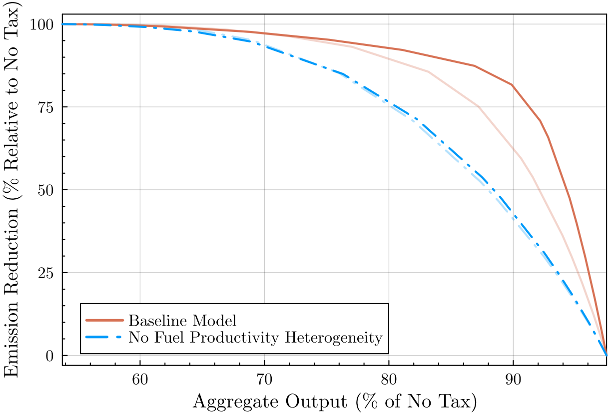
Effect of Doubling Elasticity of Demand ρ

Policy Results – Extent of Reallocation Depends on Demand Elasticity (ρ)



Effect of Doubling Elasticity of Demand ρ

Policy Results – Extent of Reallocation Depends on Demand Elasticity (ρ)



Effect of Doubling Elasticity of Demand ρ

More elastic demand

- Consumers more willing to substitute between steel varieties
- Carbon tax becomes more effective
- Only true when allowing for fuel productivity heterogeneity

This Result is Consistent with Empirical Literature

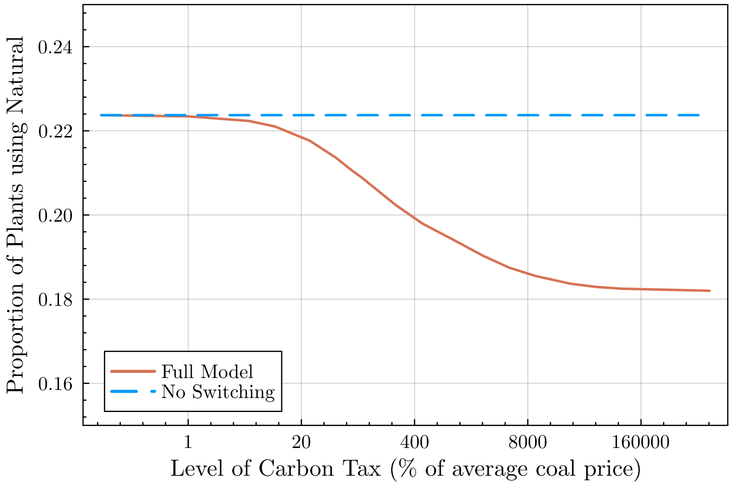
- Recent empirical literature studying the effect of European Energy Crisis (2x natural gas prices, 1.5x electricity prices) (Fontagne, Martin, Orefice 2023; Moll, Schularick and Zachmann 2023; Dussaux 2021; Alpino, Citino and Frigo 2023)

  1. Energy-intensive firms increased their output prices more than other firms (Alpino, Citino and Frigo 2023)
  2. Rise in energy prices triggered a reallocation of production and workers from energy-intensive to energy-efficient firms (Dussaux 2021)

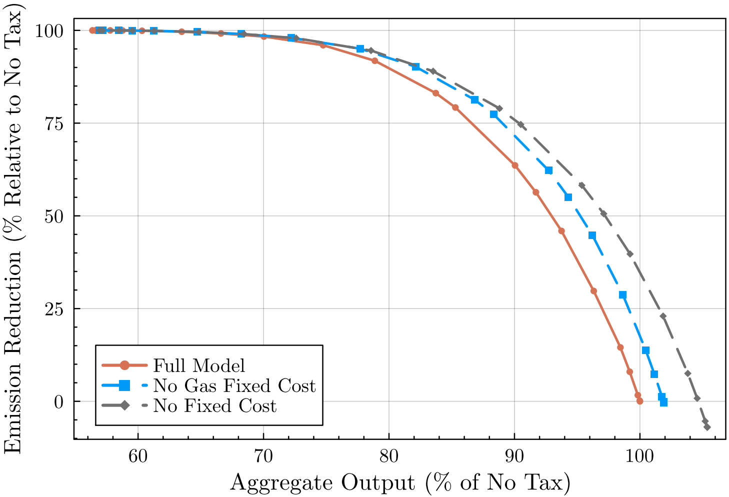
- Najjar and Cherniwchan (2021) show that reallocation of output across plants explains 50% of canadian manufacturing clean-up in small particular matter

Reduced-form evidence

Beyond Output Recomposition – Carbon Tax does not Increase Gas Adoption



Fixed Costs Increase Output Cost of Emission Reduction



Alleviating Technology Lock-in – Subsidy Towards Natural Gas Adoption

Permanent 10% subsidy (4 million per adoption) together with carbon tax (SCC at $\$51/tCO_{2e}$)

- Fraction of plants utilizing natural gas from 0.19 to 0.24: not large coal users
- Over 90% of subsidy goes towards plants who would add natural gas in absence of subsidy (40 year horizon) $\rightarrow$ free riders
- Emissions goes up together with output due to option value of new fuel
  - Plants do not drop coal to keep option value
- Overall cost is substantial ($2.7 billion), but minimal welfare effect (0.003%)

▸ Full welfare analysis

Conclusion

- Developed a novel dynamic production model of fuel choices.
- Estimate the model with Indian Steel manufacturing plants.
- I find that heterogeneity in **ability** and **incentives** to substitute is important to understand how firms respond to changes in fuel costs
- Using novel channels, I quantify the production cost of emission reduction induced by carbon tax.
  1. Heterogeneity in fuel productivity reduces trade-off
  2. Fixed Costs increase trade-off
- I show that subsidizing natural gas adoption is ineffective at reducing emissions compared to carbon tax

Thank You!

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Source of Heterogeneity in Fuel Productivity – Examples

...Across fuel types:

- **Steel technologies:** Electric-arc furnaces (electricity, natural gas) are more productive than coal furnaces at using physical units (heating potential) of the underlying fuels (Worrell, Blinde, Neelis, Blomen and Masanet 2010).

...Within fuel types

- **Unobserved fuel quality:** for example, high grade coal (Anthracite, Bituminous) has a higher energy content for a given physical unit relative to lower grade coal (Lignite, Sub-Bituminous)

...Energy retrofit

- Heterogeneity on how efficiently agents use the heating potential of fuels (Christensen, Francisco and Myers 2022).

Back to main

Contribution to Literature on Fuel Substitution

Wang and Lin (2017) Stern (2012), Ma et al. 2008, Pindyck (1979) Fuss (1977)

- Translog production function to estimate partial substitution elasticities
- Some papers (e.g. Hyland and Haller, 2018) recover aggregate elasticities, but no story as to why they differ
- Some papers going back to Joskow and Mishkin (1977) allow for discrete choice between fuel sets: no dynamic switching and not within production function.

Contribution: Heterogeneity in fuel productivity, dynamic switching between fuel sets

1. Reallocation in production induced by heterogeneous exposure to price change $\rightarrow$ aggregate substitution elasticities differ from individual ones
2. Technology lock-in

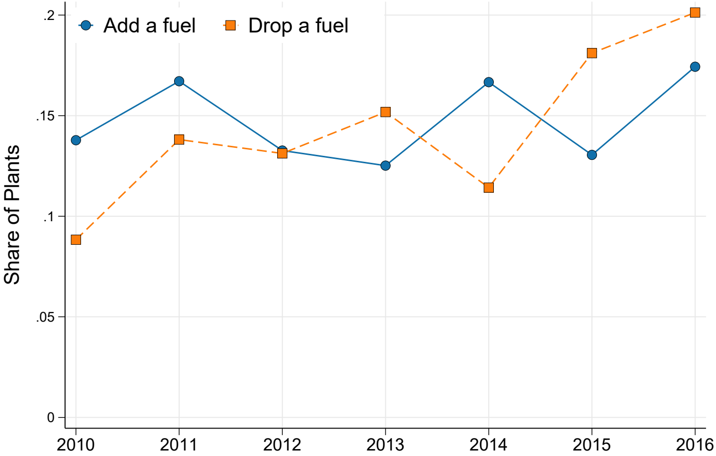
Back to main

Contribution to Literature on Carbon Policy in Manufacturing

- Structural models tend to overestimate output cost of carbon tax (Fowlie, Reguant and Ryan 2016, Ryan 2012)
- Literature on tax incidence captures heterogeneity between producers and consumers (Ganapati, Shapiro and Walker 2020)
  - I show that there is significant heterogeneity within producers based on exposure variation
- Literature technology lock-in quite similar but does not allow for fuel substitution (Hawkins-Pierot and Wagner, 2022)
  - Fuel substitution helps understand whether technology lock-in is driven by large investment costs vs. lack of incentives to substitute
  - Fuel productivity explains selection of firms into technologies

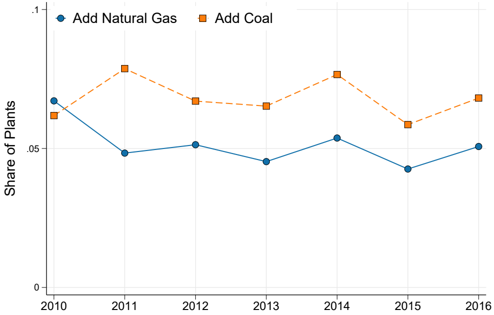
Back to main

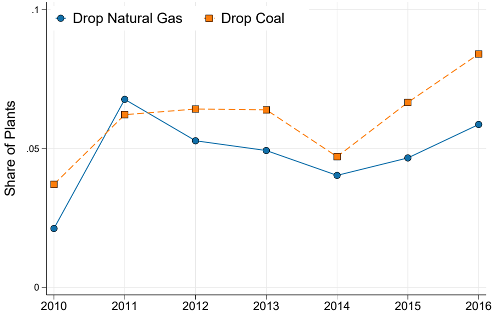
Fuel Switching by Year



Back to main

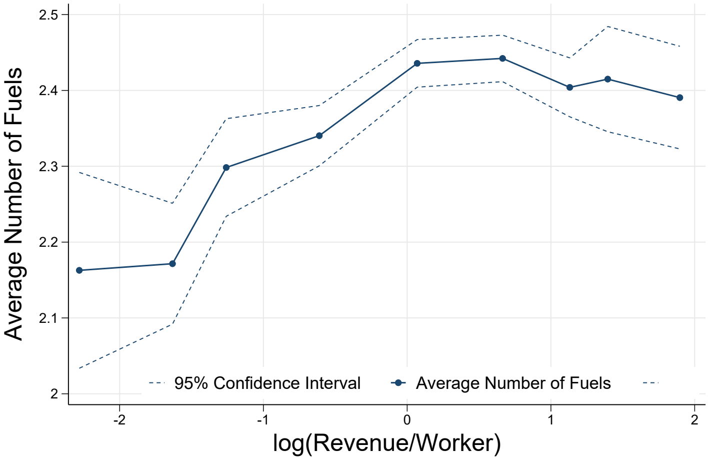
Fuel Switching by Year and Fuels





Back to main

Number of Fuels and Productivity



▸ Back to main

Static Production Decisions in Two Stages: (1) Cost-Minimization

$$\min_{\{e_{fit}\}_{f\in\mathcal{F}_{it}}} \left\{ \sum_{f\in\mathcal{F}_{it}} p_{fit} e_{fit} \right\} \quad s.t. \quad \tilde{E}_{it} = \left(\sum_{f\in\mathcal{F}_{it}} (\psi_{fit}\tilde{e}_{fit})^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}$$

The achieved minimum of this problem is an energy cost function $\mathcal{C}(\tilde{E}_{it})$ that satisfies:

$$\mathcal{C}(\tilde{E}_{it}) = \left(\sum_{f\in\mathcal{F}_{it}} \left(\frac{\tilde{p}_{fit}}{\psi_{fit}}\right)^{1-\lambda} \right)^{\frac{1}{1-\lambda}} \tilde{E}_{it}$$
$$= p_{\tilde{E}_{it}} \tilde{E}_{it} = \sum_{f\in\mathcal{F}_{it}} p_{fit} e_{fit}$$

▸ Back to main

Static Production Decisions in Two Stages: (1) Profit-Maximization

$$\pi(\mathbf{s}_{it}, \mathcal{F}_{it}) = \max_{K_{it}, M_{it}, L_{it}, E_{it}} \left\{ \left(\frac{e^{\Gamma_t}}{N_t} \right)^{\frac{1}{\rho}} P_t^{\frac{1+\rho(\theta-1)}{(\theta-1)\rho}} Y_{it}^{\frac{\rho-1}{\rho}} - w_t L_{it} - r_{kt} K_{it} - p_{mit} M_{it} - p_{Eit} E_{it} \right\}$$

$$s.t. \quad \tilde{Y}_{it} = z_{it} \left[\alpha_K \tilde{K}_{it}^{\frac{\sigma-1}{\sigma}} + \alpha_L \tilde{L}_{it}^{\frac{\sigma-1}{\sigma}} + \alpha_M \tilde{M}_{it}^{\frac{\sigma-1}{\sigma}} + \alpha_E \tilde{E}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\eta\sigma}{\sigma-1}}$$

Back to main

Price of Energy Captures all Novel Channels of Heterogeneity

$$p_{E_{it}} = \left(\sum_{f \in \mathcal{F}_{it}} \left(p_{fit} / \psi_{fit} \right)^{1-\lambda} \right)^{\frac{1}{1-\lambda}}$$

1. Fuel set $\mathcal{F}_{it}$: larger fuel sets lowers $p_{E_{it}}$ (option value)
2. Fuel productivity ψ_{fit} : higher fuel productivity lowers $p_{E_{it}}$
3. Fuel prices p_{fit} : higher fuel prices lower $p_{E_{it}}$

Back to main

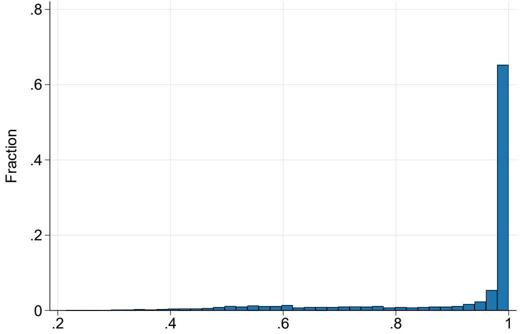
Construction of Output Price

Output price is weighted average of products sold

$$P_{it} = \sum_k s_{kit} P_{kit}$$

- s_{kit} : sales share of product k.

- Most plants produce a single product
- Multiprod plants have dominant product



Sales Share of Main Product by Plant-Year

Back to main

Elasticity of Demand – Results and Robustness

	Baseline	Lagged fuel expenditures as share		
Elasticity of Demand $\hat{\rho}$	-4.201***	-4.669^{+}	-4.016*	-3.089**
	(0.894)	(2.695)	(1.851)	(0.942)
Year FE	Y	Y	Y	Y
Region x Year FE			Y	
State x Year FE				Y
N	8,517	4,088	4,088	4088

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Back to main

Normalization of the CES Around Geometric Mean

Following Grieco, Li and Zhang (2016), I explicitely normalize the CES production function around the geometric mean of each variable $\overline{X} = \left(\prod_{i=1}^{n}\prod_{t=1}^{T} X_{it}\right)^{\frac{1}{nT}}$ to estimate the production function:

$$\frac{Y_{it}}{\overline{Y}} = z_{it}\left(\alpha_K\left(\frac{K_{it}}{\overline{K}}\right)^{\frac{\sigma-1}{\sigma}} + \alpha_L\left(\frac{L_{it}}{\overline{L}}\right)^{\frac{\sigma-1}{\sigma}} + \alpha_M\left(\frac{M_{it}}{\overline{M}}\right)^{\frac{\sigma-1}{\sigma}} + \alpha_E\left(\frac{E_{it}}{\overline{E}}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\eta\sigma}{\sigma-1}}$$

$$s.t. \quad \alpha_L + \alpha_K + \alpha_M + \alpha_E = 1$$

Consistency Between Demand and Production Function

Quantity observed: $\ln Y_{it} = \underbrace{\ln Q_{it}}_{\text{true quantity}} + \underbrace{\omega_{it}}_{\text{quantity measurement error}}$

Demand equation:

$$\ln Y_{it} = \Lambda_t - \rho \ln P_{it} + \underbrace{e_{it}}_{\text{ex-post demand shock}} + \omega_{it}$$

$$= \Lambda_t - \rho \ln P_{it} + \epsilon_{it}$$

Then, observed revenue is: $\ln R_{it} = \ln(P_{it} Y_{it}) = \ln(P_{it} Q_{it}) + u_{it}$

Can allow for measurement error in prices as well ($\omega_{it} \neq u_{it}$)

Back to main

Details: Identification of inner production function

$$\ln \psi_{eit} = (1-\rho_{\psi_e})(\mu_0^{\psi_e} + \mu_i^{\psi_e}) + \mu_t^{\psi_e} - \rho_{\psi_e}\mu_{t-1}^{\psi_e} + \rho_{\psi_e} \ln \psi_{eit-1} + \epsilon_{it}^{\psi_e}$$

Using AR(1) for $\ln \psi_{eit}$, rearrange value added energy production function:

$$\underbrace{\ln \tilde{E}_{it} - \ln e_{eit}}_{y_{it}} = \Gamma_t + \rho_{\psi_e}(\underbrace{\ln \tilde{E}_{it-1} - \ln e_{eit-1}}_{y_{it-1}})$$
$$+ \frac{\lambda}{\lambda-1}\left(\underbrace{\ln \frac{\sum_{f\in\mathcal{F}_{it}} s_{fit}}{s_{eit}}}_{x_{it}} - \rho_{\psi_e} \underbrace{\ln \frac{\sum_{f\in\mathcal{F}_{it-1}} s_{fit-1}}{s_{eit-1}}}_{x_{it-1}}\right) + \mu_i^* + \epsilon_{it}^{\psi_e}$$

canonical form with common parameter restrictions:

$$y_{it} = \Gamma_t + \rho y_{it-1} + \beta_1 x_{it} - \beta_2 x_{it-1} + \mu_i^* + \epsilon_{it} \qquad s.t. \;\; \beta_2 = \rho\beta_1$$

Back to main

Details: Identification of inner production function

$$\ln \psi_{eit} = (1 - \rho_{\psi_e})(\mu_0^{\psi_e} + \mu_i^{\psi_e}) + \mu_t^{\psi_e} - \rho_{\psi_e}\mu_{t-1}^{\psi_e} + \rho_{\psi_e} \ln \psi_{eit-1} + \epsilon_{it}^{\psi_e}$$

Using AR(1) for $\ln \psi_{eit}$, rearrange value added energy production function:

$$\ln \tilde{E}_{it} - \ln e_{eit} = \Gamma_t + \rho_{\psi_e}(\ln \tilde{E}_{it-1} - \ln e_{eit-1}) + \frac{\lambda}{\lambda - 1}\left(\ln \frac{\sum_{f \in \mathcal{F}_{it}} s_{fit}}{s_{eit}} - \rho_{\psi_e} \ln \frac{\sum_{f \in \mathcal{F}_{it-1}} s_{fit-1}}{s_{eit-1}}\right) + \mu_i^* + \epsilon_{it}^{\psi_e}$$

Lagged dependent variable ($\ln \tilde{E}_{it-1} - \ln e_{eit-1}$) correlated with fixed effect (μ_i^*):
system GMM from Blundell and Bond (1998)

Back to main

Details: Identification of inner production function

$$\ln \psi_{eit} = (1-\rho_{\psi_e})(\mu_0^{\psi_e} + \mu_i^{\psi_e}) + \mu_t^{\psi_e} - \rho_{\psi_e}\mu_{t-1}^{\psi_e} + \rho_{\psi_e} \ln \psi_{eit-1} + \epsilon_{it}^{\psi_e}$$

Using AR(1) for $\ln \psi_{eit}$, rearrange value added energy production function:

$$\ln \tilde{E}_{it} - \ln e_{eit} = \Gamma_t + \rho_{\psi_e}(\ln \tilde{E}_{it-1} - \ln e_{eit-1}) + \frac{\lambda}{\lambda-1}\left(\ln \frac{\sum_{f\in\mathcal{F}_{it}} s_{fit}}{s_{eit}} - \rho_{\psi_e} \ln \frac{\sum_{f\in\mathcal{F}_{it-1}} s_{fit-1}}{s_{eit-1}}\right) + \mu_i^* + \epsilon_{it}^{\psi_e}$$

Contemporaneous fuel spending shares correlated with shock to electricity productivity ($\epsilon_{it}^{\psi_e}$): instrument fuel spending shares with $t-1$ fuels prices (assuming persistent)

Back to main

Switching Costs Matrix $\mathcal{K}(\mathcal{F}' \mid \mathcal{F}_{it}, s_{it}; \theta)$

		$\mathcal{F}'$			
		oe	**oge**	**oce**	**ogce**
$\mathcal{F}$	**oe**	0	κ_g	κ_c	$\kappa_g + \kappa_c$
	oge	$-\gamma_g$	0	$-\gamma_g + \kappa_c$	κ_c
	oce	$-\gamma_c$	$-\gamma_c + \kappa_g$	0	κ_g
	ogce	$-\gamma_g - \gamma_c$	$-\gamma_c$	$-\gamma_g$	0

Back to main

State Transition Assumptions

Issue 1: Dimensionality (12 state variables)

1. Assume that plants rent capital flexibly at rent rate r_{kt}
2. Plants do not forecast rental rate of capital r_{kt} and wage w_t
3. Assume $\rho_{p_f} = \rho_{\psi_f} = \rho_f$, and write ratio of productivity/price as single state:

$$\mathbb{E}[\ln(\psi_{fit}/p_{fit}) \mid \mathcal{I}_{it}] = (1 - \rho_f)(\mu_0^f + \mu_t^f + \mu_i^f) + \rho_f \ln(\psi_{fit-1}/p_{fit-1})$$

4. Normally distributed **correlated shocks** between all AR(1) state variables and discretize the state space following Farmer and Akira Toda (2017)

These assuptions are not necessary for identification

Back to main

State Transition Assumptions

Issue 2: Productivity/prices for fuels that plants are not using

1. Start at initial condition

$$\mathbb{E}\left[\ln(\psi_{fit+1}/p_{fit+1}) \mid f \notin \mathcal{F}_{it}\right] = \mu_0^f + \mu_t^f + \underbrace{\mu_i^f}_{\text{plant-specific systematic fuel } f \text{ productivity}}$$

2. Estimate distribution of μ_i^f jointly with switching costs

Back to main

Estimating Switching Costs θ and Distribution of μ_i^f Jointly (E-M)

I assume that μ_i^f follows a finite mixture distribution with K support points μ_k^f (Arcidiacono and Jones, 2003)

Using Law of Total Probability, I can condition likelihood on distribution of μ_i^f

$$\begin{aligned} \ln \mathcal{L}(\mathcal{F} \mid \theta) &= \sum_{i=1}^{n} \ln \left[\prod_{t=1}^{T} Pr(\mathcal{F}_{it+1} \mid \mathcal{F}_{it}, s_{it}; \theta) \right] \\ &= \sum_{i=1}^{n} \ln \left[\sum_{k} Pr(\mu_k^f) \left[\prod_{t=1}^{T} Pr(\mathcal{F}_{it+1} \mid \mathcal{F}_{it}, s_{it}, \mu_i^f = \mu_k^f; \theta) \right] \right] \end{aligned}$$

- Intuition: back-out distribution of comparative advantages μ_i^f that rationalize observed choice paths.

Back to main

Estimating Switching Costs θ and Distribution of μ_i^f Jointly (E-M)

I assume that μ_i^f follows a finite mixture distribution with K support points μ_k^f (Arcidiacono and Jones, 2003)

Using Law of Total Probability, I can condition likelihood on distribution of μ_i^f

$$\ln \mathcal{L}(\mathcal{F} \mid \theta^0) = \sum_{i=1}^{n} \ln \left[\sum_k Pr(\mu_k^f) \left[\prod_{t=1}^{T} Pr(\mathcal{F}_{it+1} \mid \mathcal{F}_{it}, s_{it}, \mu_i^f = \mu_k^f; \theta^0) \right] \right]$$

1. Initialize unconditional distribution of comparative advantages $Pr(\mu_k^f)$ and take first guess of fixed costs θ^0

Back to main

Estimating Switching Costs θ and Distribution of μ_i^f Jointly (E-M)

I assume that μ_i^f follows a finite mixture distribution with K support points μ_k^f (Arcidiacono and Jones, 2003)

Using Law of Total Probability, I can condition likelihood on distribution of μ_i^f

$$\ln \mathcal{L}(\mathcal{F} \mid \theta) = \sum_{i=1}^{n} \ln \left[\sum_{k} Pr(\mu_k^f) \left[\prod_{t=1}^{T} Pr(\mathcal{F}_{it+1} \mid \mathcal{F}_{it}, s_{it}, \mu_i^f = \mu_k^f; \theta^0) \right] \right]$$

2. Solve model and get probability of a plant's choice path for each type k μ_k^f

Back to main

Estimating Switching Costs θ and Distribution of μ_i^f Jointly (E-M)

I assume that μ_i^f follows a finite mixture distribution with K support points μ_k^f (Arcidiacono and Jones, 2003)

Using Law of Total Probability, I can condition likelihood on distribution of μ_i^f

$$\rho(\mu_k^f \mid \mathcal{F}_i, s_i; \theta^0) = \frac{\pi_{fk}^0 \left[\prod_{t=1}^T \left[\prod_{\mathcal{F} \subseteq \mathbb{F}} \left[Pr(\mathcal{F}_{it} \mid s_{it}, \mu_i^f = \mu_k^f; \theta^0) \right]^{\mathbb{I}(\mathcal{F}_{it} = \mathcal{F})} \right] \right]}{\sum_k \pi_k^0 \left[\prod_{t=1}^T \left[\prod_{\mathcal{F} \subseteq \mathbb{F}} \left[Pr(\mathcal{F}_{it} \mid s_{it}, \mu_i^f = \mu_k^f; \theta^0) \right]^{\mathbb{I}(\mathcal{F}_{it} = \mathcal{F})} \right] \right]}$$

3. Get posterior probability that plant i is type k given choice path $\rho(\mu_k^f \mid \mathcal{F}_i, s_i; \theta^0)$

Back to main

Estimating Switching Costs θ and Distribution of μ_i^f Jointly (E-M)

I assume that μ_i^f follows a finite mixture distribution with K support points μ_k^f (Arcidiacono and Jones, 2003)

Using Law of Total Probability, I can condition likelihood on distribution of μ_i^f

$$Pr(\mu_k^f) = \frac{\sum_{i=1}^{n} \rho(\mu_k^f \mid \mathcal{F}_i, s_i; \theta^0)}{n} \quad \forall k$$

4. Update unconditional distribution

Back to main

Estimating Switching Costs θ and Distribution of μ_i^f Jointly (E-M)

I assume that μ_i^f follows a finite mixture distribution with K support points μ_k^f (Arcidiacono and Jones, 2003)

Using Law of Total Probability, I can condition likelihood on distribution of μ_i^f

$$\hat{\theta} = \arg\max_{\theta} \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{k} \rho(\mu_k \widehat{\mid \mathcal{F}_i, s}_i; \theta^0) \ln Pr(\mathcal{F}_{it+1} \mid \mathcal{F}_{it}, s_{it}, \mu_i = \mu_k; \theta)$$

5. Find the fixed costs θ that maximize conditional likelihood, keeping posterior probability constant
6. repeat 2-5 until convergence of unconditional likelihood

Back to main

Decomposition of Average Differences in Energy Price

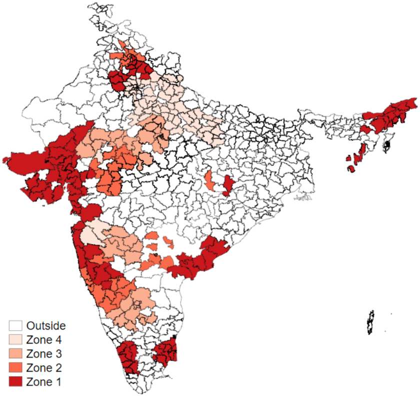
		OCE	OGE	OGCE
Total Difference	Percent (%) Difference with OE	-65.65	-71.54	-86.97
Option Value		36.14	5.42	6.3
Fuel Productivity	Percent (%) of Total	62.6	97.75	94.84
Fuel Prices		1.25	-3.18	-1.14

Table: Shapley Decomposition of the Difference in Average Marginal Cost of Energy Between Fuel Sets

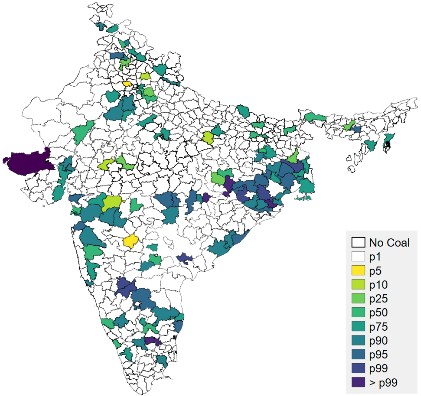
Fuel Productivity explains most of the differences

Back to main

Distribution of Coal vs. Natural Gas Pipelines by Districts



Natural Gas Pipeline Network – 2016



Distribution of Coal Usage

Back to main

Relationship between Hicks-Neutral Productivity and Fuel Adoption

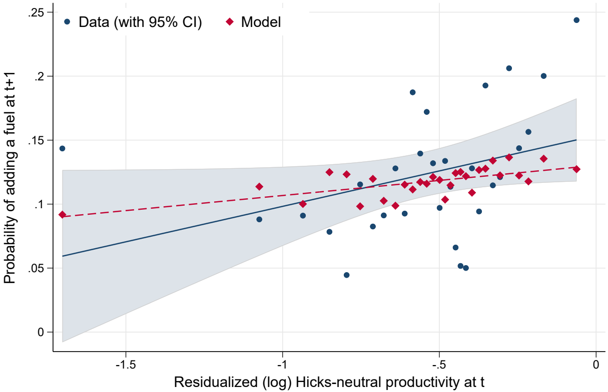
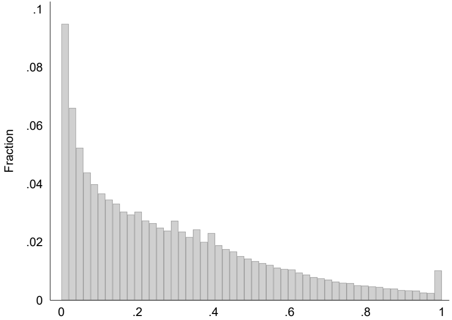


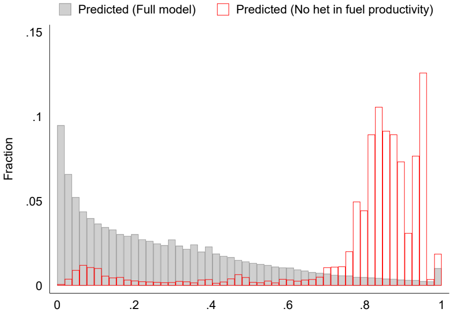
Figure: Adding a fuel at $t+1$ against Hicks-neutral productivity at t

Back to main

Fuel Expenditure Shares when Fuel Productivity is not Included



Data

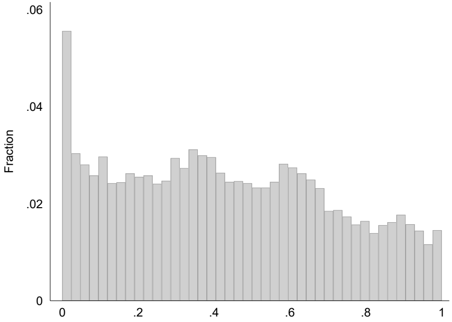


Model

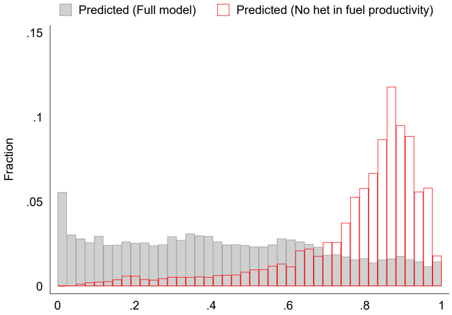
Oil

▸ Back to main

Fuel Expenditure Shares when Fuel Productivity is not Included



Data

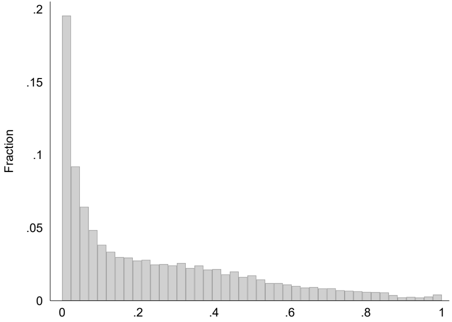


Model

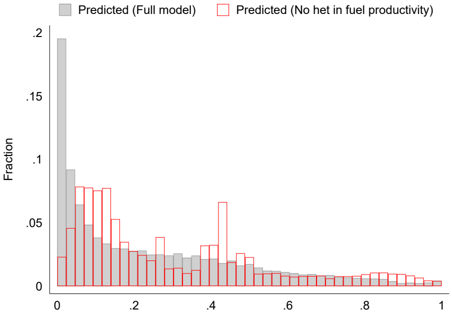
Coal

▸ Back to main

Fuel Expenditure Shares when Fuel Productivity is not Included



Data



Model

Gas

Back to main

Elasticity of Energy Price with Respect to Relative Fuel Prices

Application of *envelope theorem*:

$$\frac{\partial \ln p_{E_{it}}}{\partial \ln \tilde{p}_{cit}} = \underbrace{\frac{\left(\tilde{p}_{cit}/\tilde{\psi}_{cit}\right)^{1-\lambda}}{\sum_{f\in\mathcal{F}_{it}}\left(\tilde{p}_{fit}/\tilde{\psi}_{fit}\right)^{1-\lambda}}}_{\text{relative coal expenditure ratio} \to \text{increasing in relative coal productivity}}$$

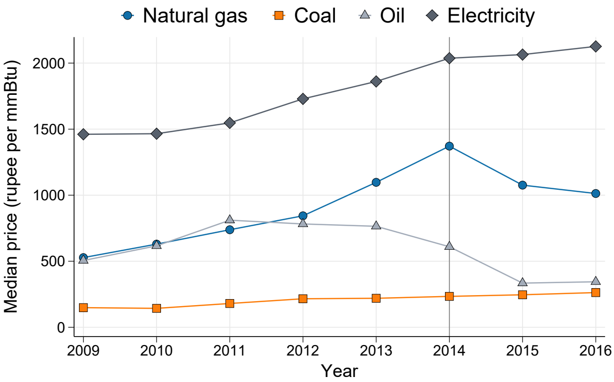
Elasticity increasing in relative fuel productivity:

$$\frac{\partial^2 \ln p_{E_{it}}}{\partial \ln \tilde{p}_{cit} \partial \tilde{\psi}_{cit}} = \frac{(\lambda-1)\psi_{cit}^{\lambda-2}\tilde{p}_{cit}^{1-\lambda}\left[\sum_{f\in\mathcal{F}_{it}\setminus c}\left(\tilde{p}_{fit}/\tilde{\psi}_{fit}\right)\right]}{\left(\sum_{f\in\mathcal{F}_{it}}(\tilde{p}_{fit}/\tilde{\psi}_{fit})^{1-\lambda}\right)^2} > 0 \qquad \text{if} \quad \lambda > 1$$

▸ Back to main

Validation Exercice: Aggregate Variation in Natural Gas Prices

Motivation: Steady increase in natural gas prices (up until 2014), followed by significant decrease



Validation Exercice: Aggregate Variation in Natural Gas Prices

$$\Delta y_{it} = \beta_0 + \beta_{up}\left(D_t(+) * \frac{\sum_{f \setminus g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \beta_{down}\left(D_t(-) * \frac{\sum_{f \setminus g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \epsilon_{it}$$

- Δy_{it}: Change in (log) output price, output quantity
- $D_t(+)$: Dummy if aggregate natural gas price increased
- $D_t(-)$: Dummy if aggregate natural gas price decreased
- $\frac{\sum_{f \setminus g} s_{fit-1}}{\sum_f s_{fit-1}}$ measure exposure (high spending share on other fuels = $\downarrow$ direct exposure)
- Contol for other input prices, year fixed effects, tfp

Validation Exercice: Aggregate Variation in Natural Gas Prices

$$\Delta y_{it} = \beta_0 + \beta_{up}\left(D_t(+) * \frac{\sum_{f \setminus g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \beta_{down}\left(D_t(-) * \frac{\sum_{f \setminus g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \epsilon_{it}$$

	$\Delta \ln Y_{it}$		$\Delta \ln P_{it}$	
	Model	**Data**	**Model**	**Data**
Price Decreased β_{down}				
Price Increased β_{up}				
Year Fixed Effects				
Other Controls				
N		3,445		3,445

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Back to main

Validation Exercice: Aggregate Variation in Natural Gas Prices

$$\Delta y_{it} = \beta_0 + \beta_{up}\left(D_t(+) * \frac{\sum_{f\backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \beta_{down}\left(D_t(-) * \frac{\sum_{f\backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \epsilon_{it}$$

	$\Delta \ln Y_{it}$		$\Delta \ln P_{it}$	
	Model	**Data**	**Model**	**Data**
Price Decreased β_{down}	-			
Price Increased β_{up}	$+$			
Year Fixed Effects				
Other Controls				
N		3,445		3,445

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

▸ Back to main

Validation Exercice: Aggregate Variation in Natural Gas Prices

$$\Delta y_{it} = \beta_0 + \beta_{up}\left(D_t(+) * \frac{\sum_{f \backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \beta_{down}\left(D_t(-) * \frac{\sum_{f \backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \epsilon_{it}$$

	$\Delta \ln Y_{it}$		$\Delta \ln P_{it}$	
	Model	**Data**	**Model**	**Data**
Price Decreased β_{down}	-	-1.145**		
		(0.477)		
Price Increased β_{up}	+	0.652*		
		(0.368)		
Year Fixed Effects		Yes		
Other Controls		Yes		
N		3,445		3,445

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Back to main

Validation Exercice: Aggregate Variation in Natural Gas Prices

$$\Delta y_{it} = \beta_0 + \beta_{up}\left(D_t(+) * \frac{\sum_{f\backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \beta_{down}\left(D_t(-) * \frac{\sum_{f\backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \epsilon_{it}$$

	$\Delta \ln Y_{it}$		$\Delta \ln P_{it}$	
	Model	**Data**	**Model**	**Data**
Price Decreased β_{down}	-	-1.145**	+	
		(0.477)		
Price Increased β_{up}	+	0.652*	-	
		(0.368)		
Year Fixed Effects		Yes		
Other Controls		Yes		
N		3,445		3,445

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Back to main

Validation Exercice: Aggregate Variation in Natural Gas Prices

$$\Delta y_{it} = \beta_0 + \beta_{up}\left(D_t(+) * \frac{\sum_{f\backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \beta_{down}\left(D_t(-) * \frac{\sum_{f\backslash g} s_{fit-1}}{\sum_f s_{fit-1}}\right) + \epsilon_{it}$$

	$\Delta \ln Y_{it}$		$\Delta \ln P_{it}$	
	Model	**Data**	**Model**	**Data**
Price Decreased β_{down}	-	-1.145**	+	1.241***
		(0.477)		(0.477)
Price Increased β_{up}	+	0.652*	-	-0.631*
		(0.368)		(0.371)
Year Fixed Effects		Yes		Yes
Other Controls		Yes		Yes
N		3,445		3,445

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Back to main

Welfare Analysis of Natural Gas Subsidy

To implement the subsidy, I use proceeds from carbon tax to finance 10% subsidy on natural gas adoption.

Per-period welfare defined as in Fowlie, Reguant and Ryan (2016):

$$w_t(\tau, s) = \underbrace{\nu_t(\tau, s)}_{\text{consumer surplus}} + \underbrace{\Pi(\tau, s)}_{\text{producer surplus}} + \underbrace{G(\tau, s)}_{\text{net gov. revenue}} - \underbrace{\sum_f \sum_i \gamma_f e_{fit}(\tau, s)}_{\text{externality damages}}$$

$$= \underbrace{\nu_t(\tau, s)}_{\text{consumer surplus}} + \underbrace{\sum_{i=1}^{N} \pi_{it}(\tau, s)}_{\text{variable profits}} - \underbrace{\sum_i^{N} \Big(\sum_{\mathcal{F}' \subseteq \mathbb{F}} \mathcal{K}(\mathcal{F}' \mid \mathcal{F}_{it}) \mathbf{I}(\mathcal{F}_{it+1} = \mathcal{F}' \mid \tau, s) \Big)}_{\text{total fixed costs}}$$

Welfare Results

	Carbon Tax	**Carbon Tax + 10% Subsidy**	**Difference**
	Billion U.S Dollars	*Billion U.S Dollars*	*Million U.S. Dollars*
Total Welfare	63.415	63.417	1.18
Variable Profit	22.58	22.60	19.18
Consumer Surplus	22.21	22.22	13.62
Total Fixed Costs (*Paid by plants + subsidy*)	-18.633	-18.601	31.61
Externality Damages/Tax Revenue	2.64	2.65	9.78

▸ Back to main