Virtual Seminar on Climate Economics

Federal Reserve Bank of San Francisco

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Dynamic Responses to Carbon Pricing in the Electricity Sector

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Virtual Seminar on Climate Economics
Federal Reserve Bank of San Francisco

Motivation (1)

Understand regulation's impact on geographic concentrations of production

- Important consequence of many regulations
- In this paper's setting in the electricity sector:
  - No changes in a static setting
  - Can change with dynamics

Motivation (2)

Does carbon pricing exacerbate hot spots?

ENVIRONMENT

Environmental Groups Say California's Climate Program Has Not Helped Them

February 24, 2017 · 9:06 AM ET
Heard on Morning Edition

EMILY GUERIN

FROM KPCC

- Source of political debate
- Theoretically possible
- Outcomes depend on the cost structure of industry

Research questions: How does carbon pricing impact the spatial distribution of local air pollution?

1. Does carbon pricing lead to **production re-allocation**?

2. Does carbon pricing impact **firm efficiencies**?

3. How does the carbon price redistribute local air pollutants **compared to a no/more stringent carbon policy** scenario?

4. How do market outcomes compare to a more targeted **policy to internalize air pollution** costs?

This paper answers these questions in the electricity industry in California.

Why this empirical setting?

Why California?

- Implemented cap-and-trade program in 2013

- On-going debates around equity impacts of the program

Why electricity?

- **16% (28%)** of greenhouse gas (GHG) emissions in **CA (US)**; large share of non-transportation sources in CA (US): 30% (39%); also contributes to local air pollution

Emissions by source

- Relatively competitive industry, inelastic demand in short-term, dynamic production decisions

Previous work

- **GHG and local air quality**

  Meng & Hernandez-Cortes (w.p. 2019); Walsh (w.p. 2018)
  Policy reports: Parry et al. (IMF 2014); Cushing et al. (2018)

- **Emissions trading and local air quality**

  Fowlie, Holland, and Mansur (2014); Fowlie (2010); Muller and Mendelsohn (2007)

- **Electricity markets**

  Borenstein, Bushnell, and Wolak (2002); Mansur (2008); Mansur and Cullen (2015); Fabra and Reguant (2014)

- **Model and estimation**

  Rust (1987); Hopenhayn (1992); Ryan (2012); Fowlie, Reguant, and Ryan (2016); Cullen (2015); Cullen and Reynolds (2017)

Industry characteristics that motivate modeling choices

- Fossil-portfolio is dominated by natural gas

  ▸ Unit summary statistics

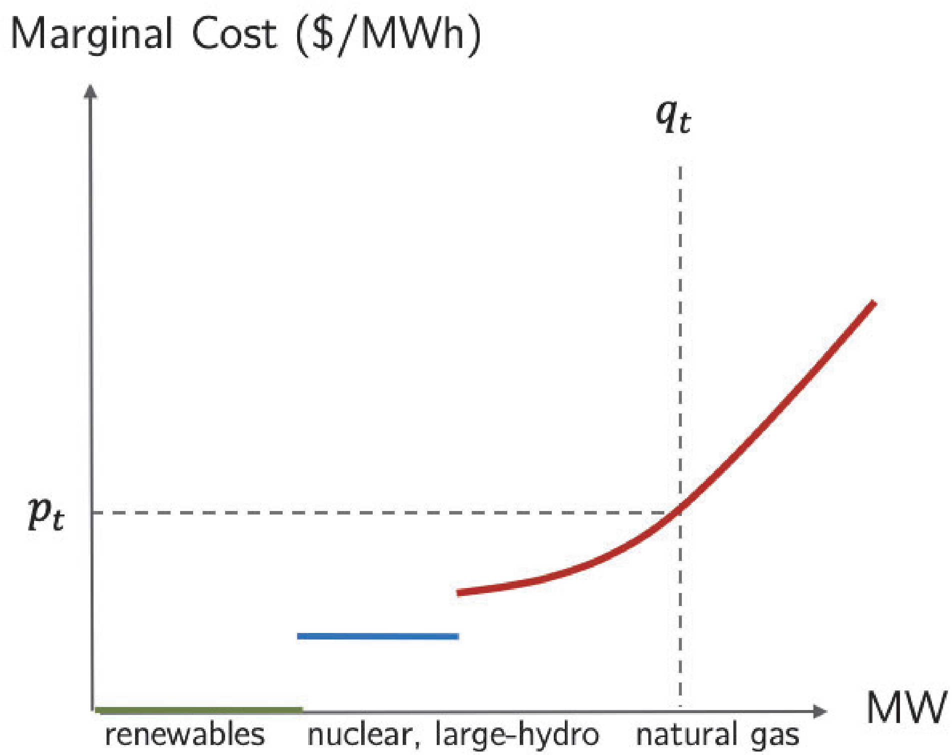
- Relatively competitive market
  - Market significantly reformed since earlier work

- Most electricity bought and sold in hourly wholesale markets
  - Substantial variation in hourly demand

- Hourly demand inelastic to wholesale prices in the short term

- Start-up costs make production a dynamic decision ▸ Hourly profits

Supply and demand in hourly markets



▸ Example empirical supply curve

Impact of carbon price on marginal costs

Firm **efficiency**, $\omega_{\mathbf{i}}$, fuel per KWh, **determines marginal costs**, mc_i.

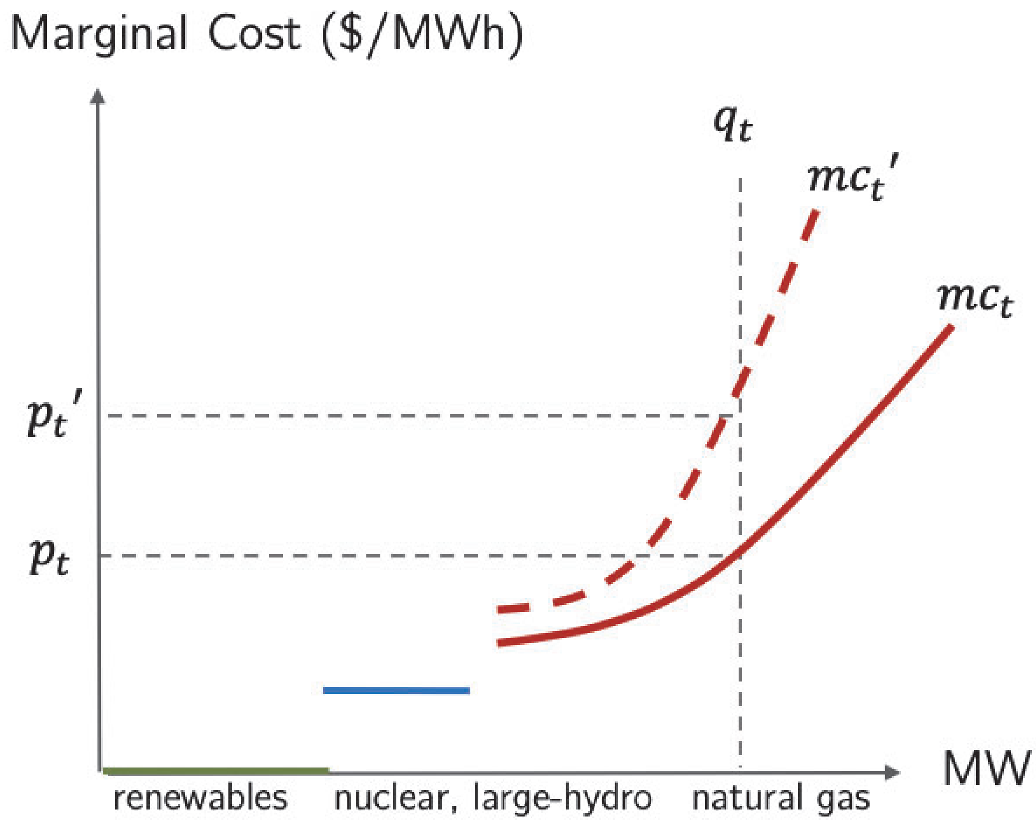
$$\begin{aligned} mc_i &= \omega_i c^f + \omega_i e^f \tau \\ \frac{\partial}{\partial \tau} mc_i &= \omega_i e^f \end{aligned} \tag{1}$$

Carbon price increases marginal costs **more** for **less** efficient units.

- ω_i: Btu per KWh (heat rate)
- c^f: $ per Btu (fuel price)
- e^f: emissions per Btu (emissions intensity)
- τ: $ per ton $CO2_e$ (carbon price)

Impact of carbon price in static setting

When marginal costs completely determine supply curve, carbon price preserves merit order $\rightarrow$ **no production re-allocation**.



Start-up costs, κ, allow for production re-allocation.

Impact of carbon price in dynamic setting

Consider two inframarginal firms **A** and **B** with same q and same total costs:

$$\begin{aligned} \kappa_A + mc_A q = \kappa_B + mc_B q \\ mc_A < mc_b \\ \rightarrow \kappa_A > \kappa_B \end{aligned} \tag{2}$$

- Carbon price increases marginal costs more for firm **B** since $mc_A < mc_B$
- What happens to κ? Start-up costs dominated by non-fuel components
- $\Rightarrow$ **A** is now more likely to operate.

Average generation and CO2 by unit by hour | Engineering estimates of start up costs by component

Data

Electricity market data

- **Production quantities:** Unit-specific **hourly electricity output** from continuous emissions monitoring systems (CEMS)
- **Emission quantities:** Hourly **emissions of NO_x**, SO_2, and CO_2 from CEMS → *emissions intensities*
- **Unit capacities:** EIA reporting requirements
- **Unit efficiency (heat rate):** EIA reporting requirements; inferred measure from CEMS → *inferred measure of efficiency investment*
- **Investment costs:** *Some* self-reported capital expenditures from SNL Financial → *use to bound estimate of investment costs*
- **Prices:** **Carbon allowance** prices from the Intercontinental Exchange (ICE); **fuel prices** from federal reporting requirements and Bloomberg spot prices → *average input costs*

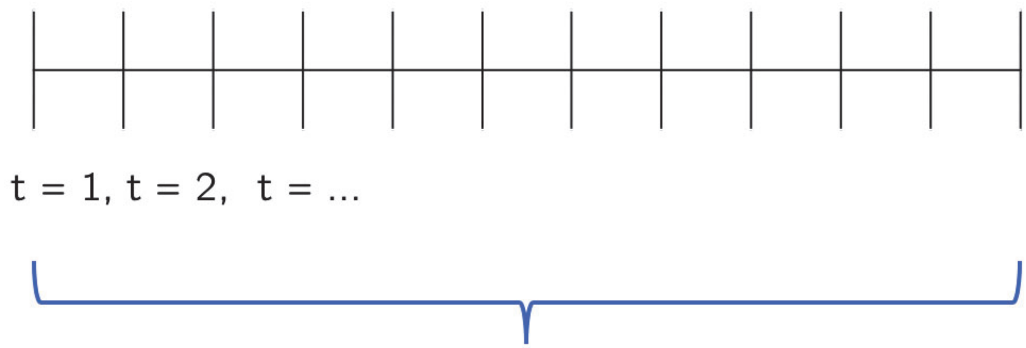
Marginal damages from air pollutants

- **Damages from air pollution:** County-specific estimates of marginal damages by pollutant from Air Pollution Emission Experiments and Policy (APEEP) analysis model (Muller et al. 2019)

Model & estimation overview

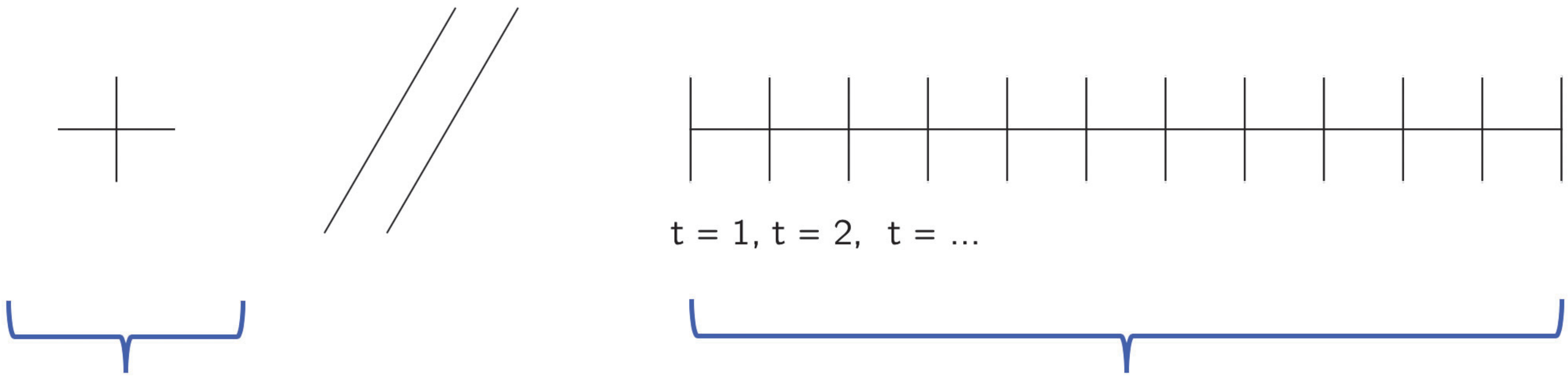
1. Timing
2. Production decision
3. Investment decision
4. Cost minimization problem
5. Identification
6. Calibration
7. Estimation procedure

Firm optimization problem and timeline



Production decision:
Firm i makes hourly
operation decisions: $\mathbf{a}_{it} \mid [\dots], \boldsymbol{\omega}_{\mathbf{i}}$

Firm optimization problem and timeline



Investment decision:
Firm i makes investment decision $j \in J$ to improve its heat rate: $\boldsymbol{\omega_i} = \boldsymbol{\omega_i}'(1+\widetilde{\boldsymbol{\delta}}) - j_i$

Production decision:
Firm i makes hourly operation decisions: $\mathbf{a}_{it} \mid [\ldots], \boldsymbol{\omega_i}$

Firm production decision

Firm i makes operating decision $a_{it} \in \{0, 1\} \rightarrow q_{it}$:

$$q_{it} = \begin{cases} q_{imax} & \text{if } P_t \geq mc_i \text{ and } a_{it} = 1 \\ q_{imin} & \text{if } P_t < mc_i \text{ and } a_{it} = 1 \\ 0 & \text{if } a_{it} = 0 \end{cases} \tag{3}$$

- q_{it}: MWh produced by firm i if hour t
- $q_{imax(min)}$: unit-specific max (min) ▸ Kernel density generation plots
- P_t: wholesale electricity price in hour t
- mc_i: $\omega_i c^f + \omega_i e^f \tau$

Per period profits

$$\pi_t(q_{it}, P_t, mc_i, l_{it}) = \begin{cases} q_{it}(P_t - mc_i) & \text{if } a_{it} = 1 \text{ and } l_{it} = 1 \\ q_{it}(P_t - mc_i) - \kappa_i & \text{if } a_{it} = 1 \text{ and } l_{it} = 0 \\ 0 & \text{if } a_{it} = 0 \end{cases} \tag{4}$$

- l_{it} : a_{it-1} (lagged operating state)
- κ_i: start-up costs

Observe everything except κ_i

States and transitions in production problem

States

$\mathbf{s} = \{\eta_t, h_t, l_{it}, \omega_i^j, ic\}$

{demand shock, hour, lag operating state, efficiency, input costs}

Transitions

$\eta_{t+1} = f(\eta_t | h_t)$ - conditional AR (1)

$h_{t+1} = h_t + 1 - 1(h_t = 24) * 24$

$l_{it} = a_{it-1}$

Deterministic states

$ic = c^f + e^f \tau$

$mc(\omega_i)|j_i$

Choice-specific value functions for production

Value function for each j investment decision:

$$V^{2j}(\eta_t, h_t, l_{it}, \omega_i^j, ic) = \max_{a_{it}\in\{0,1\}} \mathbb{E}\Big\{ \sum_{t=0}^{\infty} \delta^t [q_{it}(P(\eta_t) - mc(\omega_i^j, ic)) - \mathbb{1}(l_{it} = 0, a_{it} = 1) \cdot \kappa_i] \Big\} \quad (5)$$

- j: discrete investment choice
- h_t: hour of the day
- ic: inputs cost $=$ carbon price τ $+$ fuel costs c^f
- δ: discount rate, exogenous and known

Efficiency investment decision

$$V^1(\mathbf{s}) = \max_{j \in J} \{\tilde{\delta}\mathbb{E}[V^{2j}(\mathbf{s})] - \Gamma(j_i, v_i)\} \tag{6}$$

$$\Gamma = \gamma j_i^\alpha + v_i \tag{7}$$

- γ: investment cost per unit of j_i
- α: parameter governing the rate at which marginal investment costs increase in size of investment
- v_i: stochastic shock to investment costs
- $\tilde{\delta}$: discount rate between investment and production

One-time investment decision to minimize production costs over next three years.

Estimating the model as the solution to a cost minimization problem

- Use cost minimization problem as a **mechanism to find competitive equilibrium outcomes**.
- Equivalence **demonstrated to hold in this setting by Cullen and Reynolds (2017)**; proof follows intuition in earlier work (Lucas and Prescott (1971), Jovanovic (1982), and Hopenhayn (1992)).
- **Necessary conditions:** Firms are price taking, "small" relative to market demand, and have rational expectations about future demand shocks; the demand shock process is consistent over time.

The cost minimization problem

- Per period costs of generation G:

$$G = \sum_{i=1}^{N} [mc_i q_i - \mathbb{1}(l_{it} = 0, a_{it} = 1) \cdot \kappa_i] \tag{8}$$

- In production decision:

$$W^{j2}(\mathbf{s}) = \max_{q \in \mathcal{Q}} \{-G(\mathbf{s}, \mathbf{q}) + \delta \mathbb{E}[W^{2j}(\mathbf{s}')]\} \tag{9}$$

- In investment decision:

$$W^{1}(\mathbf{s}) = \max_{j \in J} \{\tilde{\delta} \mathbb{E}[W^{j2}(\mathbf{s})] - \Gamma(j, v)\} \tag{10}$$

Identification and estimation strategy for unknown parameters

- **Start-up costs**, $\kappa_{\mathbf{i}}$
  Identification: Based on the difference between empirical production and the solution to the cost minimization problem.
  Estimation: Estimates from literature; generalized method of moments (GMM).
  ▸ Estimation procedure

- **Investment costs**, γ
  Identification: Based on observed investment and the solution to the cost minimization problem.
  Estimation: Capital expenditures in SNL data; compare production cost savings to investment conditional choice probabilities (ICCPs).
  ▸ Estimation procedure

Calibrate the model to California's fossil-fuel electricity portfolio

Use data to establish representative unit type groups

Type Num.	Num. Units	Size MW	2012 HR	MC Rank	Start-up Cost*	Start-up Cost Rank
1	7	121	7308	1	9680	8
2	9	145	7565	3	11600	9
3	7	94	12783	8	7520	4
4	13	95	13567	10	7600	5
5	31	170	7362	2	13600	10
6	22	74	10535	5	5920	1
7	10	76	9911	4	6080	2
8	23	107	12823	9	8560	7
9	31	90	10543	6	7200	3
10	30	105	11889	7	8400	6

(*) Using calibrated estimate of $80 per MW

Kmeans and Scree plot analysis

Overview of estimation procedure

1. Estimate demand shock process ▸ Demand shock process results.
2. Recover policy functions for production using policy function iteration and initial estimate of start-up costs.
3. Simulate market outcomes with recovered policy functions.
4. Estimate start-up costs by comparing simulations to empirical production.
5. Estimate investment costs by comparing simulated production cost savings to ICCPs.
6. Simulate counterfactual outcomes in different input cost states.

Theoretical predictions

1. **Market share, ζ_i, weakly decreasing among less efficient units, $\frac{\partial^2 \zeta_i}{\partial \tau \partial \omega_i} \leq 0$.**

   Intuition: Carbon price increases marginal cost more for less efficienct units, $\frac{\partial^2 mc_i}{\partial \tau \partial \omega_i} > 0$.

2. **Investments weakly increase and occur among the more efficient units.**

   Intuition: Carbon price increases returns to efficiency improvement; returns are larger when operating more.

Theoretical predictions

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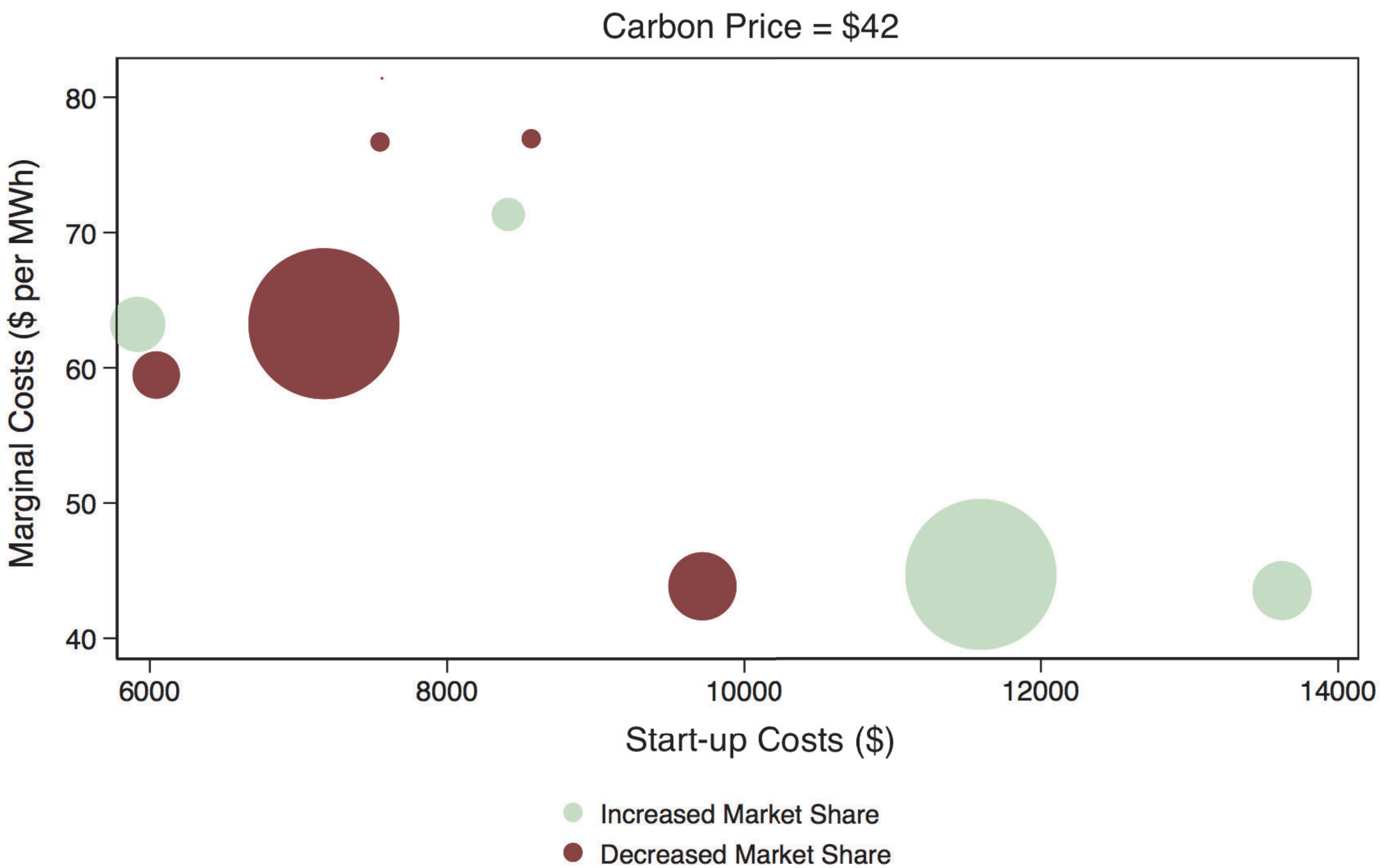
Comparing market outcomes across carbon prices

- Simulate production and investment across alternative input cost states, $\tau = \{\$0, \$13, \$42\}$ per ton CO_{2e}.

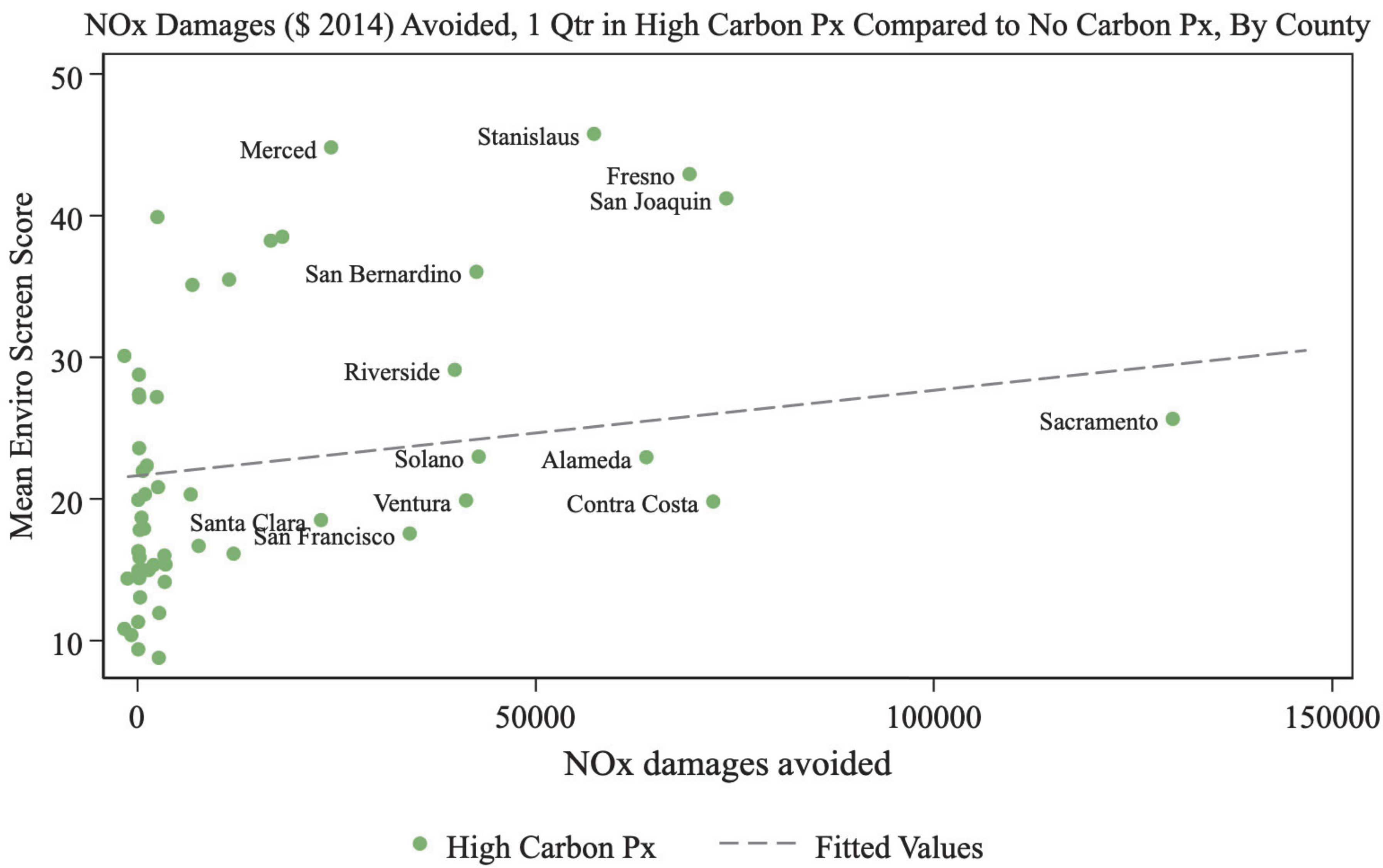
Model fit

Production re-allocation across carbon prices

- **Current carbon prices** lead to **minimal spatial re-allocation** of production and emissions.
- **Higher carbon prices do re-allocate production**, increasing for units with relatively higher fixed start-up and lower marginal costs.



High carbon price outcomes by pre-existing pollution score



Market outcomes with location-specific air pollution tax and carbon policy

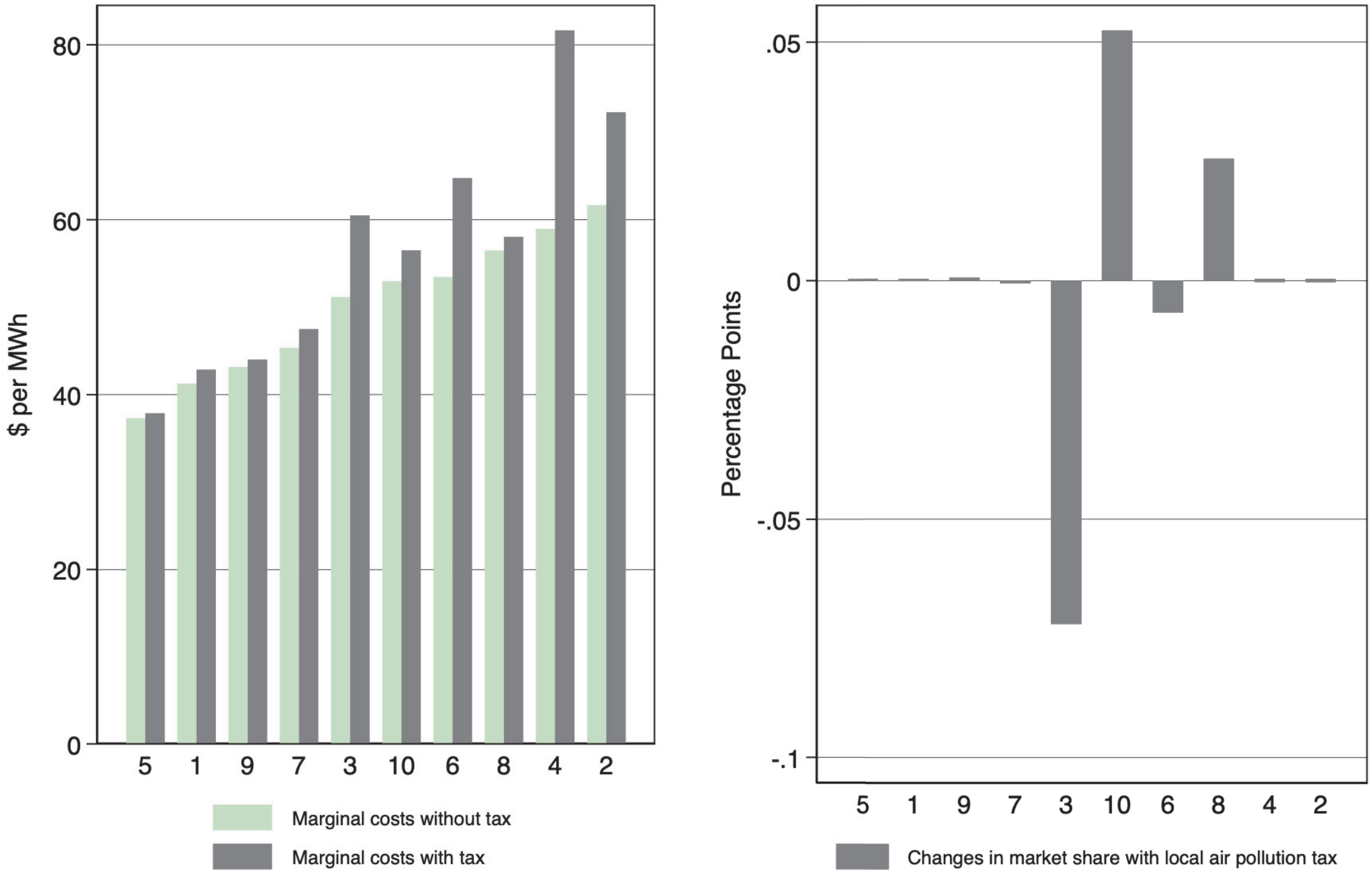
Tax on local air quality leads to new marginal cost for unit type i in locality k:

$$mc_{ik} = \omega_i(c^f + e^f \tau^{ghg}) + \omega_i \iota \tau_k^x \tag{11}$$

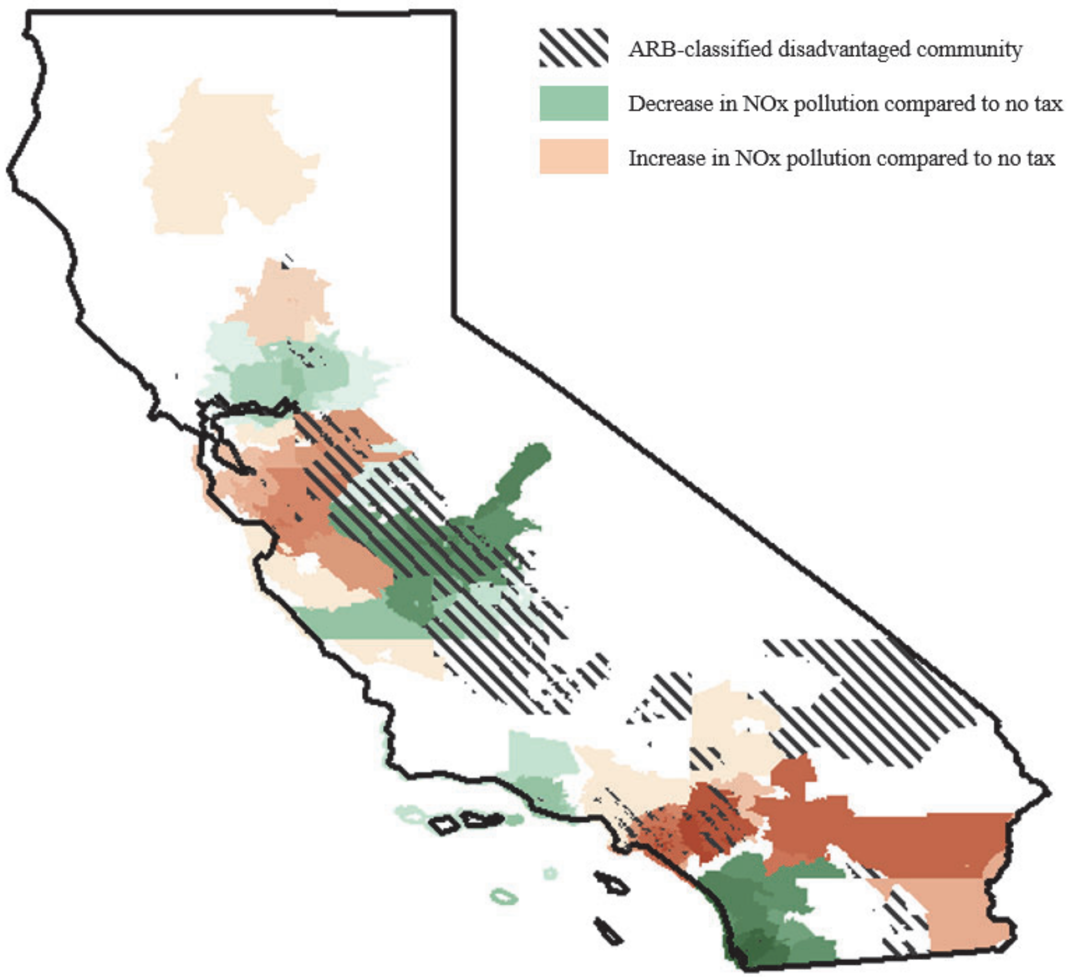
- ι: NO_x emissions per Btu
- τ_k^x: tax on NO_x for units in locality k

Impact of tax on marginal costs

Location-specific tax leads to re-ranking of unit types in terms of marginal cost $\rightarrow$ change in market shares.



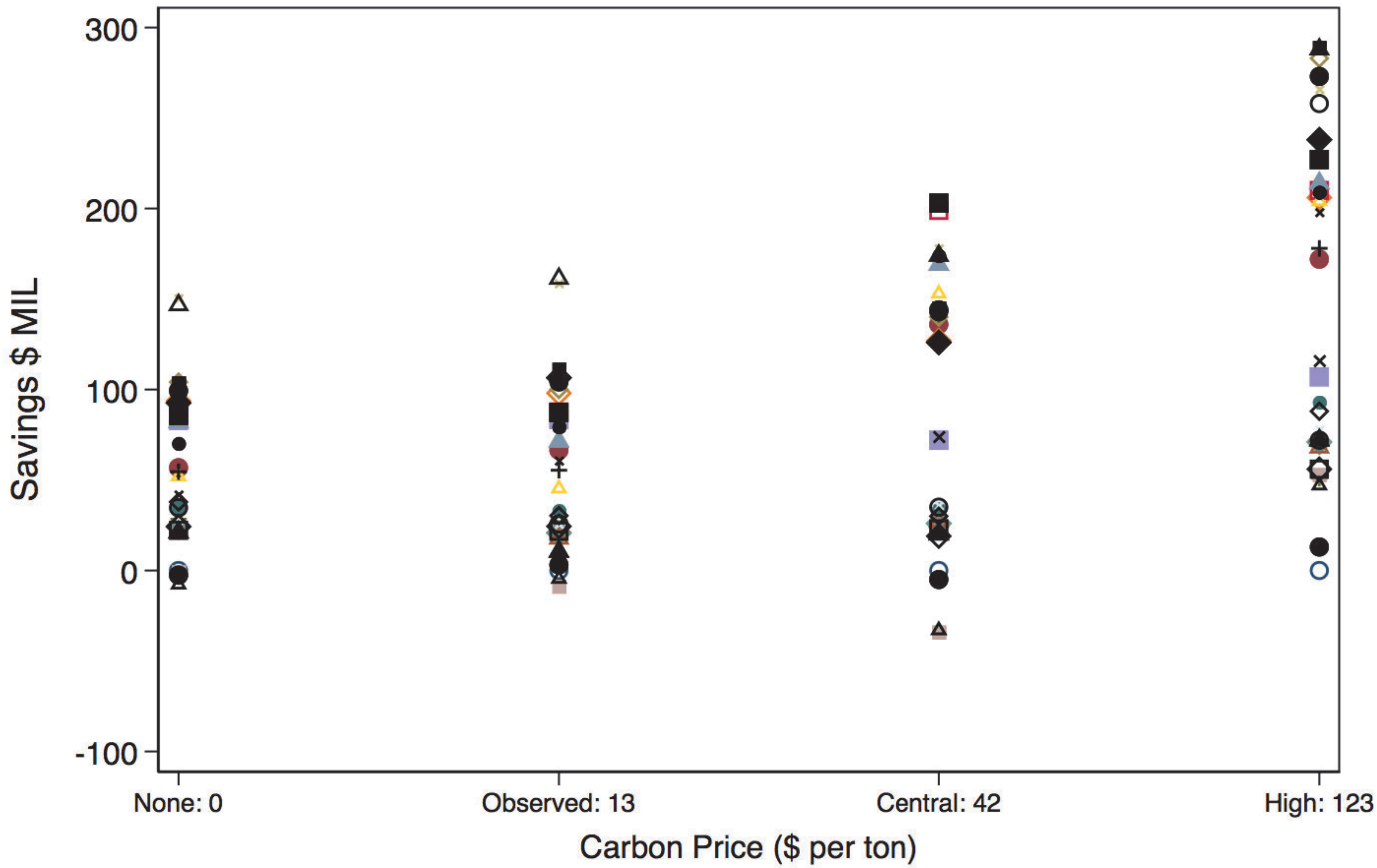
Pigovian tax on local air pollution scenario



- Changes in marginal cost ranking and leads to **more production re-allocation** compared to high carbon price scenario, increasing air pollution benefits.
- **Concentrates air pollution benefits** in communities with **larger pollution burdens**.

Market outcomes across investment portfolios

Gross private returns increase in carbon price for many but not all scenarios.



Conclusion

- **Current carbon policy scenario:** minimal spatial re-allocation of production $\rightarrow$ minimal co-benefits (and co-costs) from local air quality impacts.

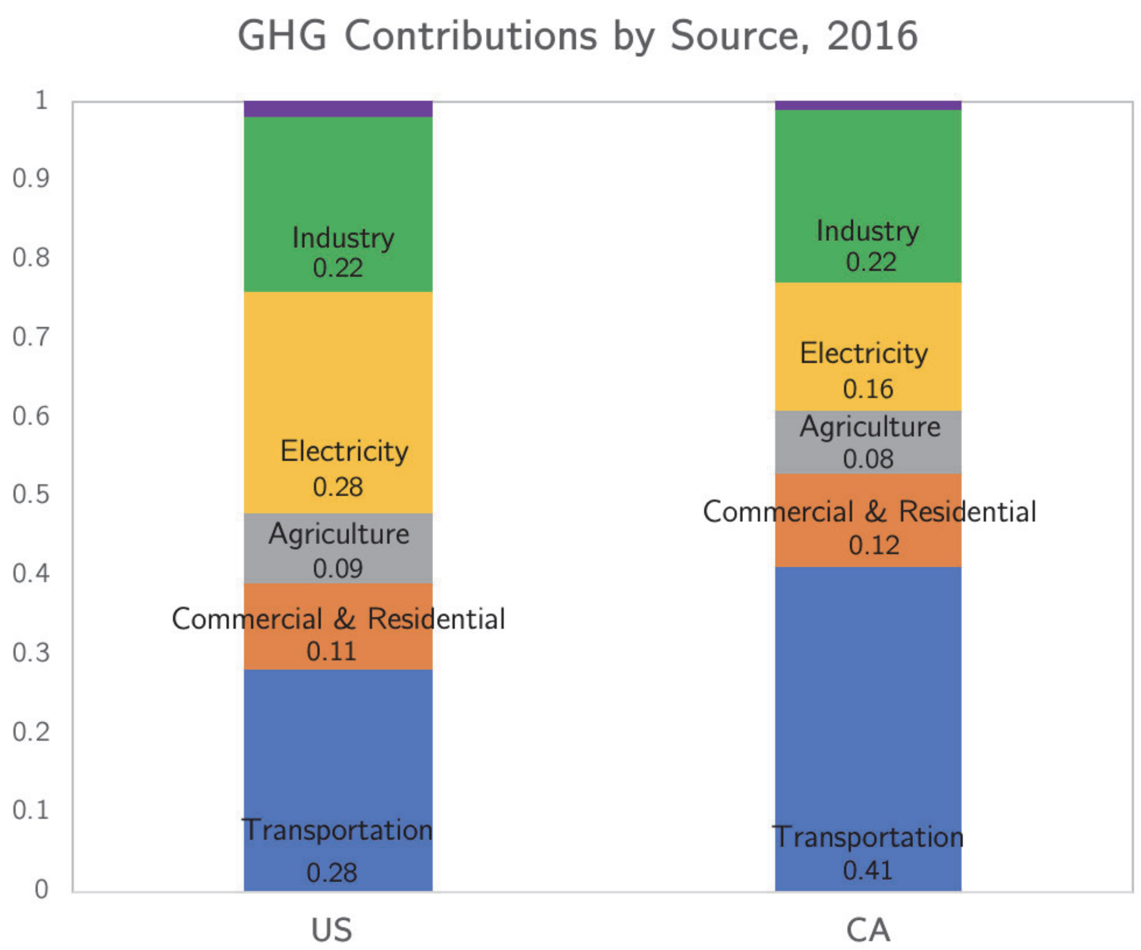
- **Stringent carbon policy scenario:** some spatial re-allocation of production $\rightarrow$ aggregate co-benefits from avoided NO_x damages; some evidence of benefits accruing in heavily polluted regions

- **Pigovian tax on NO_x scenario:** increases the benefits from NO_x damages avoided; concentrates benefits in disproportionately polluted regions.

- **Efficiency investment scenarios:** largest benefits when efficiency improvements occur in the cleanest, most frequently utilized units.

Appendix

Electricity's contribution to GHG emissions



Source: U.S. EPA (2016), California Air Resources Board (2016).

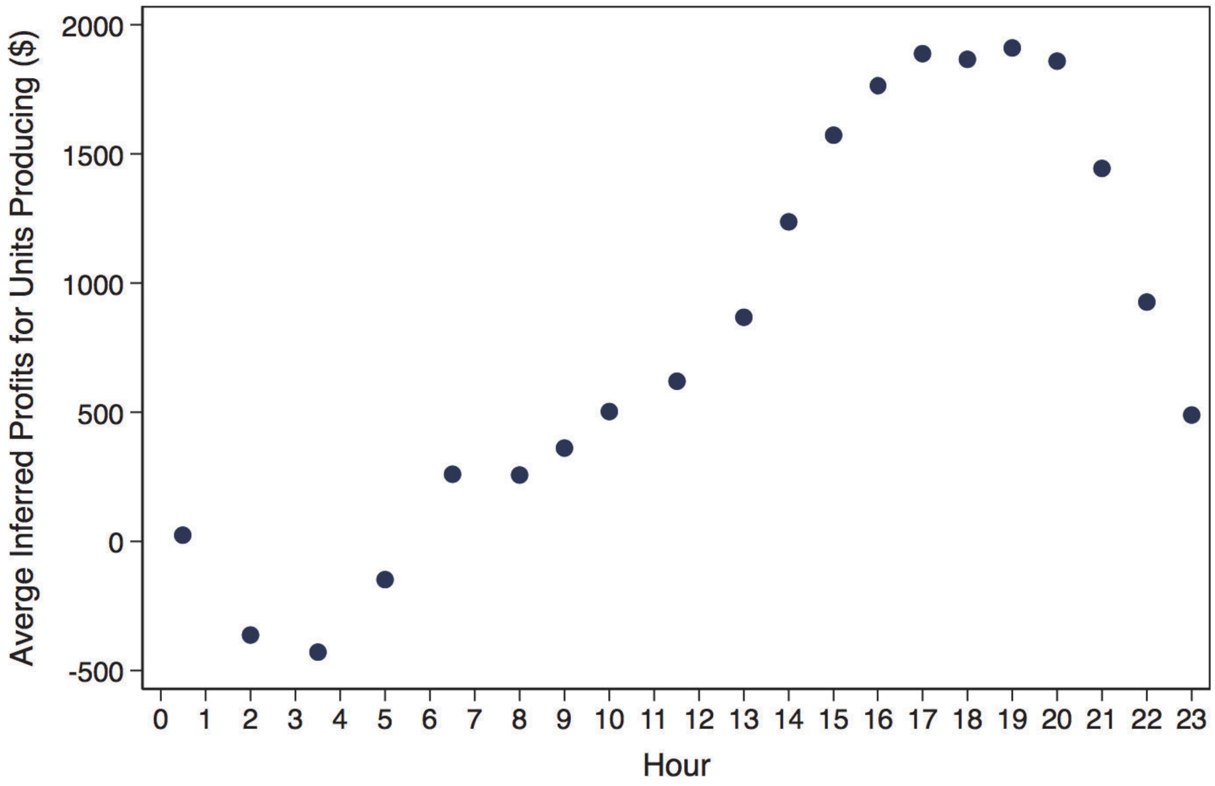
Back to empirical setting

Unit summary statistics, CA 2012 - 2015

	2012	2013	2014	2015
Units producing	221	197	207	201
Steam Turbine	50	41	39	37
Gas Turbine	90	85	87	87
Combined Cycle	81	71	81	77
Natural Gas	221	193	207	201
Coal	0	4	0	0
Retired	2	0	0	1
Put in Service	11	26	1	0
Mean Capacity MW	139	160	134	136
Total Capacity GW	30.6	31.5	27.8	27.2
Num. Units with Capacity Change Up		5	11	7
Mean MW Capacity Up		4	7	7
Num. Units with Capacity Change Down		5	6	9
Mean MW Capacity Down		10	2	4
Mean Heat Rate (Btu per KWh)	14318	12797	14046	12244
Prct of Hours Operating	.35 (.32)	.31 (.31)	.35 (.33)	.35 (.32)

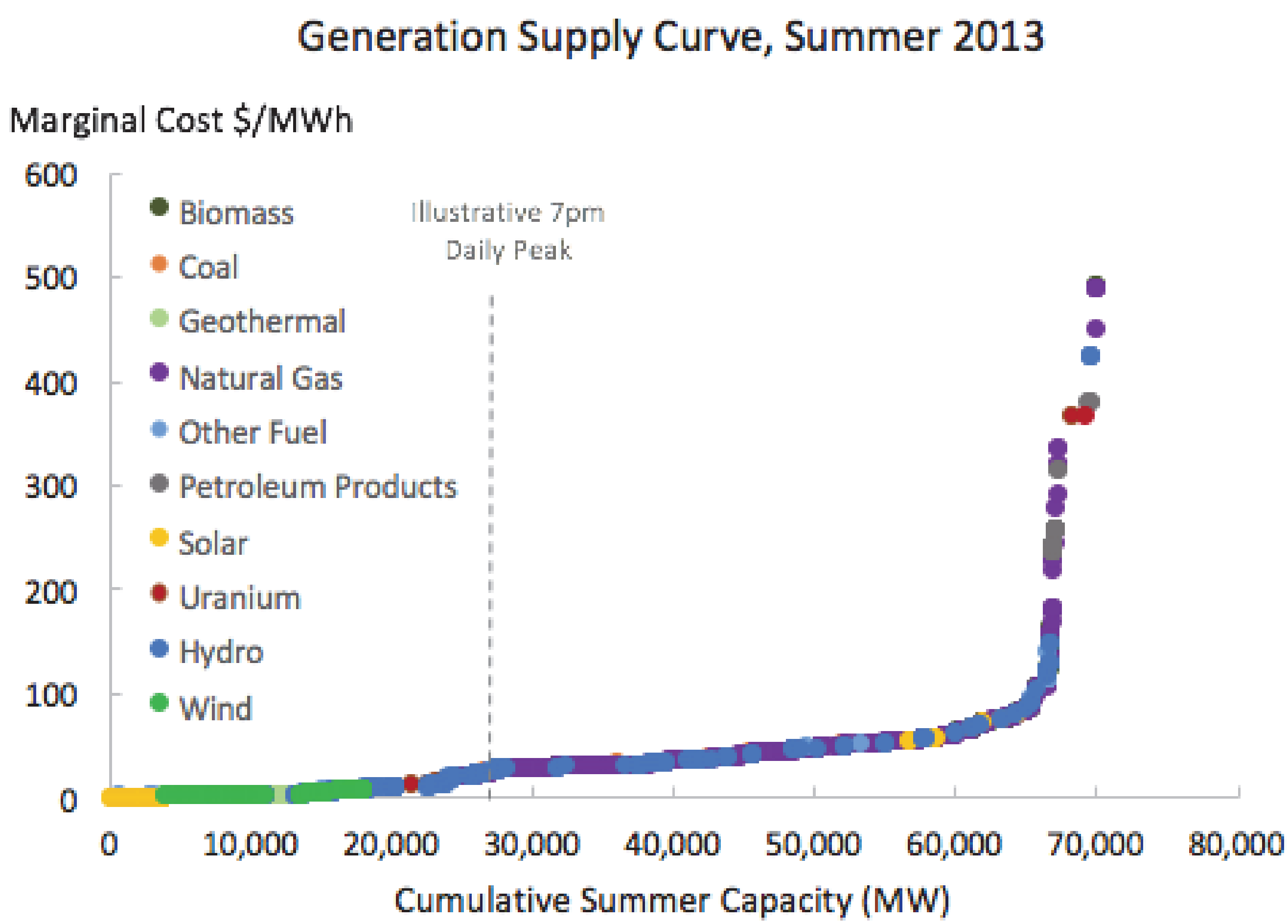
Back to industry context

Large unobserved start-up costs make production decisions dynamic



Back to industry context

Supply curve for illustrative hour in CA



Source: Data from SNL

Back to supply and demand

Demand shock process (1)

AR (1) specification conditional on hour is highly predictive of next period demand.

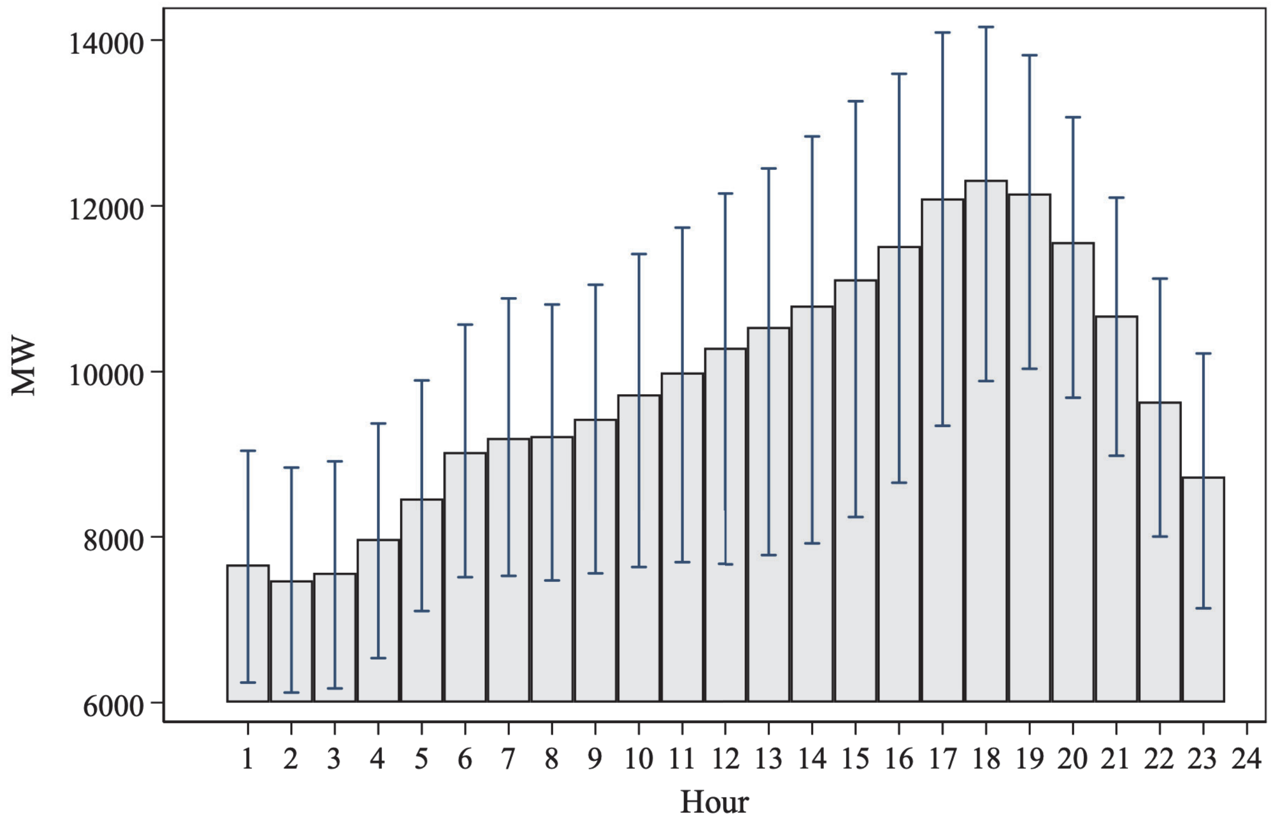
	Curent Period Demand Shock
Last Period Demand Shock	0.97***
	(0.00)
Hour Fixed Effect	Yes
R-squared	0.950
N	2159

Standard errors shown in parenthesis. $^{***}p < 0.001$, $^{**}\ p < 0.01$, $^{*}p < 0.05$.

Back to estimation overview

Demand shock process (2)

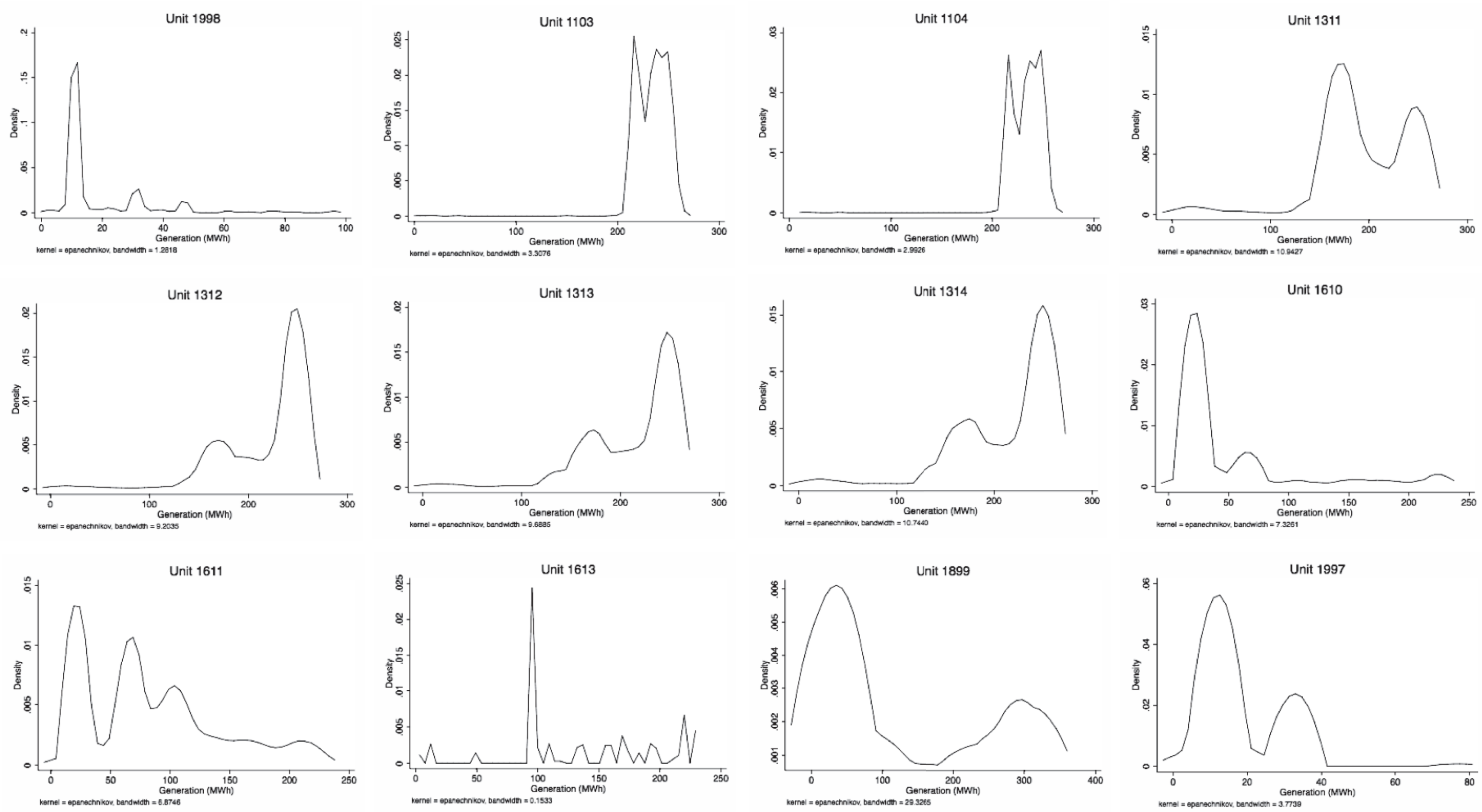
Residual demand provided by fossil-fuel portfolio varies significantly throughout the day, with “duck”-like shape.



Error bars show the 25th to 75th percentile of hourly demand shocks.

Back to estimation overview

Kernel density plots of generation for sample units

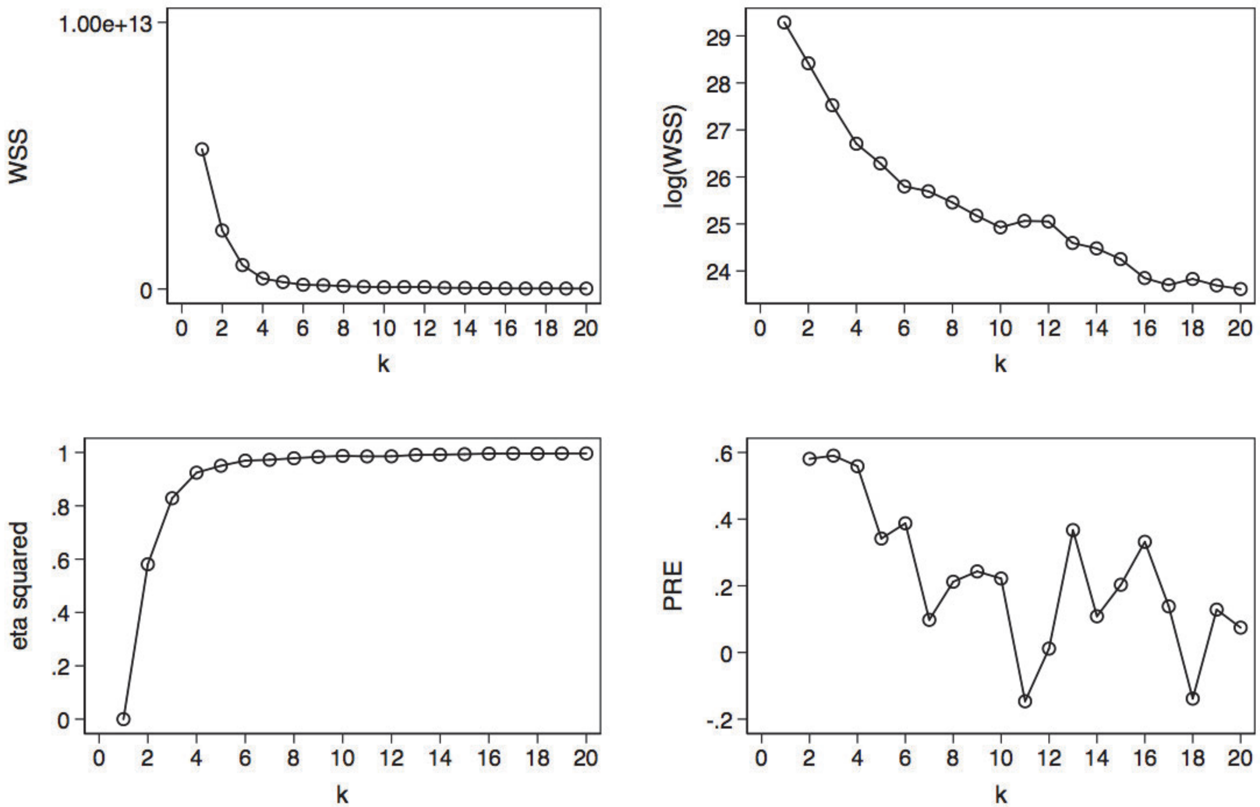


2013, Q2

Production decision

Identifying number of unit type groups

Use k-means and scree plot analysis to establish unit type groups.



Performance of K-means Clustering by Number of Groups

Back to Calibration

Estimating start-up costs with GMM

- Assemble N-length vectors of empirically observed dispatch by unit type in each state, $\mathbf{q}^{\mathbf{e}}(s)$.
- Assemble N-length vectors of dispatch implied by production for given start-up costs from the model, $\mathbf{q}^*(s, \kappa^0)$.
- Construct a S-length vector of moments corresponding to S number of like states: $g(s, \kappa^0) = \sum_{i=1}^{N}(\mathbf{q}^*(s, \kappa^0) - \mathbf{q}^{\mathbf{e}}(s))^2$.
- Estimate $\hat{\kappa}$:

$$\begin{aligned} Z(\kappa) &= g(s, \kappa)' \hat{W} g(s, \kappa) \\ \hat{\kappa} &= \underset{\kappa \in \varkappa}{\arg\min}\, Z(\kappa) \end{aligned} \tag{12}$$

- $\varkappa$ is the set of positive real numbers
- $\hat{W}$ is estimated as $(g(s, \hat{\kappa})g(s, \hat{\kappa})')^{-1}$

Back to Identification

Estimating investment costs with ICCPs

- Recover policy functions for production across J investment scenarios.
- Simulate market outcomes; sum discounted production costs for three years for each investment scenario, V^j.
- Draw an initial investment cost γ^0; select optimal investment policy based on the simulated production costs, V^j, and the investment costs, $\Gamma(\mathbf{j}, \mathbf{v}, \gamma)$:

$$\mathbf{j}^*(\gamma^0) = \arg\max_{j \in J}(V^j + \Gamma(\mathbf{j}, \mathbf{v}, \gamma^0)). \tag{13}$$

- Use data to estimate investment conditional choice probabilities (ICCPs) across c unit investment types.
- Use ICCPs to simulate S discrete investment moments, c-length vectors of investment decisions by unit type; $\mathbf{j}_{\mathbf{sim}}$ denotes the c by S matrix of simulated moments.
- Assemble $g(\cdot, \gamma^0) = (\mathbf{j}_{\mathbf{sim}} - \mathbf{j}^*(\gamma^0))^2$, squared deviations from the simulated moments and optimal investments based on simulated production costs.
- Reshape $g(\cdot, \gamma^0)$ into a M-sized vector; estimate $\hat{\gamma}$:

$$\begin{aligned} Q(\gamma) &= g(\cdot, \gamma)' \hat{W} g(\cdot, \gamma) \\ \hat{\gamma} &= \arg\min_{\gamma \in \Theta} Q(\gamma) \end{aligned} \tag{14}$$

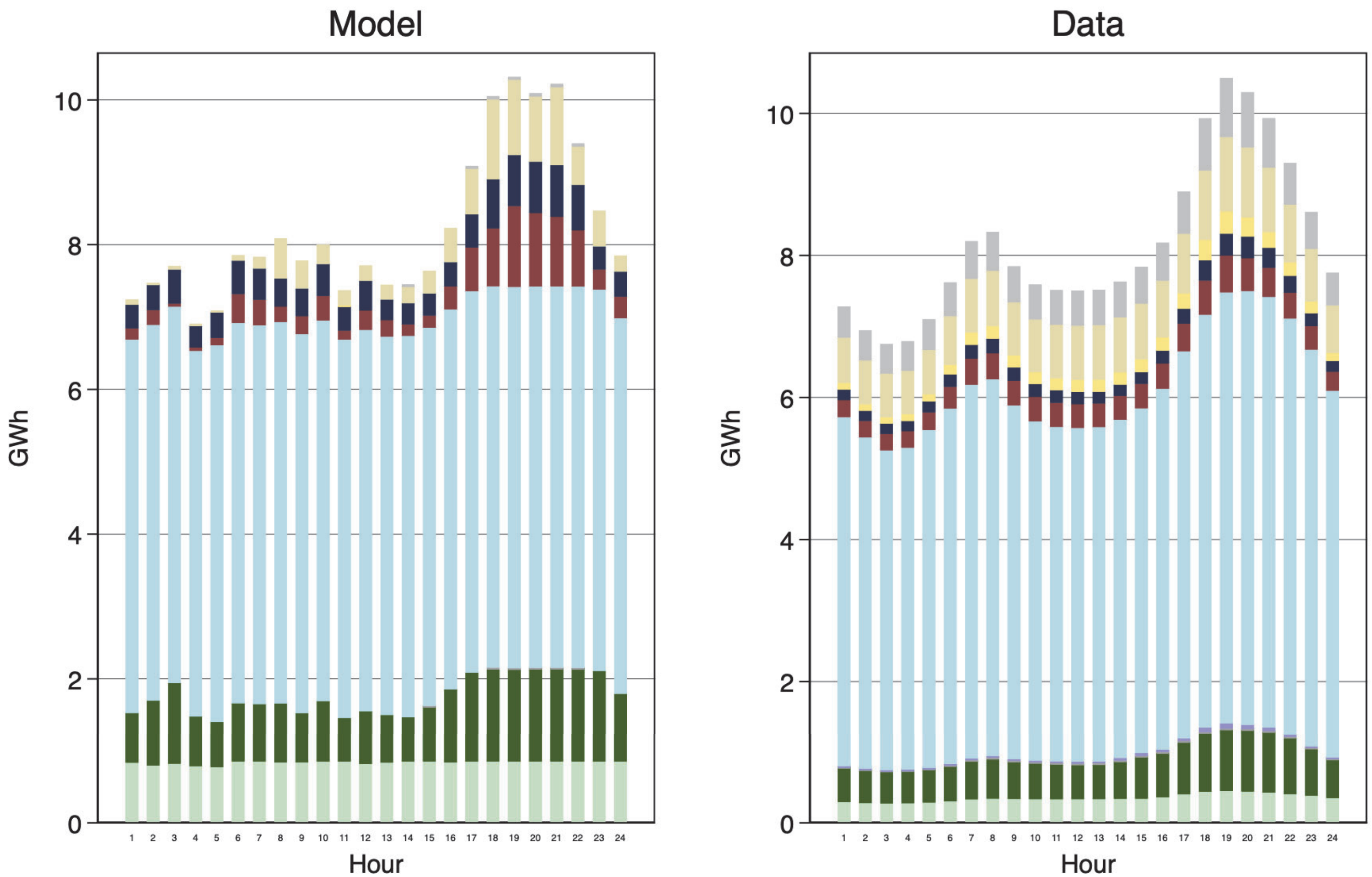
- Θ is the set of positive real numbers; $\hat{W}$ is estimated as $(g(\hat{\gamma})g(\hat{\gamma})')^{-1}$

Back to Identification

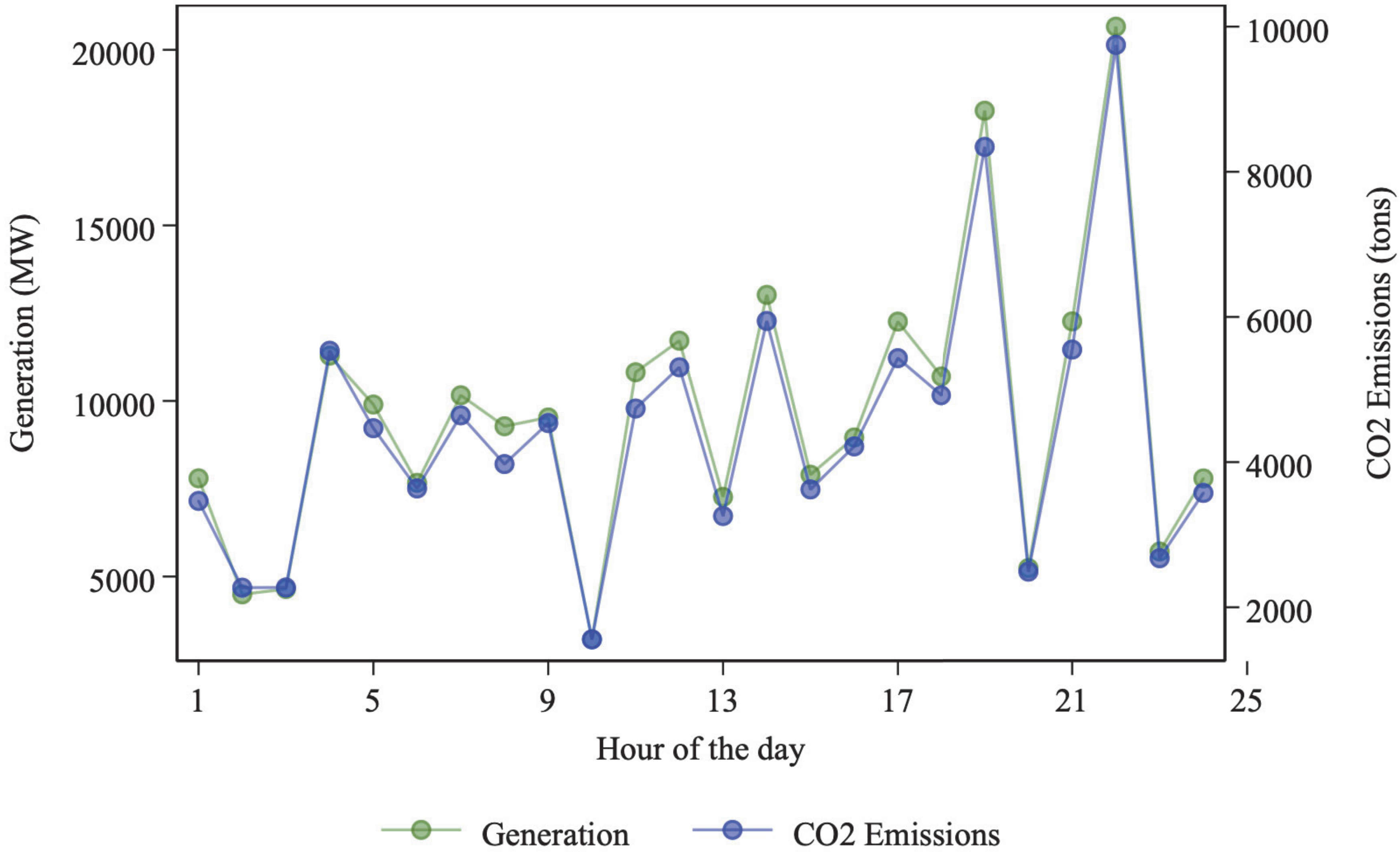
Model fit

Back to Results

- Total generation sensitive to demand shock discretization;
- Market shares not statistically different from empirical dispatch for most firm types, with exceptions for some higher cost units;
- Fit expected to improve with own estimate of start-up costs.



Average unit generation and emissions by hour



Back to Impact of carbon price in dynamic setting

Engineering estimates of start-up costs

Components of Start-up Costs for Typical Cold Start, $/MW

Combustion turbine type:	Maintenance & Capital Costs	Variable Operations & Maintenance	Auxiliary Power, Water, Chemicals	Fuel Costs (+)	Total
Gas-fired combined cycle	80	1	n/a	1	83
Gas-fired simply cycle large frame	60	1	1	1	63
Gas-fired steam	80	2	11	40	133

(+) Estimated fuel cost of $4.5 per MMBtu
Source: National Renewable Energy Laboratory (NREL) Power Plant Cycling Costs, April 2012

Back to Impact of carbon price in dynamic setting