A Policy by Any Other Name: Unconventional Industrial Policy in the US Solar Industry

Jacob T. Bradt
The University of Texas at Austin
jacob.bradt@austin.utexas.edu

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Political revealed preference for "second-best" climate policies

Biden: "Climate means jobs"

- Political constraints on "first-best" climate policy
  - 2010: Cap-and-trade fails in Senate
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- Technology-specific demand subsidies:
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  - Additional motivation: industrial policy
- How effective are demand subsidies for industrial policy?

Effect of demand subsidies on industry growth is ambiguous

- New technologies often characterized by learning-by-doing (LBD)

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  3. Size of any strategic incentives

Research questions

→ How effective are consumer subsidies as a tool for stimulating infant industries?

→ How do consumer subsidies compare to more conventional industrial policies?

→ What is the best approach to target growth in specific clean technologies?

Preview of analysis

- Application: residential solar photovoltaic (PV) installations in California (CA)
  - CA accounts for half of all solar installations in US over 2000-2020
  - California Solar Initiative: $2.2 billion in subsidies w/ goal of creating "self-sufficient" market
- Develop a structural model of entry/exit for CA PV installers with endogenous learning-by-doing (LBD) following Ericson and Pakes, 1995

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  3. California Solar Initiative (CSI) $\uparrow$ # installations by 4%, # firms by 9%
  4. CSI is welfare enhancing (?), but similar entry subsidies yield greater welfare gains

Related literature

- Economics of clean technologies and solar PV policies
  - Armitage, 2022; Butters et al., 2023; De Groote and Verboven, 2019; Gerarden, 2022; Gillingham and Tsvetanov, 2019; Hughes and Podolefsky, 2015; Langer and Lemoine, 2022; Pless and Van Benthem, 2019; van Benthem et al., 2008 ...

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- Learning-by-doing: Theory and estimation
  - Arrow, 1962; Benkard, 2000; Besanko et al., 2010; Bollinger and Gillingham, 2019; Cabral and Riordan, 1994; Covert, 2015; Covert and Sweeney, 2022; Fudenberg and Tirole, 1983; Ghemawat and Spence, 1985; Irwin and Klenow, 1994; Kellogg, 2011; Levitt et al., 2013; Spence, 1981; Thompson, 2001, 2007; Thornton and Thompson, 2001 ...

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- Estimation of dynamic games
  - Aguirregabiria et al., 2021; Bajari et al., 2007; Barwick and Pathak, 2015; Barwick et al., 2021; Collard-Wexler, 2013; Ericson and Pakes, 1995; Fowlie et al., 2016; Kalouptsidi, 2018; Pakes et al., 2007; Ryan, 2012; Sweeting, 2013 ...

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- Estimation of dynamic games
  - $\rightarrow$ I demonstrate a method to recover firms' learning curves within a dynamic game

Outline

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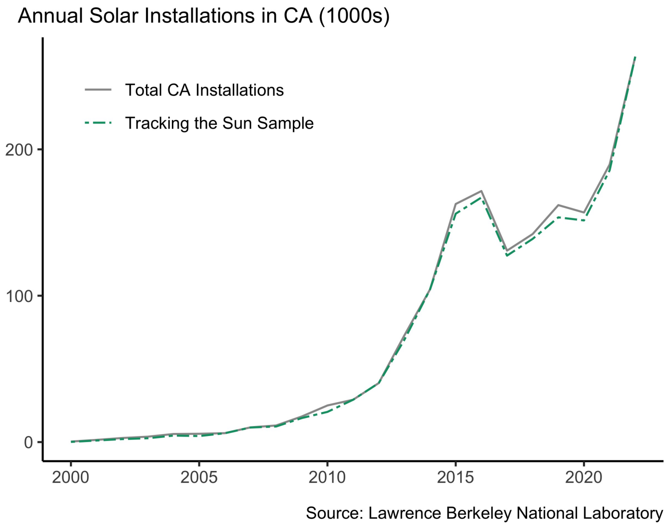
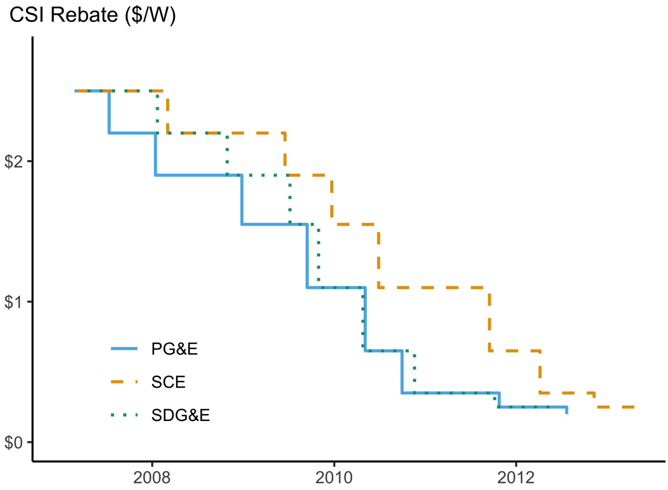
Data: Berkeley Lab's "Tracking the Sun" database



- Covers 98% of CA residential PV installations for 2000-2020
- System-level data on installer, date, county, cost, rebate
- Merge with hardware cost data from CPUC (2008-2013)

▸ Summary stats.

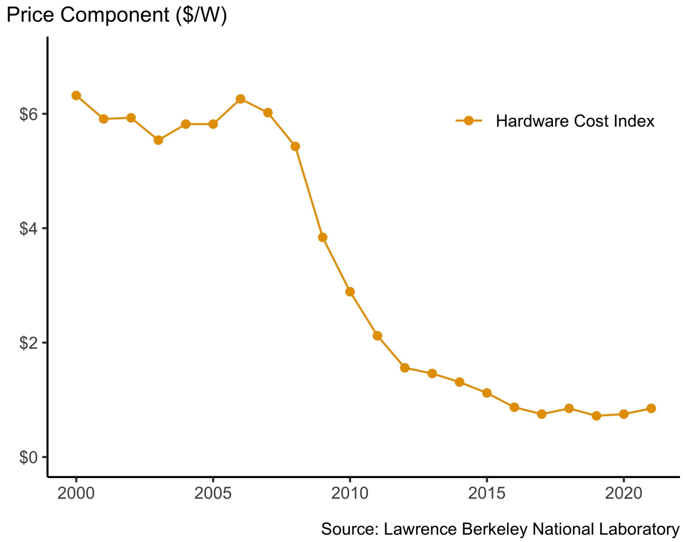
Solar PV is heavily subsidized in CA



Source: Lawrence Berkeley National Laboratory

- California Solar Initiative (CSI)
  - Explicit goal of establishing "self-sufficient solar industry"
  - $2.2 billion budget paid for by ratepayers
- Other incentives
  - Investment tax credit (ITC)
  - Net Energy Metering ▸ Details

Fact #1: Intermediary installers play a large role in PV market



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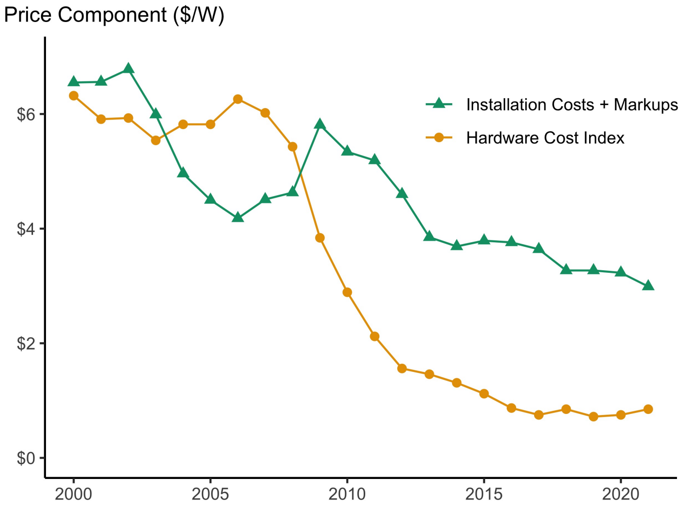

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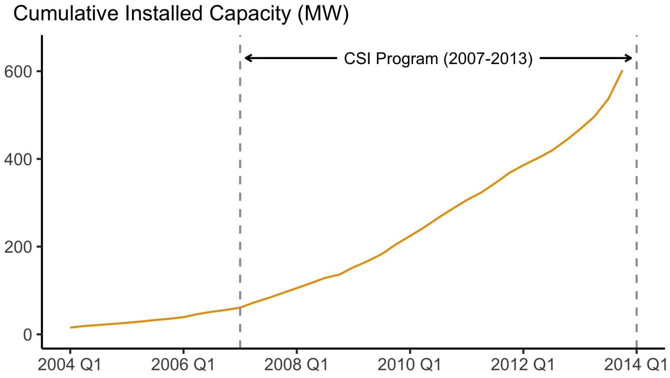
- Persistent decline in PV module costs (see Gerarden, 2022)
- Suggestive evidence of installer LBD (Bollinger and Gillingham, 2019; Nemet, 2019)

Fact #2: CA solar PV market saw rapid growth during CSI



- From 2007-2013:
  - Residential capacity ↑ 10×
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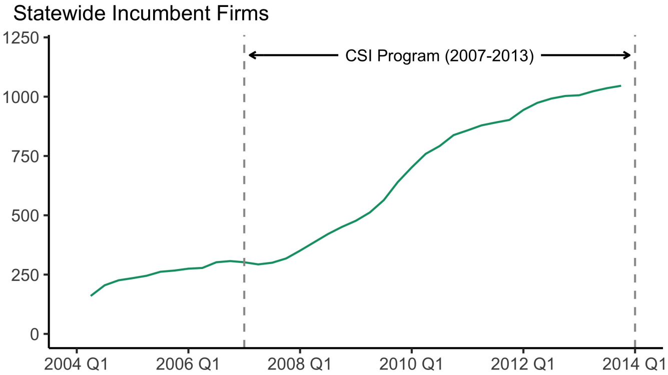

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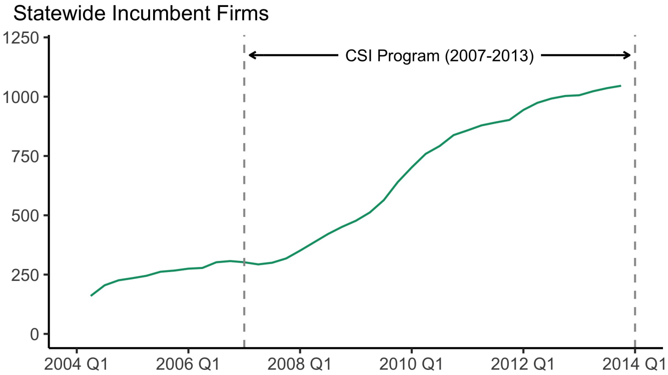
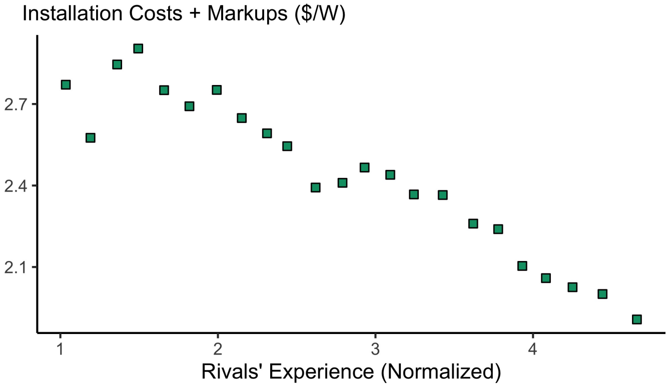


- From 2007-2013:
  - Residential capacity ↑ 10×
  - Incumbent installers ↑ 6×
- Observe higher entry rates at higher rebate levels ▸ Details

Source: Lawrence Berkeley National Laboratory

Fact #3: Rivals' experience is negatively correlated with costs



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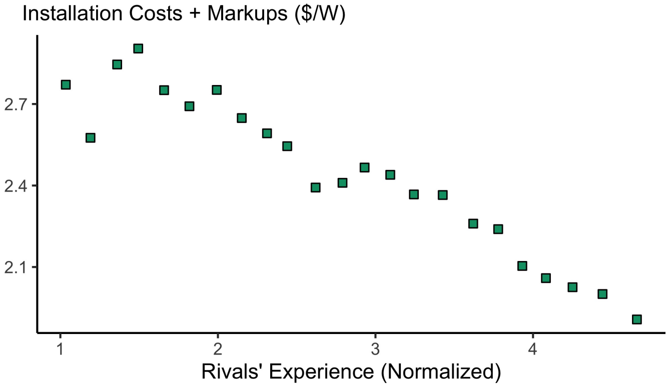

- Conditional on own-experience, market-time factors
- Suggestive empirical facts
  - Impact of CSI?
  - Role of learning?
  - Impact of other policies?

Source: Lawrence Berkeley National Laboratory

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Why do I need a (dynamic) model?

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1. Do not directly observe installation costs, where installer learning might occur

$$\underbrace{\text{installed price}}_{\text{observed data}} = \underbrace{\text{hardware cost}}_{\text{observed data}} + \underbrace{\text{installation costs} + \text{installer margin}}_{\text{unobserved}}$$

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3. Model with estimated parameters allows me to simulate counterfactual policies

Model overview

Incumbents ($j \in \mathcal{J}_{mt}$)

Potential Entrants ($j \in \bar{N}_m$)

Consumers ($i \in \mathcal{I}_{mt}$)

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Incumbents ($j \in \mathcal{J}_{mt}$) | Potential Entrants ($j \in \bar{N}_m$) | Consumers ($i \in \mathcal{I}_{mt}$)

- Differentiated products offered across markets m and periods t

- Two dynamic decisions:
    1. q^*_{jmt} conditional on experience (E_{jmt}) and parameters ($\boldsymbol{\theta}^c$)
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- Myopic, but account for durability
- Random coefficients nested logit

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Model timing and equilibrium

In each period t and market m:

- Firms observe market state s_{mt}
- Incumbents draw κ_{jmt}
- Incumbents compete in quantities
- Incumbents draw ϕ_{jmt}
  Potential entrants draw ω_{jmt}
- Entry and exit implemented
- Industry evolves to s_{mt+1}

s_{mt} is the union of an aggregate demand state, d_{mt}, and the states of all incumbents s_{jmt}:

$$s'_{jmt} = \Big[\ \underbrace{E_{jmt}}_{\text{experience}} \quad \overbrace{h_{jmt}}^{\text{hardware costs}} \quad \underbrace{\xi_{jmt}}_{\text{quality}}\ \Big]$$

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κ_{jmt} is a private productivity shock

$\rightarrow$ Assume κ_{jmt} follows

$$\kappa_{jmt} = \rho\kappa_{jmt-1} + \nu_{jmt}$$

where $\mathbb{E}[\nu_{jmt}] = 0$ and ρ is a parameter to be estimated

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Incumbents choose quantities to maximize current profits and expected future profits:

$$\max_{q_{jmt}} \left[\pi_j(s_{mt}, q_{jmt}) + \beta \int V_j(s_{mt+1}) dF(s_{mt+1} | s_{mt}, q_{mt}) \right]$$

Installer payoffs   Quantity-setting game   Demand model

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  Potential entrants draw ω_{jmt} $\longrightarrow$ Assume private scrap value (ϕ_{jmt}) and entry cost (ω_{jmt}) are i.i.d. exponential

$$F_\phi \sim \exp(1/\sigma_\phi)$$
$$F_\omega \sim \exp(1/\sigma_\omega)$$

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- **Entry and exit implemented** $\longrightarrow$
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Exit if:

$$\phi_{jmt} > \underbrace{CV(s_{mt})}_{\text{continuation value}}$$

Enter if:

$$\omega_{jmt} \leq \underbrace{VE(s_{mt})}_{\text{entry value}}$$

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- Industry evolves to s_{mt+1} → Assume exogenous states (ξ_{jmt}, h_{jmt}) are first-order Markov

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Markov Perfect Equilibrium

- Firms' strategies condition on other firms' strategies

→ Assume well-approximated by moment-based Markov Equilibrium concept

Installer payoffs | Quantity-setting game | Demand model | Exit decision | Entry decision | State transitions

Estimation overview

Follow two-step estimation of Bajari et al., 2007

1. Estimate static parameters "offline"

2. Estimate dynamic parameters

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1. Estimate static parameters "offline"
   - Empirical policy function for exit ‣ Exit policy estimation
   - Demand parameters ‣ Demand estimation ‣ Demand results
   - Exogenous state transitions ‣ Aggregate states ‣ Individual states

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   2.1 Quantity FOC + exit probability $\longrightarrow$ learning and exit parameters ▸ Quantity FOC ▸ Exit moment

   $\rightarrow$ Nests value function approximation ▸ Details

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Estimation uses quarterly data for 44 California counties from 2008 to 2013

Identification of production cost parameters

- Key identification challenge: firms may have serially correlated productivity shocks, κ_{jmt}

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▸ Product mkt. FOC ▸ Cost structure

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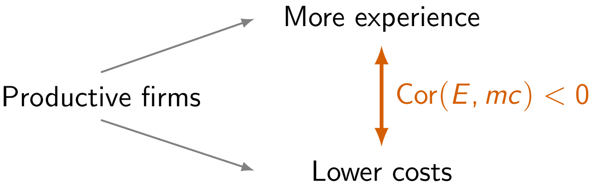

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Productive firms → More experience

Productive firms → Lower costs

More experience ↕ Lower costs: $\text{Cor}(E, mc) < 0$

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$\rightarrow$ Currently: GMM with moments based on $\mathbb{E}[\nu_{jmt}] = 0$

$\rightarrow$ In progress: GMM with moments based on $\mathbb{E}[Z_{jmt}\nu_{jmt}] = 0$, where Z_{jmt} is a vector of current and lagged cost-/demand-shifters

▸ Product mkt. FOC ▸ Cost structure

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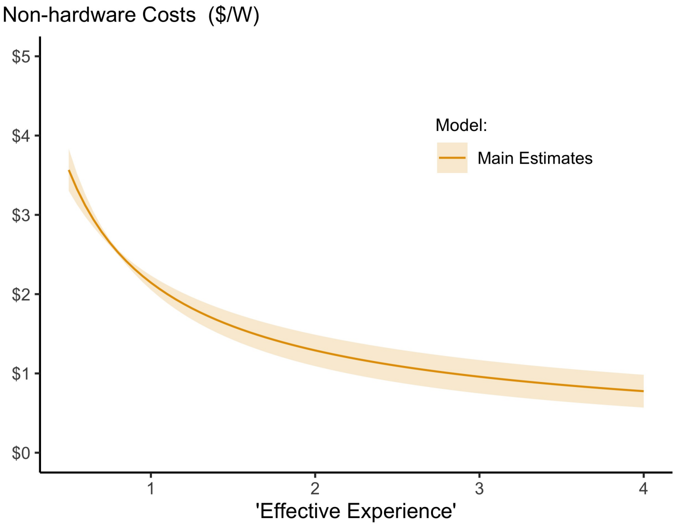
Result #1: Installation firms experience substantial learning-by-doing



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▸ Effective exp. ▸ Full results

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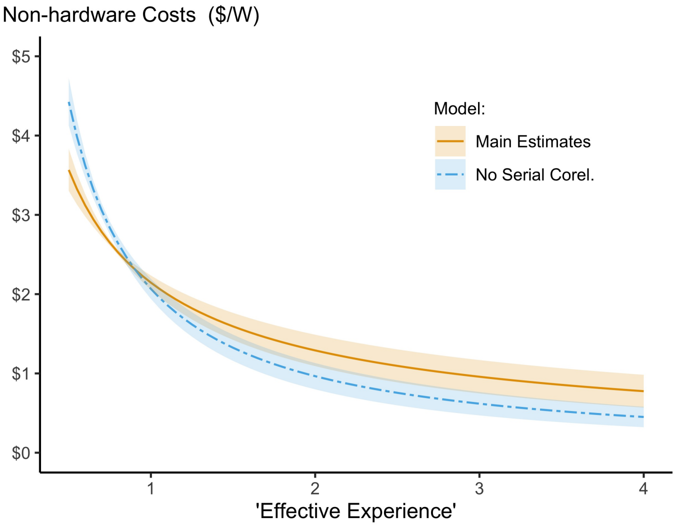

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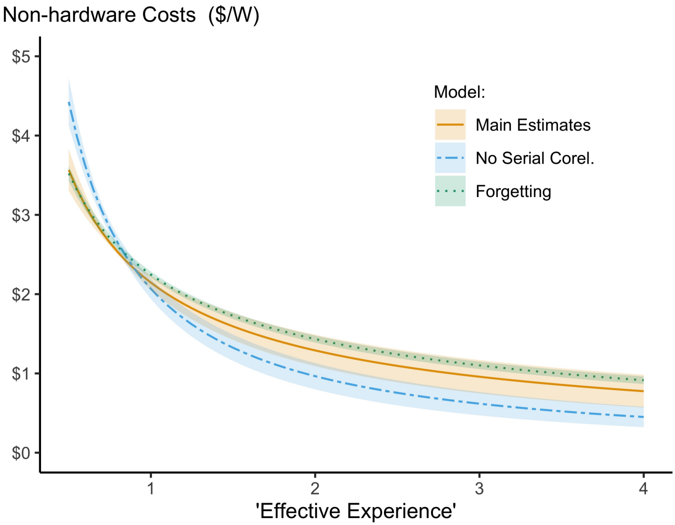

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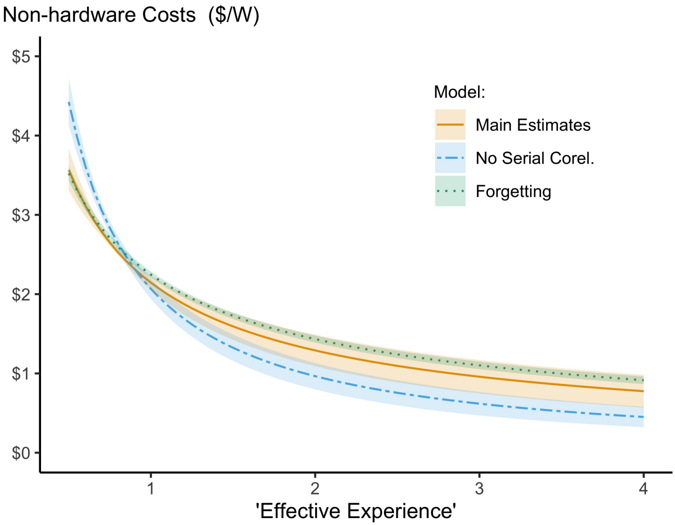
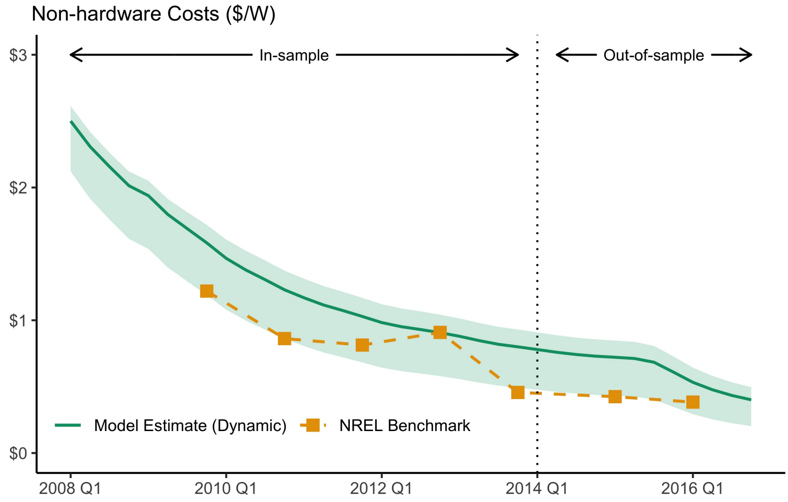


- "Effective experience"
  - → Aggregates own and industry experience
  - → Normalize by industry experience in 2008 Q1
- How much did CA installers actually learn?

▸ Effective exp. ▸ Full results

Result #1: Installation costs declined 65% from 2008-2013



- 25% of observed PV price reductions
- Note: NREL benchmark not used in estimation

Source: Author's calculations, National Renewable Energy Laboratory

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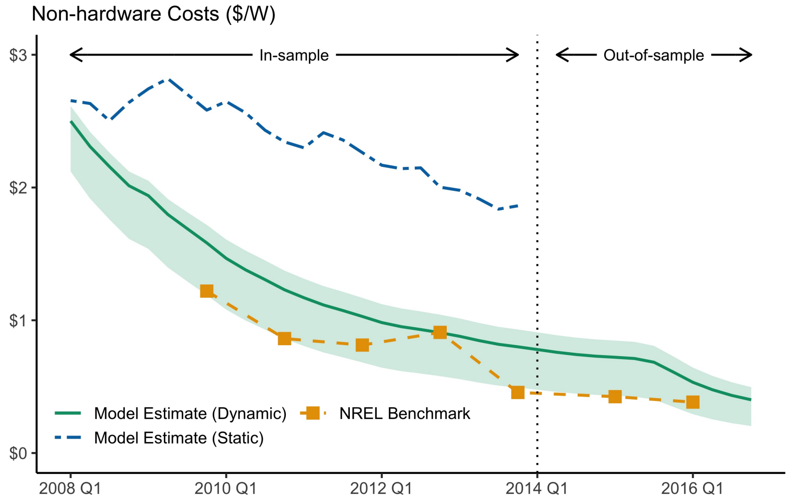
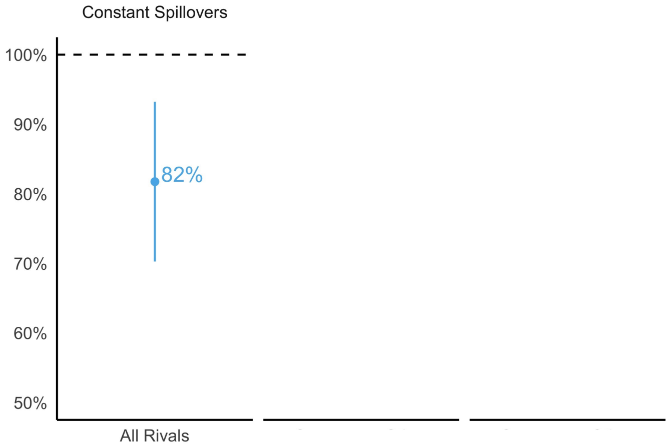


- 25% of observed PV price reductions
- Note: NREL benchmark not used in estimation
- Static estimates tell a different story

Source: Author's calculations, National Renewable Energy Laboratory

Result #2: Rivals' experience is 82% as effective as own experience

Impact of Spillovers Relative to Own Experience



- Total contribution of rivals' experience is substantial

▸ Effective exp. ▸ Total contribution ▸ Regulator learning ▸ Full results

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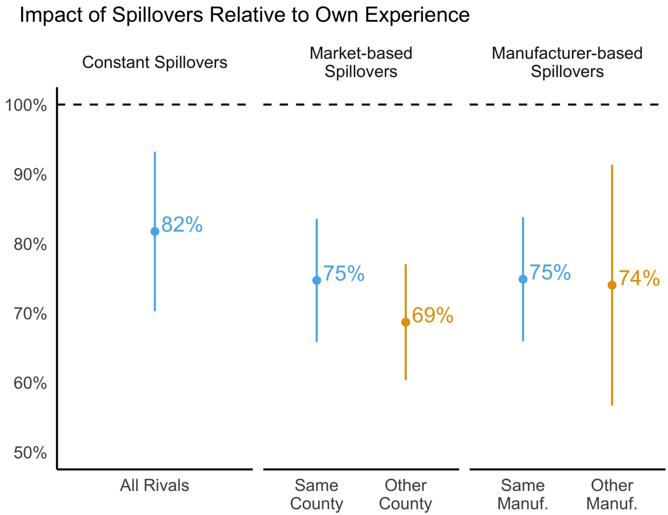

- Total contribution of rivals' experience is substantial
- Spillovers appear stronger within a county
- Active area of ongoing research

▸ Effective exp. ▸ Total contribution ▸ Regulator learning ▸ Full results

Outline

Simulating policy counterfactuals

- Counterfactuals:
  1. Alternative CSI design
  2. Entry subsidies
  3. Alternative climate policies

Simulating policy counterfactuals

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    1. Alternative CSI design $\longrightarrow$ Removing CSI
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  - Follow method of Sweeting, 2013 ("parametric policy iteration")
  - Generates single industry path Details

- Baseline: Simulated model outcomes under the baseline policies Baseline fit

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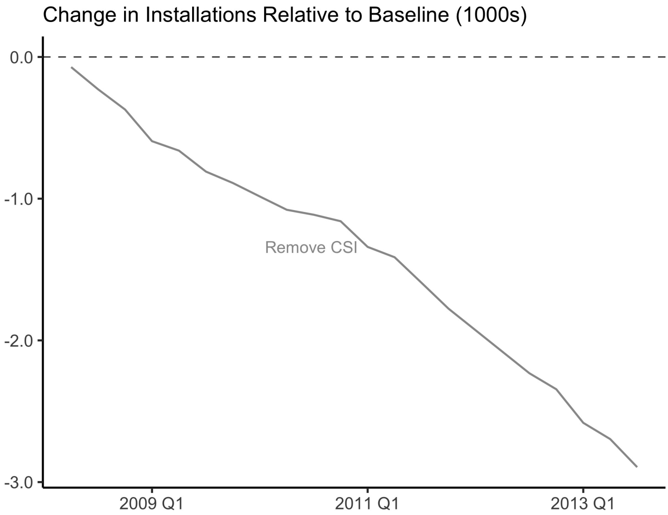
- Welfare measures:
  - Consumer surplus + producer surplus $\rightarrow$ directly from the model
  - Environmental benefits $\rightarrow$ Sexton et al., 2021

Result #3: CSI increased installations 4%, active firms 9%



- Installer industry contracts when CSI removed
  - $\rightarrow$ Fewer installations

▸ Alternative CSI designs

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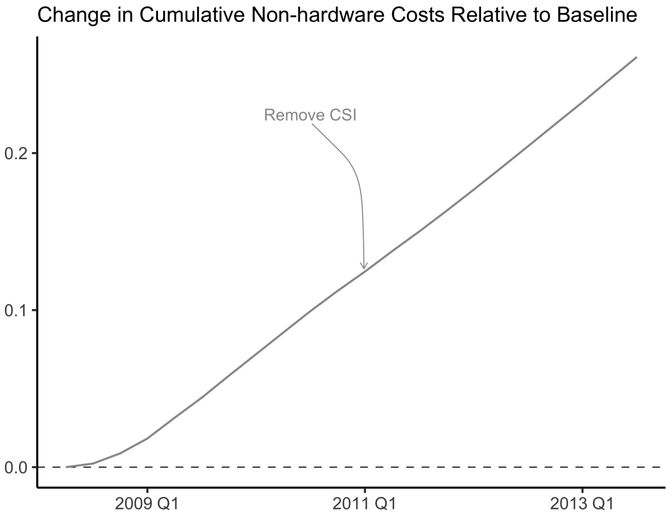

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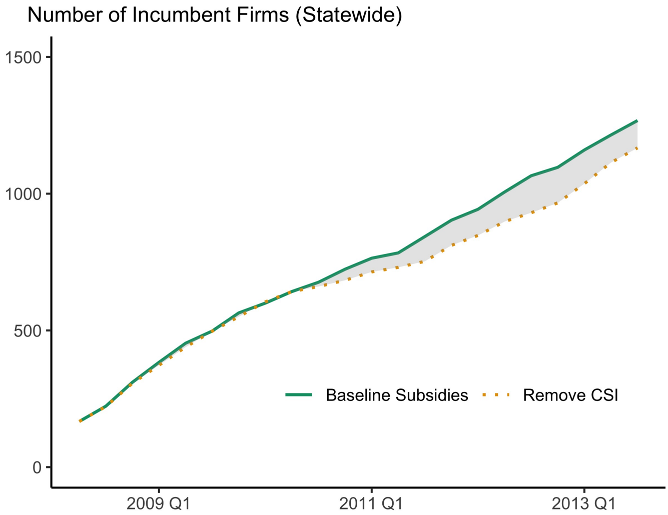

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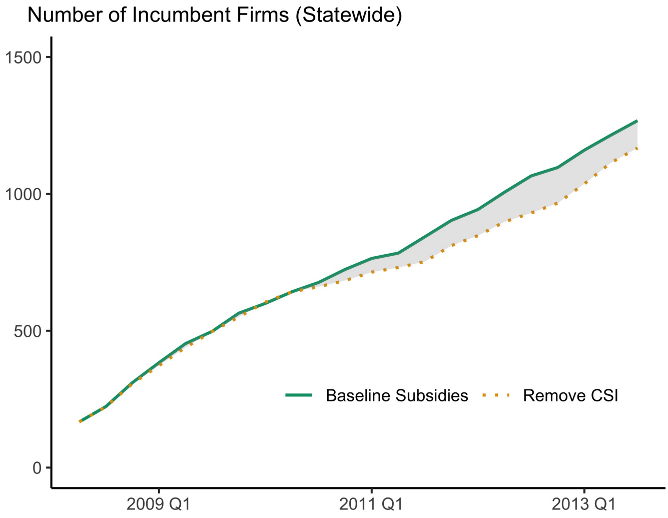

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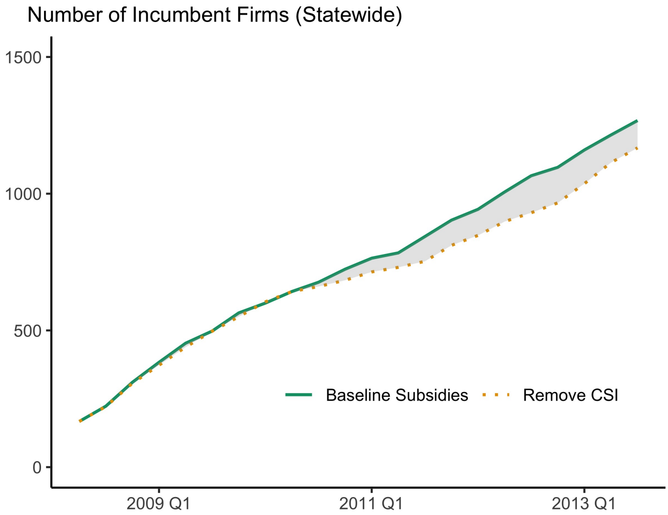

- Installer industry contracts when CSI removed
  - → Fewer installations
  - → Higher costs
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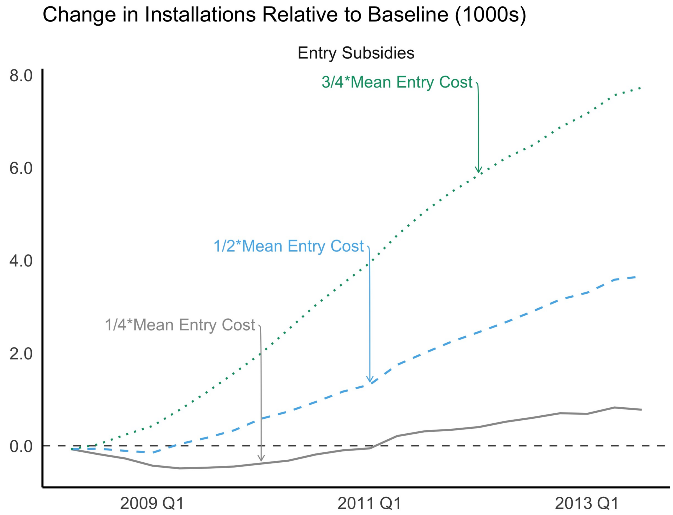
- Consistent with industry learning as main driver ▸ Evidence
- CSI subsidies are welfare enhancing

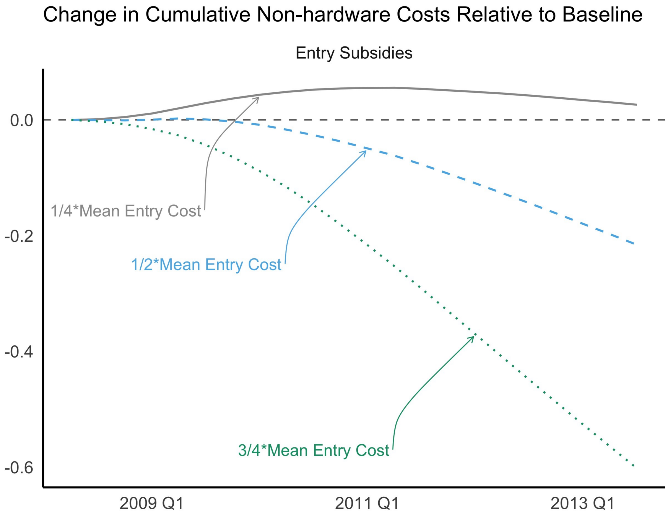
▸ Alternative CSI designs ▸ Welfare

Result #4: Entry subsidies outperform CSI



- Replace CSI with entry subsidies
  - → More installations

Result #4: Entry subsidies outperform CSI



- Replace CSI with entry subsidies
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  - → (Mostly) lower costs

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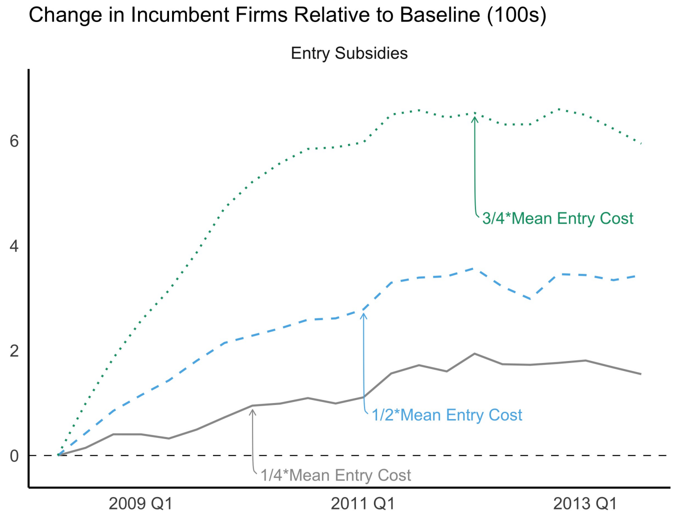

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  - → More net entry ▸ Details

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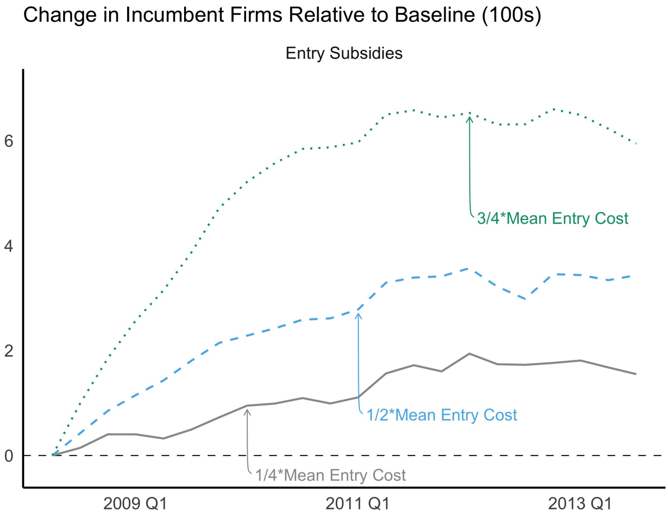

- Replace CSI with entry subsidies
  - $\rightarrow$ More installations
  - $\rightarrow$ (Mostly) lower costs
  - $\rightarrow$ More net entry ▸ Details
- Entry subsidies yield $>$ welfare
  - Driven by high # inframarginal consumers, firms under CSI
  - Caveat: Fiscal costs

▸ Welfare

Outline

Conclusion: Not all “second-best” policies are equal

- Develop a structural model of entry/exit for CA PV installers with endogenous learning-by-doing (LBD) following Ericson and Pakes, 1995

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- Findings:
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  2. Large industry learning spillovers
  3. California Solar Initiative (CSI) led to industry growth
  4. CSI is welfare enhancing, but similar entry subsidies yield greater welfare gains

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- Develop a structural model of entry/exit for CA PV installers with endogenous learning-by-doing (LBD) following Ericson and Pakes, 1995
- Findings:
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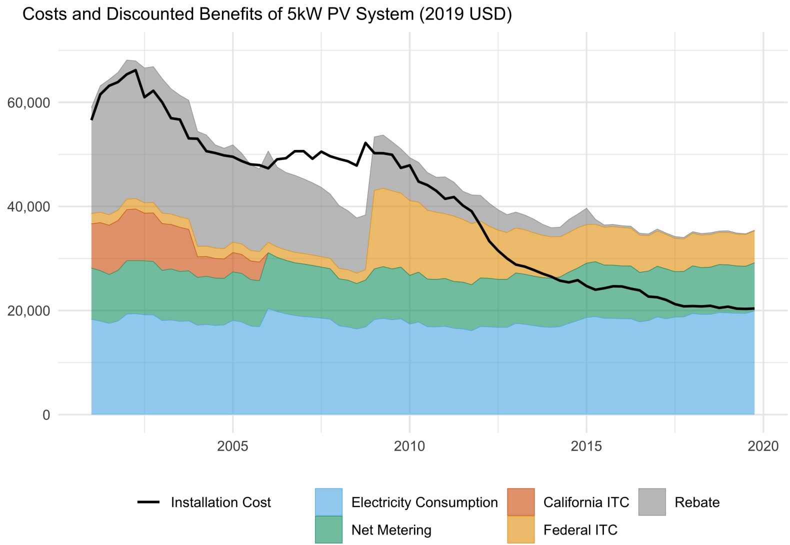
  2. Large industry learning spillovers
  3. California Solar Initiative (CSI) led to industry growth
  4. CSI is welfare enhancing, but similar entry subsidies yield greater welfare gains
- The clean energy transition will be labor intensive $\longrightarrow$ incentivizing experience today can make labor intensive technologies cheaper tomorrow

Thank you!

Please reach out with comments/questions
jbradt@g.harvard.edu
www.jacobbradt.com

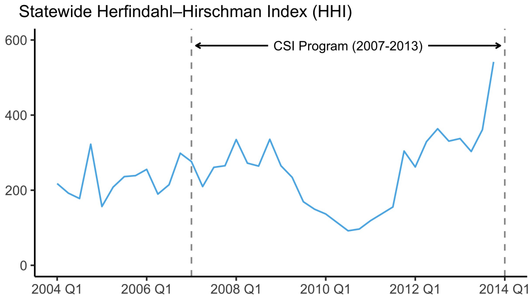
Backup Slides

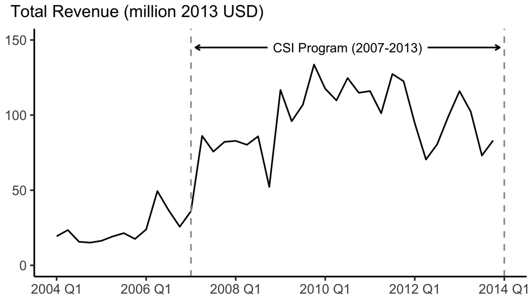
Other solar PV adoption incentives in CA



Go back

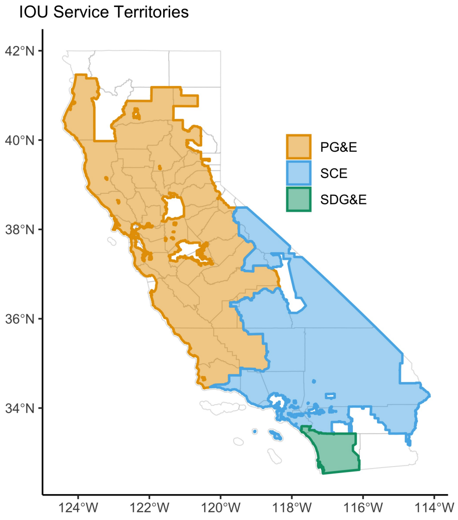
CA solar installer market concentration and revenues

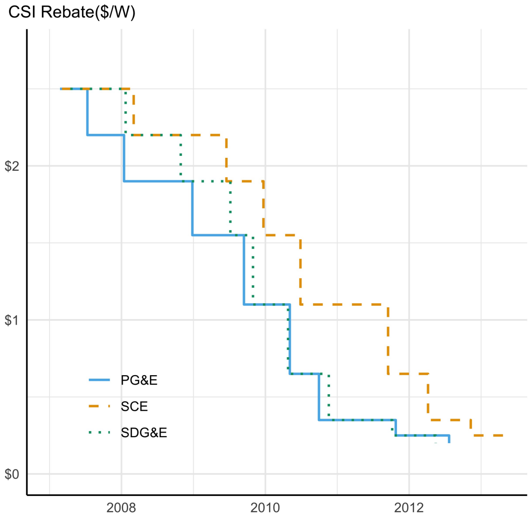




▸ Go back

Spatial and temporal variation in CSI rebates





▸ Go back

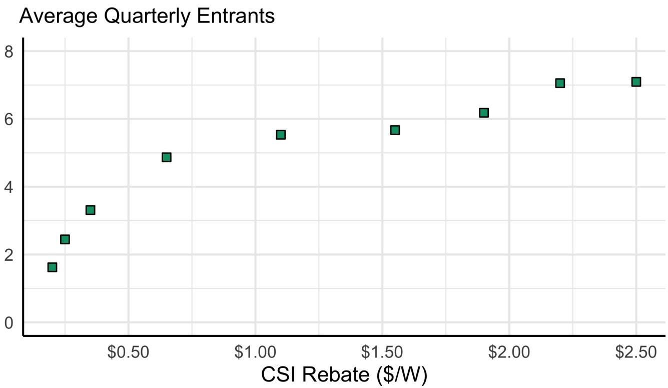
Demand Data: Summary Statistics

	Mean	SD	Min	Max
Number of Installations	2.59	4.02	1	138
Total Installed Capacity (kW)	14.36	20.30	0.92	583.95
Market Share (%)	0.00	0.01	0.00	0.35
Market Share: Inside (%)	4.66	8.04	0.13	100.00
Average Installed Price (2013 $/W)	6.69	1.79	1.54	12.03
Average Hardware Cost (2013 $/W)	4.25	1.54	0.00	10.58
Own Experience: In-market (kW)	128.37	275.11	0.00	3643.05
Own Experience: Out-of-market (kW)	1184.95	2706.12	0.00	18 355.82
Rival Experience: In-market (MW)	11.12	10.49	0.13	52.00
Rival Experience: Out-of-market (MW)	253.10	97.41	81.79	444.24
Rival Experience: Same Manufacturer (MW)	24.02	28.72	0.00	108.49
Rival Experience: Other Manufacturer (MW)	240.19	99.24	66.61	445.04
N		17,852		

- Aggregate to county-quarter level
- Focus on residential/non-utility scale, household-owned systems

▸ Go back

Observe more firms entering at higher CSI rebates



- Use spatial/temporal variation in CSI rebates ▸ Variation
- Informative, but ultimately limited result
  - → Quantify impact of CSI?
  - → Role of learning?
  - → Underlying mechanisms?

Source: Lawrence Berkeley National Laboratory, author's calculations

▸ Go back

Demand for solar PV systems

- Following random coefficients nested logit of Grigolon and Verboven, 2014, indirect utility of solar adoption is given by

$$u_{ijmt} = \alpha_i^p (p_{jmt} - r_{jmt}) + \alpha_i' X_{jmt} + \xi_{jmt} + \bar{\xi}_j + \bar{\xi}_t + \underbrace{\zeta_{igmt} + (1-\eta)\varepsilon_{ijmt}}_{\sim T1EV}$$

where

- p_{jmt}, r_{jmt}, and X_{jmt} are a firm's price, available rebate, and vector of observable attributes
- ξ_{jmt} is unobservable product quality
- $\bar{\xi}_j$, $\bar{\xi}_t$ are firm and time fixed effects
- $g \in \{\text{no installation, installation}\}$ indicates the nest group
- ζ_{igmt} is an idiosyncratic group preference
- η characterizes the correlation of utilities from installers within a given market
- $\alpha_i = \frac{\alpha}{y_i}$ and $\beta_i = \log(y_i)$ capture preference heterogeneity, with $y_i =$ household income

▸ Go back (model overview)

Installer payoffs

- An incumbent active in period t in market m therefore earns product market profits:

$$\pi_j(s_{mt}, q_{jmt}; \theta^c) = \Big(p_j(s_{mt}, q_{jmt}) - mc_j(s_{mt}; \theta^c)\Big) q_{jmt}$$

  where $p_j(s_{mt}, q_{jmt})$ is firm j's market-time-specific price per watt, which is defined by the inverse demand curve

- Value function for incumbent j in market m at time t is given by:

$$V_j(s_{mt}, \phi_{jmt}) = \pi_j(s_{mt}, q^*_{jmt}) + \max\Big\{\phi_{jmt}, CV_j(s_{mt})\Big\}$$

  where $CV_j(s_{mt}) = \mathbb{E}\big[V_j(s_{mt+1}|s_{mt}, q^*_{mt})\big]$; q^*_{mt} is the vector of optimal quantities chosen by incumbents in the market; and β is a common discount factor

▸ Go back (model overview)

Product market game

- Incumbent firms' quantity-setting problem as follows:

$$\max_{q_{jmt}} \left(\pi_j(s_{mt}, q_{jmt}) + \beta \int V_j(s_{mt+1}) dF(s_{mt+1}|s_{mt}, q_{mt}) \right)$$

where $F(s_{mt+1}|s_{mt}, q_{mt})$ is the transition kernel for the state s_{mt} conditional on q_{mt}, the vector of quantity choices by incumbent firms in the market: $q'_{mt} = \begin{bmatrix} q_{1mt} & \dots & q_{Jmt} \end{bmatrix}$

- Optimal quantity-setting satisfies the following FOC:

$$0 = \underbrace{\frac{\partial}{\partial q_{jmt}} \pi_j(s_{mt}, q_{jmt})}_{\text{marginal static profits}} + \underbrace{\frac{\partial}{\partial q_{jmt}} \beta \int V_j(s_{mt+1}) dF(s_{mt+1}|s_{mt}, q_{mt})}_{\text{dynamic ``markdown''}}$$

Go back (model overview) Go back (FOC estim.)

Product market game

- Dynamic markdown term captures incentive to price below marginal cost today for experience based cost savings tomorrow (Irwin and Klenow, 1994; Benkard, 2000)

- First term is standard price-cost-markup term from static differentiated Cournot

- Assuming quantity choice only affects state transitions (not value function), dynamic markdown term can be written as:

$$\mathbb{E}\left[V\left(s_{mt+1}\right) \times \frac{\frac{\partial}{\partial q_{jmt}} dF\left(s_{mt+1} \middle| s_{mt}, q_{mt}\right)}{dF\left(s_{mt+1} \middle| s_{mt}, q_{mt}\right)} \middle| s_{mt}, q_{mt} \right]$$

‣ Go back (model overview) ‣ Go back (FOC estim.) ‣ Markup derivation ‣ Markdown derivation

Deriving the static markup

- The first term in firm j's first-order condition can be written as:

$$\frac{\partial}{\partial q_{jmt}} \pi_j(s_{mt}, q_{jmt}) = p_j(s_{mt}, q_{jmt}) + \frac{\partial p_j(s_{mt}, q_{jmt})}{\partial q_{jmt}} q_{jmt} - mc_j(s_{mt})$$

- I can take the matrix of own-price-derivatives, Δ_{mt}, estimated from the demand model, invert the full matrix, and take the diagonal to estimate the markup term: $(\Delta_{mt}^{-1})_{(j,j)}$

▸ Go back (quantity-setting game) ▸ Go back (FOC estim.)

Deriving the dynamic markdown

- Installation price changes only affect the probability distribution of the state, not the value function $V(\cdot)$ itself, so can simplify the original dynamic markdown term to

$$\frac{\partial}{\partial q_{jmt}}\left(\beta\int V(s_{mt+1})dF(s_{mt+1}|s_{mt},q_{jmt})\right)=\beta\int V(s_{mt+1})\frac{\partial}{\partial q_{jmt}}\left(dF(s_{mt+1}|s_{mt},q_{jmt})\right)$$

- Note that for any realizable value of the state space, $dF(s_{mt+1}|s_{mt},q_{jmt})>0$ so

$$\begin{aligned}\int V(s_{mt+1})\frac{\partial}{\partial q_{jmt}}\left(dF(s_{mt+1}|s_{mt},q_{jmt})\right)&=\int V(s_{mt+1})\frac{\frac{\partial}{\partial q_{jmt}}dF(s_{mt+1}|s_{mt},q_{jmt})}{dF(s_{mt+1}|s_{mt},q_{jmt})}dF(s_{mt+1}|s_{mt},q_{jmt})\\&=\mathbb{E}\left[V(s_{mt+1})\frac{\frac{\partial}{\partial q_{jmt}}dF(s_{mt+1}|s_{mt},q_{jmt})}{dF(s_{mt+1}|s_{mt},q_{jmt})}\Big|s_{mt},q_{jmt}\right]\end{aligned}$$

- Dynamic markdown is the expectation of the product of future benefits at a given state and the relative change in the likelihood of that state resulting from a change in q_{jmt}

▸ Go back (quantity-setting game) ▸ Go back (FOC estim.)

Exit probability

- In practice, assume private scrap value ϕ_{jmt} drawn from $F_\phi \sim \exp(1/\sigma_\phi)$
- Optimal exit policy follows threshold form: firm j exits market m at time t if $\phi_{jmt} > CV(s_{mt})$, which happens with probability $p^x(s_{mt})$:

$$\begin{aligned} p^x(s_{mt}) &\equiv \Pr(\phi_{jmt} > CV(s_{mt})) \\ &= 1 - F_\phi(CV(s_{mt})) \\ &= 1 - \left(1 - \exp\left(\frac{-CV(s_{mt})}{\sigma_\phi}\right)\right) = \exp\left(\frac{-CV(s_{mt})}{\sigma_\phi}\right) \end{aligned}$$

where $CV(s_{mt}) \equiv \beta\mathbb{E}\left[V(s_{mt+1}|s_{mt})\right]$

▸ Go back (model overview)

Entry probability

- In practice, assume private entry cost ω_{jmt} drawn from $F_\omega \sim \exp(1/\sigma_\omega)$
- Optimal entry policy similarly follows threshold form: $j \in \{1, ..., \bar{N}_{mt}\}$ potential entrant enters market m at time t if $\omega_{jmt} \leq VE(s_{mt})$, which happens with probability $p^e(s_{mt})$:

$$
\begin{aligned}
p^e(s_{mt}) &\equiv \Pr(\omega_{jmt} \leq VE(s_{mt})) \\
&= F_\omega(VE(s_{mt})|s_{mt}) \\
&= 1 - \exp\left(\frac{-VE(s_{mt})}{\sigma_\omega}\right)
\end{aligned}
$$

where $VE(s_{mt}) \equiv \mathbb{E}\Big[\beta \mathbb{E}\left[V(s_{mt+1}|s_{mt})\right]\Big]$ is the value conditional on entering

▸ Go back (model overview)

State transitions

- State transitions:
  - Endogenous: experience (E_{jmt})
  - Exogenous: quality (ξ_{jmt}), hardware cost (h_{jmt}), demand state (d_{mt})
- Assume that exogenous states follow a first-order Markov process
  - $\rightarrow$ Estimate as independent AR(1) processes with county-specific intercepts to account for systematic differences across markets of differing conditions
- Experience state variables update based on endogenous quantity choices

▸ Go back (model overview)

Marginal cost structure

- Assume $mc_j(s_{mt};\theta^c,\kappa_{jmt})$ takes the following form:

$$mc_j(s_{mt};\theta^c,\kappa_{jmt}) = \overbrace{h_{jmt}}^{\text{hardware cost}} + \underbrace{w(s_{mt};\theta^c)}_{\text{installation costs}} + \kappa_{jmt}$$

- Use standard learning model (e.g., Benkard, 2000) for LBD in installation costs:

Target parameters

$$w(s_{jmt};\theta^c) = c_0 \times \left(\underbrace{\tilde{E}_j(s_{mt};\theta^E)}_{\text{Effective experience}}{}^{\gamma} \right)$$

▸ Go back (est. overview) ▸ Go back (Results)

Marginal cost structure: “Effective experience”

- Use standard learning model (e.g., Benkard, 2000) for LBD in installation costs:

Target parameters

$$w(s_{jmt};\theta^c) = c_0 \times \left(\underbrace{\tilde{E}_j(s_{mt};\theta^E)}_{\text{Effective experience}} \right)^{\gamma}$$

- Effective experience $\tilde{E}$ allows for different models of experience accumulation, for example,

Data

$$\tilde{E}(E_{jmt};\theta^E) = E_{jmt} + \underbrace{\theta_1^E}_{\text{Target parameter}} \left(\sum_m \sum_{k \neq j} E_{kmt} \right)$$

▸ Go back (est. overview) ▸ Go back (Results)

Estimating the exit policy function

- I estimate firms' exit policy function using a logit regression:

$$\Pr(\chi^{x}_{jmt} = 1 | s_{mt}) = \frac{\exp\left(h_j(s_{mt})\right)}{1 + \exp\left(h_j(s_{mt})\right)}$$

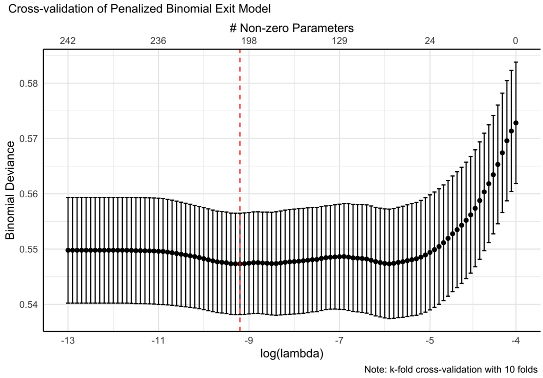
  where χ^{x}_{jmt} equals 1 if firm j exits market m in period t and 0 otherwise and $h_j(s_{mt})$ is a flexible function of the states

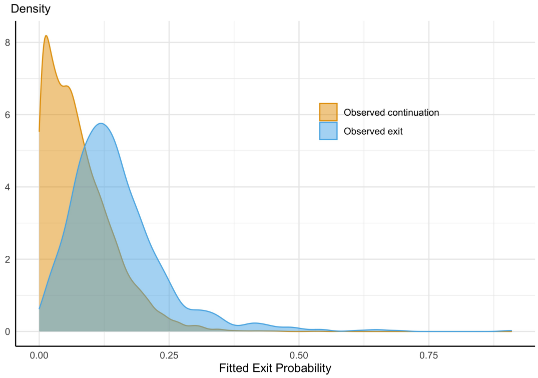
- Follow Gerarden, 2022 to determine the functional form of $h_j(s_{mt})$

- I estimate a logit model of the discrete exit decision with a full set of candidate regressors, $h_j(s_{mt})$, via penalized maximum likelihood
  - $\rightarrow$ Quadratic polynomials of the full set of state variables and the complete set of pairwise interactions as well as county and quarter fixed effects

▸ Go back

Estimating the exit policy function





▸ Go back

Demand estimation

- Estimation of RCNL model follows Berry et al., 1995 and best practices of Conlon and Gortmaker, 2020

- Derive GMM estimator based on

$$\mathbb{E}[Z_D'\xi(\theta_0^D)] = 0$$

where $\theta_0^D = (\alpha_p, \alpha', \sigma, \eta)$ is the vector of population demand parameters, $\xi(\theta^D)$ is the vector ξ_{jmt} that solves the RCNL model's market share formula

- Instruments include:
  - Price endogeneity: CSI rebates, county-quarter avg. electrician/roofer wage, and BLP instruments from Berry et al., 1995
  - Nesting parameter: Number of firms in a market and number of installations a firm finished in other markets in previous quarter
  - Preference heterogeneity: Follow Miller and Weinberg, 2017 and interact firm attributes with mean income

Go back   Demand results

Demand estimates

	Parameter	(1)	(2)	(3)	(4)	(5)
Price/Income	α_p	-0.959	-0.944	-0.599	-0.551	-0.862
		(0.303)	(0.306)	(0.22)	(0.215)	(0.352)
Nesting Parameter	η	0.901	0.901	0.901	0.901	0.902
		(0.030)	(0.028)	(0.031)	(0.028)	(0.045)
Firm Attributes						
High Efficiency	α_1		0.023		0.027	-0.27
			(0.015)		(0.015)	(0.936)
# Modules	α_2		0.076		0.071	0.712
			(0.015)		(0.014)	(1.025)
Avg. Electricity Price	α_3		-7.962		-7.433	21.114
			(1.633)		(1.535)	(141.37)
Income Interactions						
log(Income) × Constant	σ_1					1.966
						(5.867)
log(Income) × High Efficiency	σ_2					0.065
						(0.234)
log(Income) × # Modules	σ_3					-0.185
						(0.318)
log(Income) × Avg. Electricity Price	σ_4					-7.599
						(36.735)
Income Distribution				Yes	Yes	Yes
Firm, Year FE		Yes	Yes	Yes	Yes	Yes
Median Own Price Elast.		-1.4	-1.39	-1.43	-1.33	-1.09
Median Outside Diversion		10.12%	10.03%	10.07%	10.07%	10.06%
J-Statistic		51.21	62.3	51.57	62.92	53.69

County-clustered standard errors reported in parentheses

▸ Go back

Transition process: Aggregate states

	Demand (Installations)		Avg. Price ($/W)		Inclusive Value	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.853		0.4100		0.0026	
	(1.932)		(0.1057)		(0.0008)	
$(\text{Demand})_{t-1}$	0.9724	0.7191				
	(0.0380)	(0.1205)				
$(\text{Avg. Price})_{t-1}$			0.9126	0.9077		
			(0.0156)	(0.0165)		
$(\text{Inclusive Value})_{t-1}$					0.8393	0.6380
					(0.0655)	(0.1156)
County FE		Yes		Yes		Yes
Observations	885	885	885	885	885	885
R^2	0.84	0.86	0.81	0.81	0.62	0.66
Within R^2		0.43		0.80		0.34

Clustered (County) standard-errors in parentheses

Go back

Transition process: Individual states

	Own Quality		Hardware Cost ($/W)		Price ($/W)	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-1.164		0.3997		0.9885	
	(0.1895)		(0.0295)		(0.0806)	
(Own Quality)$_{t-1}$	0.8438	0.5275				
	(0.0253)	(0.0780)				
(Hardware Cost)$_{t-1}$			0.8715	0.8666		
			(0.0069)	(0.0069)		
(Price)$_{t-1}$					0.8256	0.8127
					(0.0125)	(0.0118)
County FE		Yes		Yes		Yes
Observations	5,862	5,862	5,862	5,862	5,862	5,862
R^2	0.70	0.75	0.76	0.77	0.69	0.69
Within R^2		0.24		0.76		0.67

Clustered (County) standard-errors in parentheses

▸ Go back

Estimating cost and exit parameters

- Firm's quantity-setting FOC:

marginal cost

$$0 = p_{jmt} + \underbrace{(\Delta_{mt}^{-1})_{(j,j)} \times ms_{jmt}}_{\text{static markup}} - \overbrace{mc_j(s_{mt}; \theta^c, \kappa_{jmt})}^{\text{marginal cost}} + \cdots$$

static markup

Estimating cost and exit parameters

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  - $(\Delta_{mt}^{-1})_{(j,j)} = j$-th diagonal of the inverted matrix of own-price derivatives of demand

Estimating cost and exit parameters

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  - $(\Delta_{mt}^{-1})_{(j,j)}$ = j-th diagonal of the inverted matrix of own-price derivatives of demand
  - $mc_j(s_{mt}; \theta^c, \kappa_{jmt})$ = some parameterized marginal cost function of the state, κ_{jmt}

▸ Go back (est. overview) ▸ Markup derivation ▸ Markdown derivation ▸ $V(\cdot)$ approx. ▸ Calculating $\Omega(\cdot)$ ▸ Est. algo.

Estimating cost and exit parameters

- Firm's quantity-setting FOC:

$$0 = p_{jmt} + \underbrace{(\Delta_{mt}^{-1})_{(j,j)} \times ms_{jmt}}_{\text{static markup}} - \overbrace{mc_j(s_{mt}; \theta^c, \kappa_{jmt})}^{\text{marginal cost}} + \underbrace{\beta \mathbb{E}[V_j(s_{mt+1}; \lambda) \times \Omega_j(s_{mt}, q_{mt})]}_{\text{dynamic markdown}}$$

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Estimating cost and exit parameters

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  - $V_j(s_{mt+1};\lambda)$ = firm j's value in period $t+1$, approximated as fxn. of expected states s_{mt+1}—conditional on current states and actions—and parameters λ

Go back (est. overview) | Markup derivation | Markdown derivation | $V(\cdot)$ approx. | Calculating $\Omega(\cdot)$ | Est. algo.

Estimating cost and exit parameters

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  - $\Omega_j(s_{mt}, q_{mt}) = \frac{\frac{\partial}{\partial q_{jmt}} dF(s_{mt+1}|s_{mt}, q_{mt})}{dF(s_{mt+1}|s_{mt}, q_{mt})}$

Go back (est. overview) | Markup derivation | Markdown derivation | $V(\cdot)$ approx. | Calculating $\Omega(\cdot)$ | Est. algo.

Estimating cost and exit parameters

- Firm's quantity-setting FOC:

$$0 = p_{jmt} + \underbrace{(\Delta_{mt}^{-1})_{(j,j)}}_{\text{static markup}} \times ms_{jmt} - \overbrace{mc_j(s_{mt}; \theta^c, \kappa_{jmt})}^{\text{marginal cost}} + \underbrace{\beta \mathbb{E}[V_j(s_{mt+1}; \lambda) \times \Omega_j(s_{mt}, q_{mt})]}_{\text{dynamic markdown}}$$

- Combine product market FOC, optimal exit condition to jointly estimate dynamic cost and exit parameters, $\theta = (\theta^c, \sigma_\phi)$, via non-linear GMM

Go back (est. overview) · Markup derivation · Markdown derivation · $V(\cdot)$ approx. · Calculating $\Omega(\cdot)$ · Est. algo.

Combining exit and quantity-setting FOC

- Combine quantity FOC moments w/ moment that minimizes sum of squared deviations between estimated and model-implied exit probabilities:

$$\min_{\sigma_\phi} \sum_{j,m,t} \Bigg(\underbrace{\hat{p}^x_{jmt} - \exp\left(- \frac{CV_j(s_{mt};\lambda)}{\sigma_\phi} \right)}_{\equiv \psi_{jmt}(\sigma_\phi,\lambda)} \Bigg)^2$$

  The moment condition that corresponds to the above nonlinear least squares problem is

$$\mathbb{E}\left[\frac{\partial \psi_{jmt}(\sigma_\phi, \lambda)}{\partial \sigma_\phi} \psi_{jmt}(\sigma_\phi, \lambda) \right] = 0$$

- Solve for θ satisfying quantity-setting, exit moment conditions, subject to the incumbent's ex ante value function holding

▸ Go back (est. overview) ▸ Value func. approx. details

Estimating cost and exit parameters

Estimation algorithm:

1. Solve for the value function approximating coefficients, $\hat{\lambda}^i$, for the current values of the target parameters, $\hat{\boldsymbol{\theta}}^i$, and use these to calculate $CV_j^i(s_{mt}; \hat{\lambda}^i)$;

2. Use the resulting values for $CV_j^i(s_{mt}; \hat{\lambda}^i)$ to update estimates of the target parameters via two-step GMM, with the GMM estimator $\hat{\boldsymbol{\theta}}^{i+1} = \arg\min_{\boldsymbol{\theta}} \Psi(\boldsymbol{\theta})' W^{-1} \Psi(\boldsymbol{\theta})$, where $\Psi(\boldsymbol{\theta})$ is a vector of stacked quantity-setting and exit probability moments and W is a positive definite approximation to the optimal weight matrix.

3. Calculate the L^1 norm of the difference between the new and starting sets of target parameters and check whether it is below a tolerance level, ϵ; if not, return to step 1.

Go back (est. overview) Go back (FOC)

Estimating entry parameter

- Generate entry value estimate for each potential entrant, $\hat{VE}(s_{mt})$, using
  (a) Spline coefficient estimates $(\hat{\lambda})$ evaluated at production/exit cost parameter estimates $(\hat{\theta})$
  (b) Expected values of s_{jmt} for incumbent on entry, which for deterministic states ξ_{jmt} and h_{jmt} equal their average values

- Recover σ_ω via MLE, where the log-likelihood for entry is

$$\log(f(\chi^e_{jmt}; \sigma_\omega))$$
$$= \sum_{j,m,t} \left[\chi^e_{jmt} \log\left(1 - \exp\left(\frac{-VE_j(s_{mt}; \hat{\lambda})}{\sigma_\omega}\right)\right) - (1 - \chi^e_{jmt}) \left(\frac{VE_j(s_{mt}; \hat{\lambda})}{\sigma_\omega}\right)\right]$$

with $\chi^e_{jmt} = 1$ if potential entrant j enters market m at time t and 0 otherwise

▸ Go back (est. overview)

Estimating $\Omega(s_{jmt})$

- To compute the dynamic markdown, we need to calculate the gradient of the state transition distribution with respect to quantity
- Note that the only state variable(s) directly affected by quantity decisions is experience, which is a direct function of past experience and current quantities, q
- With this assumption, only need the gradient of the probability distribution of experience with respect to quantities for Ω

▸ Go back (FOC)

Estimating $\Omega(s_{jmt})$

- Write the distribution of the relevant state variables as $dG(E_{jmt+1}|E_{jmt}, q_{jmt})$
- Taking the following model of experience accumulation:

$$\tilde{E}(E_{jmt}; \theta^E) = E_{jmt} + \theta_1^E \left(\sum_m \sum_{k \neq j} E_{kmt} \right)$$

- By definition, we know that

$$\frac{\partial}{\partial q_{jmt}} dG(E_{mt+1}|E_{mt}, q_{jmt}) = 1$$

- Which gives the following form for $\Omega(s_{mt})$:

$$\frac{\frac{\partial}{\partial q_{jmt}} dG(E_{mt+1}|E_{mt}, q_{jmt})}{dG(E_{mt+1}|E_{mt}, q_{jmt})} = \frac{1}{E_{jmt} + \theta_1^E \left(\sum_m \sum_{k \neq j} E_{kmt} \right)}$$

▸ Go back (FOC)

Value function approximation

- The ex ante value function is given by

$$\begin{aligned} V(s_{mt}) &\equiv \mathbb{E}_{\phi} V(s_{mt}, \phi_{jmt}) = \mathbb{E}_{\phi}\left[\pi(s_{mt}) + \max\{\phi_{jmt}, CV(s_{mt})\}\right] \\ &= \pi(s_{mt}) + p^x(s_{mt})\mathbb{E}[\phi_{jmt}|\phi_{jmt} > CV(s_{mt})] + (1 - p^x(s_{mt}))CV(s_{mt}) \\ &= \pi(s_{mt}) + p^x(s_{mt})\sigma_{\phi} + CV(s_{mt}) \end{aligned}$$

- Approximate $V(s_{mt})$ using cubic B-splines:

$$V(s_{mt}) = \sum_{b=1}^{B} \lambda_b a(s_{mt})$$

- So for each given value of $\theta = (\theta^E, \gamma, \kappa, \sigma_{\phi})$, solve for:

$$\hat{\lambda} = \arg\min_{\lambda} \left|\left| V(s_{mt}; \lambda) - \pi(s_{mt}; \theta) - \hat{p}^x(s_{mt})\sigma_{\phi} - CV(s_{mt}; \lambda) \right|\right|_2$$

▸ Go back (Est. overview) ▸ Go back (Cost FOC) ▸ Go back (Exit moment) ▸ Estimation algo.

Learning and exit estimates

	(1)		(2)		(3)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Production Cost Parameters						
Base Cost (c_0)	2.145	(0.046)	2.067	(0.064)	2.179	(0.006)
Learning Exponent (γ)	-0.733	(0.083)	-1.098	(0.085)	-0.649	(0.017)
Productivity Serial Correlation (ρ)	0.838	(0.099)			0.979	(0.023)
Experience Parameters						
Industry Experience: Total (θ_1^E)	0.817	(0.059)	0.854	(0.014)	0.760	(0.010)
Forgetting Parameter (δ)					0.954	(0.009)
Exit Parameter						
Mean Scrap Value (σ_ϕ)	2.488	(1.148)	4.585	(0.656)	1.351	(0.267)
N	11,581		11,581		11,581	
Spence Coef. $(1-2^\gamma)$	0.399		0.532		0.362	

S.E. bootstrapped using 200 bootstrap samples clustered by county; scrap value in $100,000s.

‣ Go back (learning curves)

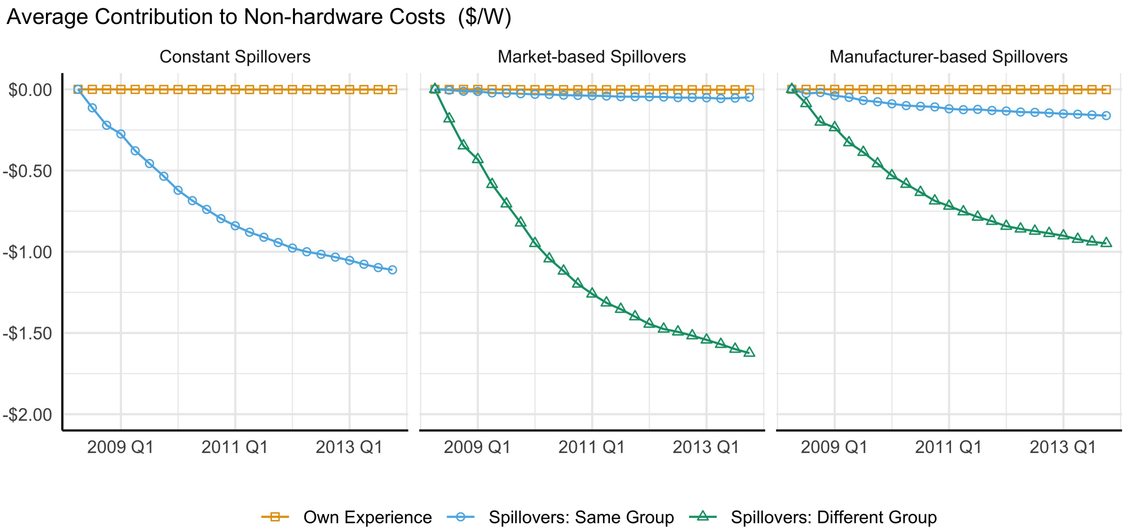
Learning and exit estimates: Alternative Spillovers

	(1)		(2)		(3)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Production Cost Parameters						
Base Cost (c_0)	2.145	(0.046)	2.041	(0.065)	2.006	(0.158)
Learning Exponent (γ)	-0.733	(0.083)	-0.887	(0.098)	-0.731	(0.099)
Productivity Serial Correlation (ρ)	0.838	(0.099)	0.860	(0.271)	0.554	(0.285)
Experience Parameters						
Industry Experience: Total (θ_1^E)	0.817	(0.059)				
Industry Experience: In Market (θ_2^E)			0.747	(0.002)		
Industry Experience: Other Market (θ_3^E)			0.687	(0.043)		
Industry Experience: Same Manuf. (θ_4^E)					0.749	(0.008)
Industry Experience: Other Manuf. (θ_5^E)					0.740	(0.088)
Exit Parameter						
Mean Scrap Value (σ_ϕ)	2.488	(1.148)	3.451	(1.262)	4.550	(1.348)
N	11,581		11,581		11,581	
Spence Coef. ($1-2^\gamma$)	0.399		0.459		0.398	

S.E. bootstrapped using 200 bootstrap samples clustered by county; scrap value in $100,000s.

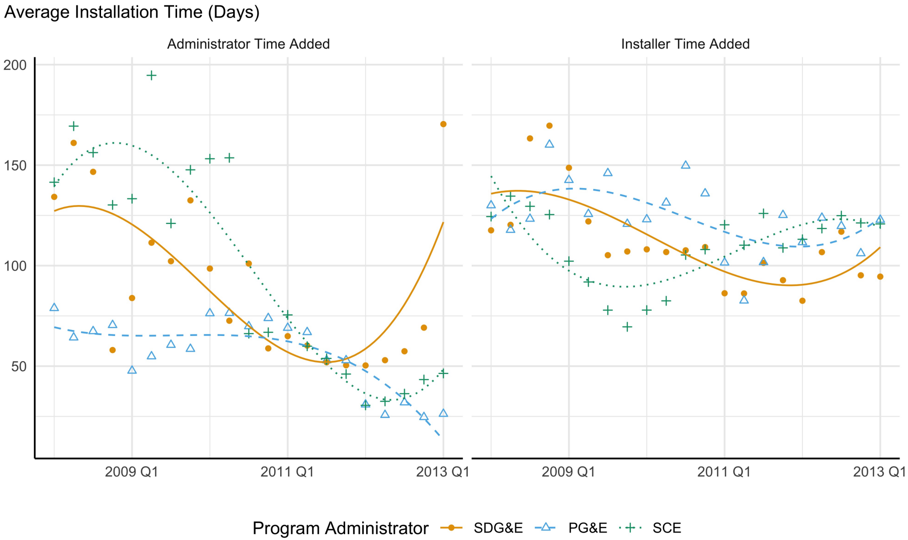
▸ Go back

Cumulative contribution to installation costs



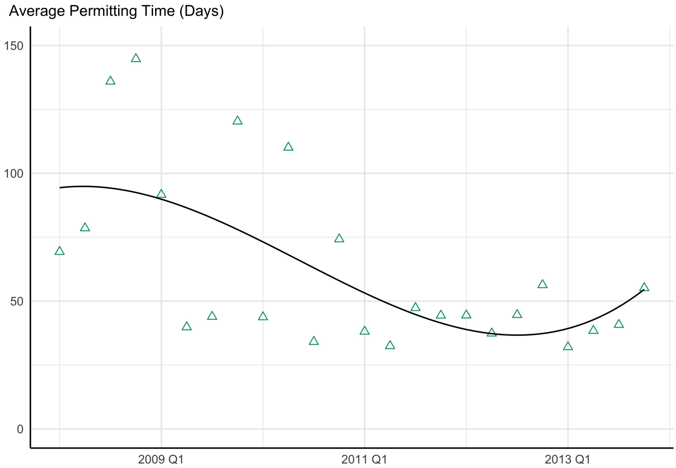
Go back

Possible regulator learning



▸ Go back

Possible regulator learning



‣ Go back

Entry estimates

	Parameter	(1)	(2)	(3)	(4)
Mean Entry Cost	σ_ω	27.286	28.665	34.931	81.240
		(1.628)	(1.696)	(3.153)	(6.687)
Potential Entrant Def.		$2\times\text{median}(\bar{N}_{mt})$	$2\times\text{mean}(\bar{N}_{mt})$	$1\times\max(\bar{N}_{mt})$	$2\times\max(\bar{N}_{mt})$
N		8,763	9,014	10,193	20,386
N^e		311	327	383	766
$\bar{\omega}_{jmt}\|\text{entry}$		9.439	9.514	9.785	10.505

- Following literature (Aguirregabiria et al., 2021), assume number of potential entrants is some function of observed entrants in each market
- External estimates: SolarCity's market capitalization in 2013 Q4 values their county-level operations at $2 million

Go back

Robustness: Alternative discount factors

Annual Discount Factor:	Parameter	$\beta = 0.8$ (1)	$\beta = 0.875$ (2)	$\beta = 0.9$ (3)
Production Cost Parameters				
Base Cost	c_0	2.004	2.145	2.303
Learning Exponent	γ	-0.979	-0.733	-0.426
Productivity Serial Correlation	ρ	0.680	0.838	1.051
Effective Experience				
Industry Experience: Total	θ_1^E	0.993	0.817	0.560
Exit Parameter				
Mean Scrap Value	σ_ϕ	1.383	2.488	4.429
N		11581	11581	11581
Spence Coefficient $(1 - 2^\gamma)$		0.256	0.399	0.493

Scrap value in $100,000s.

▸ Go back

Robustness: Alternative moments

	Parameter	Baseline Moment (1)	Alternative Moments (2)
Production Cost Parameters			
Base Cost	c_0	2.145	2.110
		(0.046)	(0.334)
Learning Exponent	γ	-0.733	-0.734
		(0.083)	(0.138)
Productivity Serial Correlation	ρ	0.838	
		(0.099)	
Common Time Trend	t		0.147
			(0.039)
Effective Experience			
Industry Experience: Total	θ_1^E	0.817	0.505
		(0.059)	(0.119)
Exit Parameter			
Mean Scrap Value	σ_ϕ	2.488	2.208
		(1.148)	(0.373)
N		11,581	18,272
Spence Coefficient $(1-2^\gamma)$		0.399	0.399
Production Cost Moment(s)		$\mathbb{E}[\nu_{jmt}] = 0$	$\mathbb{E}[Z'_{jmt} \cdot \kappa_{jmt}] = 0$

S.E. bootstrapped using 200 bootstrap samples clustered by county; scrap value in \$100,000s.

Go back

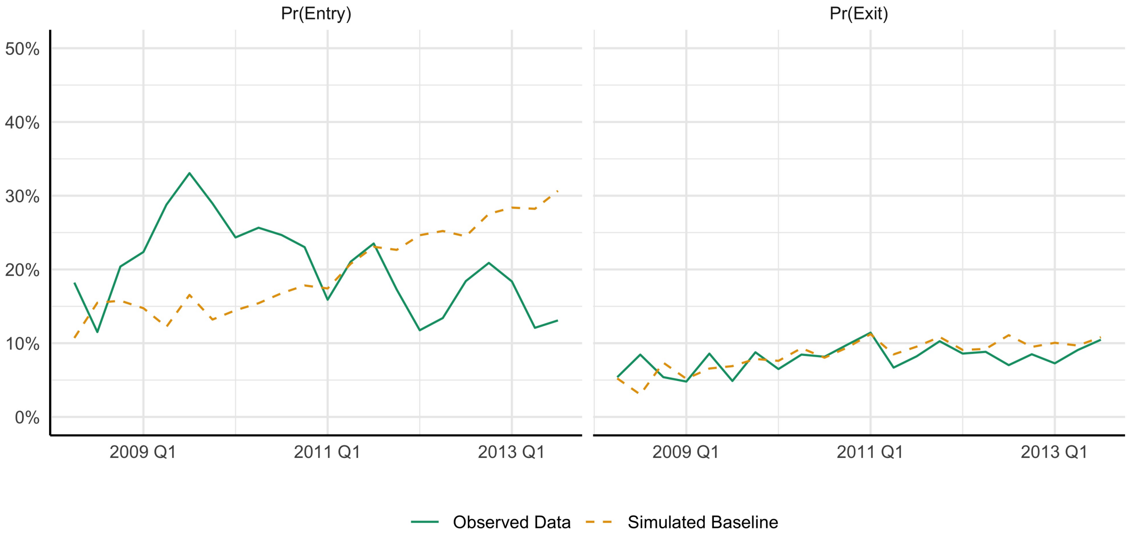
Counterfactual solution method

- Initiate counterfactuals at observed states in first period then solve period-by-period, simulating forward using solved value & policy functions, estimated state transitions

- Solve for λ, policy functions each period via fixed point iteration; for iteration i:
  1. Compute static profits at each state, $\pi_j^i(s_{mt};\hat{\theta}^c)$using equilibrium prices, $p_j^i(s_{mt})$; market shares, $ms_j^i(s_{mt})$; and continuation values, $CV_j^i(s_{mt})$ from the previous fixed point iteration
  2. Solve for the value function approximating coefficients, $\hat{\lambda}^{i+1}$ using
  $$V_j^{i+1}(s_{mt};\lambda^{i+1}) = \pi_j^i(s_{mt};\hat{\theta}^c) + \hat{\sigma}_\phi p_j^{x,i}(s_{mt}) + CV_j^{i+1}(s_{mt};\lambda^{i+1})$$
  where $\pi_j^i(s_{mt};\hat{\theta}^c)$ is from step 1
  3. Update the exit policy function, $p_j^{x,i+1}(s_{mt})$, using $\hat{CV}_j^{i+1}(s_{mt};\hat{\lambda}^{i+1})$ and the closed form solution for firms' exit probabilities
  4. Update equilibrium market shares, $ms_j^{i+1}(s_{mt})$, and prices, $p_j^{i+1}(s_{mt})$, by fixed point iteration using firms' quantity-setting first order condition
  5. Check whether $||p^{x,i+1}(s_{mt}) - p^{x,i}(s_{mt})|| < tol$, where $p^{x,i+1}(s_{mt})$ is the stacked vector of firms' exit policy functions and $tol = 10^{-4}$

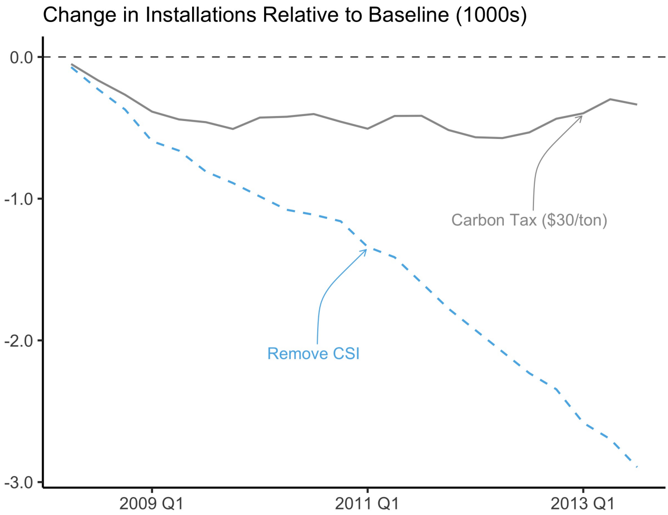
Go back

Baseline model simulation fit



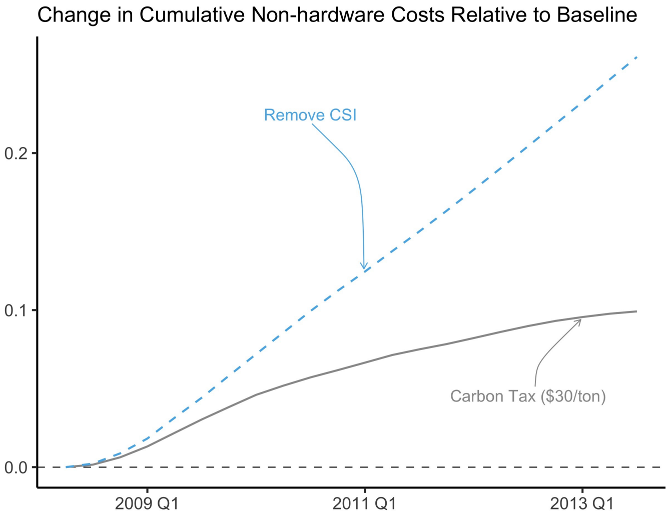
▸ Go back

Finding #3: \$30/ton carbon tax has limited impacts *on solar industry*



- Replace CSI with \$30/ton carbon tax
  - → Fewer installations

Finding #3: $30/ton carbon tax has limited impacts *on solar industry*



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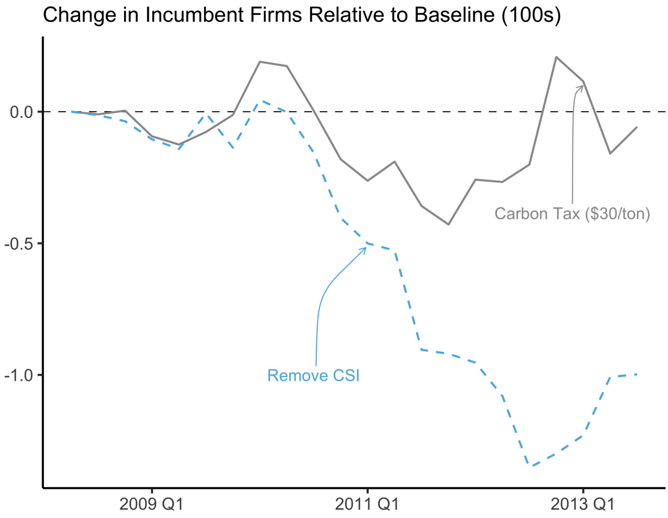

- Replace CSI with \$30/ton carbon tax
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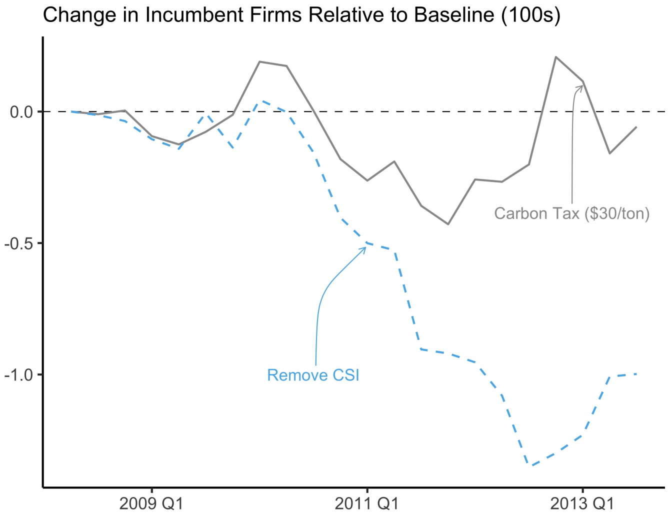
  - → Higher costs
  - → Less net entry

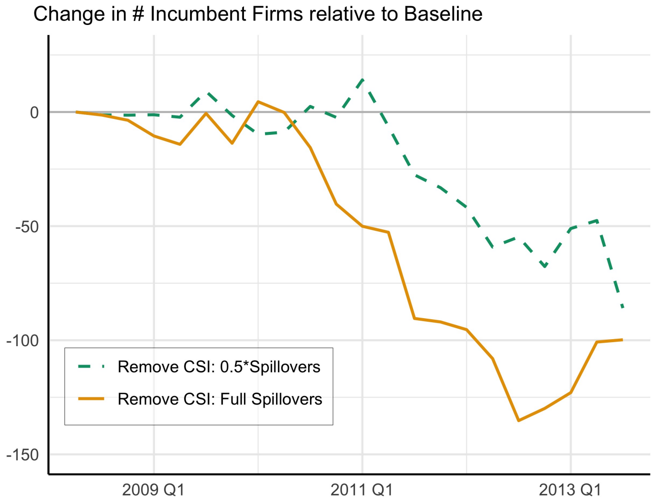
Finding #3: \$30/ton carbon tax has limited impacts *on solar industry*



- Replace CSI with \$30/ton carbon tax
  - → Fewer installations
  - → Higher costs
  - → Less net entry
- Carbon tax yields $<$ welfare
  - Driven by lower learning
  - Note: Other impacts of a tax

▸ Welfare

Qualitative findings are robust to smaller spillovers

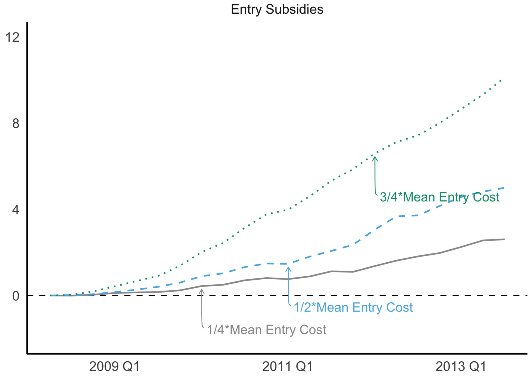


- Re-simulate baseline, no CSI counterfactual with smaller learning spillovers
- Figure shows change in # firms relative to baseline with same spillover size
- Smaller spillovers ⇒ smaller effect of CSI removal

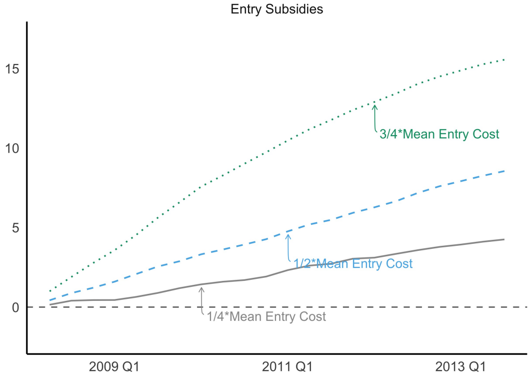
Go back

Entry subsidies induce churn: More exit, much more entry

Change in Cumulative Exits Relative to Baseline (100s)



Change in Cumulative Entrants Relative to Baseline (100s)



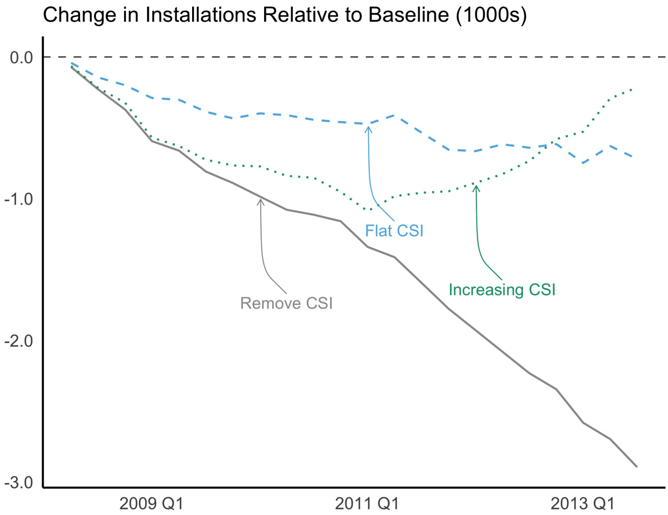
Go back

Counterfactual welfare

	Welfare Components ($M)						
Scenario	ΔCS	ΔEB	ΔRev.	$\Delta Cost_{prod}$	$\Delta\phi$	$\Delta\omega$	ΔTotal ($M)
CSI Counterfactuals:							
Remove CSI	-22.8	-6.6	-20.9	-18.8	-63.3	115.9	-16.6
Flat CSI	-0.7	-1.8	-8.5	-7.7	-39.5	57.6	-0.6
Increasing CSI	-50.0	-1.4	-11.5	-10.8	-28.6	58.1	-44.2
Entry Subsidies:							
1/4*Mean Entry Cost	134.7	1.2	-6.2	-5.7	120.7	-43.9	200.7
1/2*Mean Entry Cost	472.6	7.7	13.4	13.1	247.6	240.3	994.7
3/4*Mean Entry Cost	785.1	17.3	36.4	33.7	508.7	1089.5	2470.7
Alternative Climate Policies:							
Carbon Tax ($30/ton)	-45.1	-1.2	-9.0	-8.3	-8.9	10.4	-62.1
Remove Federal ITC	-2.3	-8.6	-48.3	-44.3	-22.3	21.5	-104.3
10% Federal ITC	-7.0	-6.2	-34.2	-31.1	-18.6	15.3	-77.7
26% Federal ITC	16.9	-2.0	-12.6	-11.2	-12.8	9.0	-12.7

▸ Go back (CSI cf) ▸ Go back (entry subsidy cf) ▸ Go back (carbon tax cf)

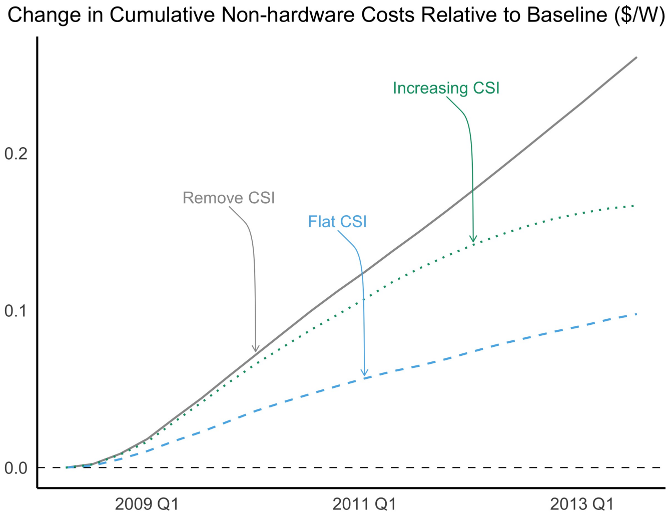
Decreasing CSI dominates alternative consumer rebate designs



- Installer industry contracts when replacing decreasing CSI with increasing or flat CSI
  - → Fewer installations

Go back

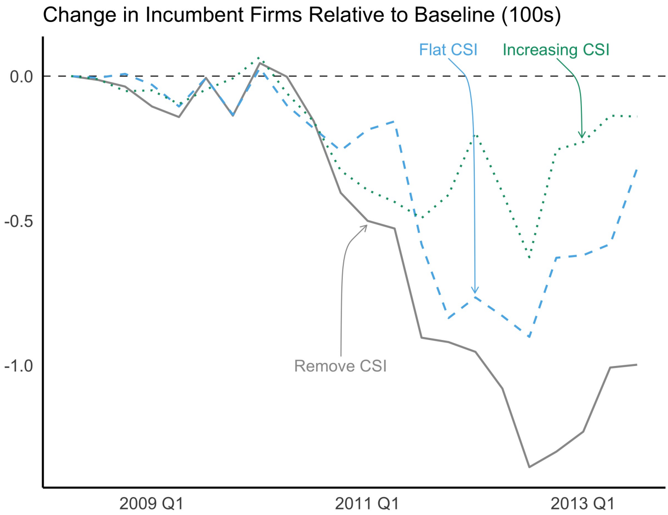
Decreasing CSI dominates alternative consumer rebate designs



- Installer industry contracts when replacing decreasing CSI with increasing or flat CSI
  - → Fewer installations
  - → Higher costs

▸ Go back

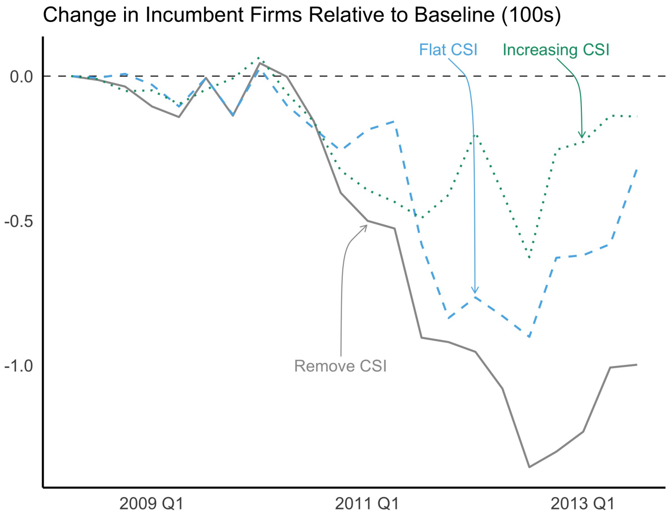
Decreasing CSI dominates alternative consumer rebate designs



- Installer industry contracts when replacing decreasing CSI with increasing or flat CSI
  - → Fewer installations
  - → Higher costs
  - → More exit, less entry

▸ Go back

Decreasing CSI dominates alternative consumer rebate designs



- Installer industry contracts when replacing decreasing CSI with increasing or flat CSI
  - → Fewer installations
  - → Higher costs
  - → More exit, less entry
- Decreasing CSI design leads to highest welfare

▸ Go back ▸ Welfare

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