Complementarities and Optimal Targeting of Technology Subsidies

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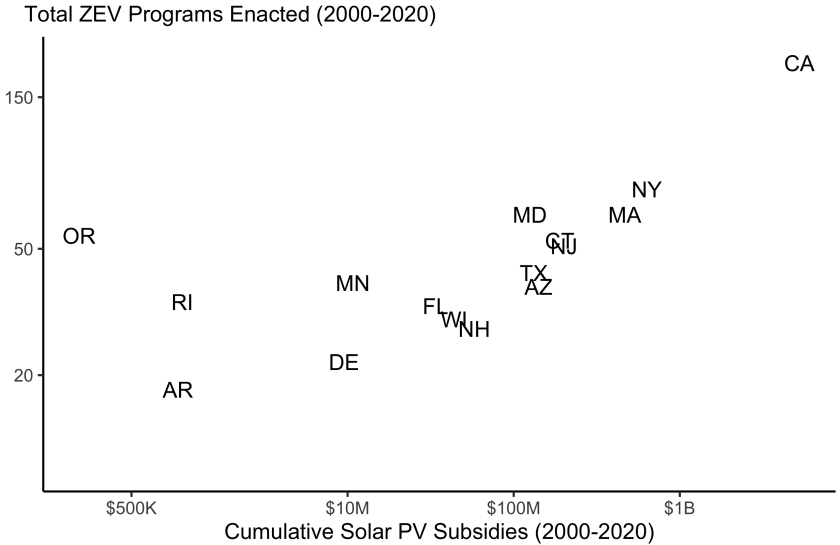
*The views expressed in this presentation are those of the authors and do not necessarily reflect those of the Federal Trade Commission or any individual Commissioner.

Overlap in funding for solar and plug-in electric vehicle (PEV) adoption



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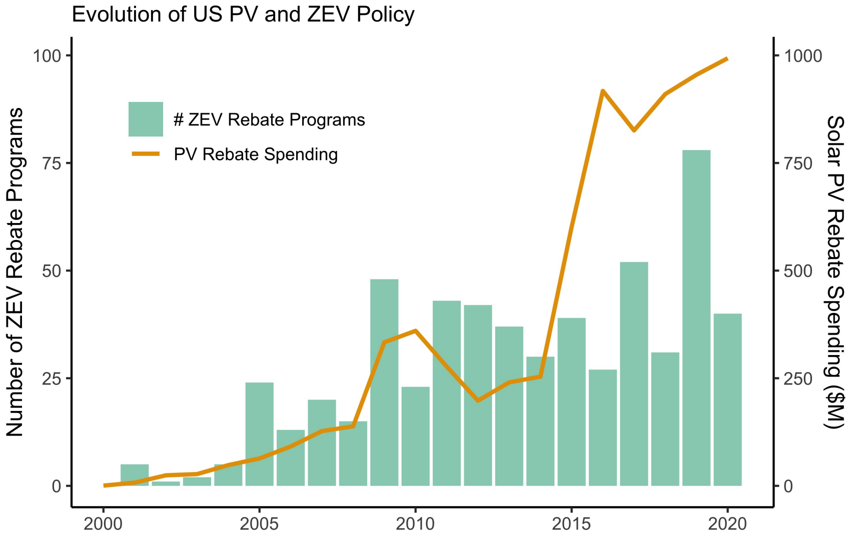

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But what if solar and PEV are complementary goods?

1. Technology complementarity: Low marginal fuel costs
   - Depends on consumption/charging behavior, solar generation
2. Policy complementarity: Net-metering
   - Excess solar generation can reduce marginal electricity costs ("roll back the meter")

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2. Policy complementarity: Net-metering
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3. Correlated preferences:
   - Unobservable preference for "green" goods

Summary

- Research question: What are the implications of complementarities for policy design?
  - $\rightarrow$ What are the efficiency costs of overlapping incentive programs?

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  - Residential solar and EV markets in Connecticut (CT) – *new revealed-preference panel*

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  - Residential solar and EV markets in Connecticut (CT) – *new revealed-preference panel*

- Today:
  1. Develop model of optimal second-best policies with complementary, clean goods
     - $\rightarrow$ Independent Pigouvian subsidies are sub-optimal
  2. CA structural evidence of complementarity in PV $\times$ PEV adoption
  3. Likely welfare losses from observed overlapping policy regime in CA
  4. New: CT revealed-preference panel validates direction; identification roadmap

Related literature

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- Economics of clean technologies and solar/PEV subsidies
  - Borenstein, 2017; De Groote and Verboven, 2019; Gillingham and Tsvetanov, 2019; Lyu, 2023; Muehlegger and Rapson, 2022; Muehlegger and Rapson, 2023; Heid et al., 2026 ...

Outline

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- Develop stylized model to demonstrate the implications of cross-technology complementarity for optimal (constrained) policy
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    1. Policymaker needs to know the full substitution matrix to reach second-best
    2. $\uparrow$ complementarity, $\downarrow$ optimal constrained policy
    3. Place greater subsidy on the technology with greatest substitutability

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- Generalizes to other settings with overlapping subsidies for complementary goods

Model setup

- N identical households consume a numeraire and four goods:

$$x_1 = \text{low-emissions electricity} \qquad x_2 = \text{high-emissions electricity}$$
$$y_1 = \text{low-emissions transportation} \qquad y_2 = \text{high-emissions transportation}$$

- Households face prices $\boldsymbol{p} = (p_1^x, p_2^x, p_1^y, p_2^y, 1)$

HH problem

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- Assume x_1 is a substitute for x_2 and y_1 is a substitute y_2, i.e.

$$\frac{\partial x_1}{\partial p_2^x} > 0 \qquad \frac{\partial x_2}{\partial p_1^x} > 0 \qquad \frac{\partial y_1}{\partial p_2^y} > 0 \qquad \frac{\partial y_2}{\partial p_1^y} > 0$$

▸ HH problem

Social planner's problem

- Social planner chooses per-unit taxes or subsidies, $\boldsymbol{\tau} = (\tau_1^x, \tau_2^x, \tau_1^y, \tau_2^y)$ to maximize utility, accounting for externalities

- First-best policy: With no constraints on $\boldsymbol{\tau}$, the following portfolio is first-best

$$\tau_1^{x*} = 0 \qquad \tau_2^{x*} = e_x N \qquad \tau_1^{y*} = 0 \qquad \tau_2^{y*} = e_y N$$

  - Standard Pigouvian taxation result
  - Tinbergen independence still holds

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- But what if we constrain $\tau_2^x = \tau_2^y = 0$?
  $\rightarrow$ Could arise due to political constraints on direct Pigouvian taxation

▸ Planner's FOC

Takeaway #1: Policymaker needs to know full substitution matrix

- Naive constrained policy: If government ignores potential interactions between electricity and transportation, will set the following subsidies

$$\tilde{\tau}_1^x = e_x N \left(\frac{\partial x_2}{\partial p_1^x}\right)\left(\frac{\partial x_1}{\partial p_1^x}\right)^{-1} \qquad \tilde{\tau}_1^y = e_y N \left(\frac{\partial y_2}{\partial p_1^y}\right)\left(\frac{\partial y_1}{\partial p_1^y}\right)^{-1}$$

▸ Naive policy

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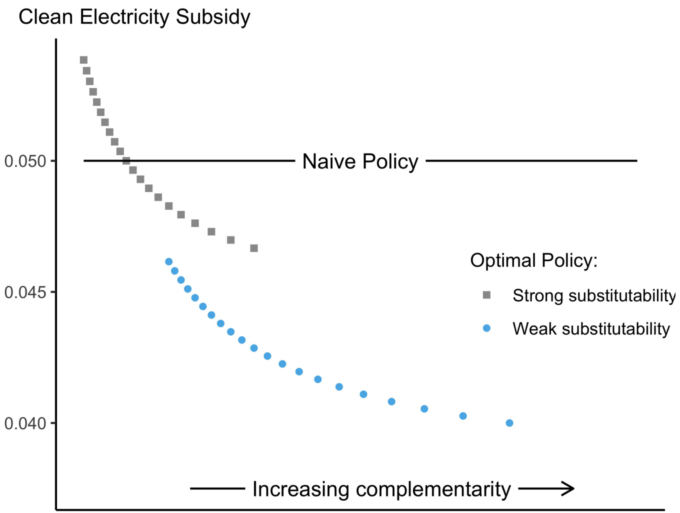
- Second-best policy: If government considers potential interactions between electricity and transportation, will set the following subsidies

$$\bar{\tau}_1^x = \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial x_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right)$$

$$\bar{\tau}_1^y = \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x} - \frac{\partial x_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x} - \frac{\partial y_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right)$$

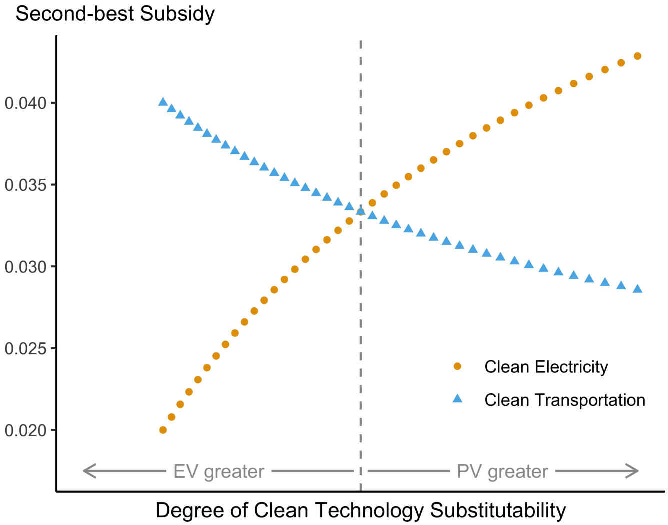
▸ Naive policy ▸ Second-best

Takeaway #2: ↑ complementarity, ↓ optimal constrained policy



- Green electricity and transportation are complements
- Optimal > naive policy when:
  - Strong within-technology substitution
  - Weak cross-technology complementarity

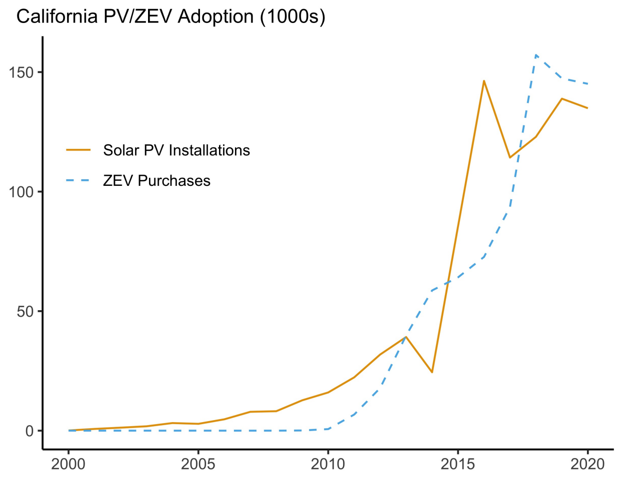
Takeaway #3: Emphasize technology with greatest impact



- Green electricity and transportation are complements
- Result depends on both
  - Direct substitution
  - Effect of cross-technology complementarity

Outline

Setting: solar and EV adoption in California

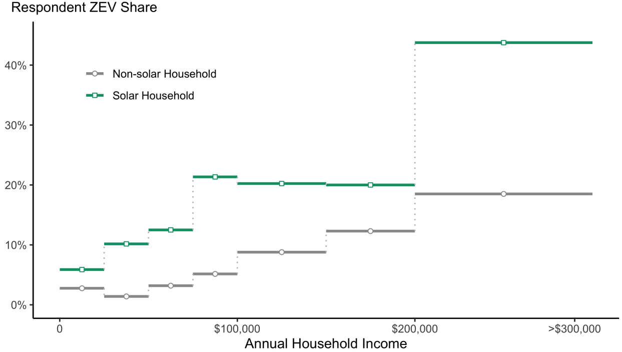


- CA: largest US market for residential PV and EVs
- Overlapping state subsidies:
  - PV: California Solar Initiative (2007–2013)
  - EV: Clean Vehicle Rebate Project (2009–2023)

Sources: LBNL, CA Energy Commission

▸ Income gradient

Headline: ZEV adoption is 4× higher among PV households



Source: California Energy Commission, CA Vehicle Survey

- But adoption-level correlation:
  1. Does *not* define complementarity
  2. Is *not* a sufficient statistic for welfare

- Need to recover **cross-price elasticities**
  → Estimate Gentzkow, 2007 bundle-choice model with complementarity

▸ Stocks & flows ▸ Alt: 2SLS

Model of co-adoption with complementarity

- Static discrete bundle choice (Gentzkow 2007). Indirect utility from bundle b:

$$u_{ib} = \sum_{j \in b} \underbrace{\alpha(p_j - r_j) + \theta' X_{ij} + \xi_j}_{\bar{u}_{ij}} + \Gamma_b + \varepsilon_{ib}$$

- Γ_b: bundle-specific complementarity term ($\Gamma_b = 0$ if $|b| = 1$)

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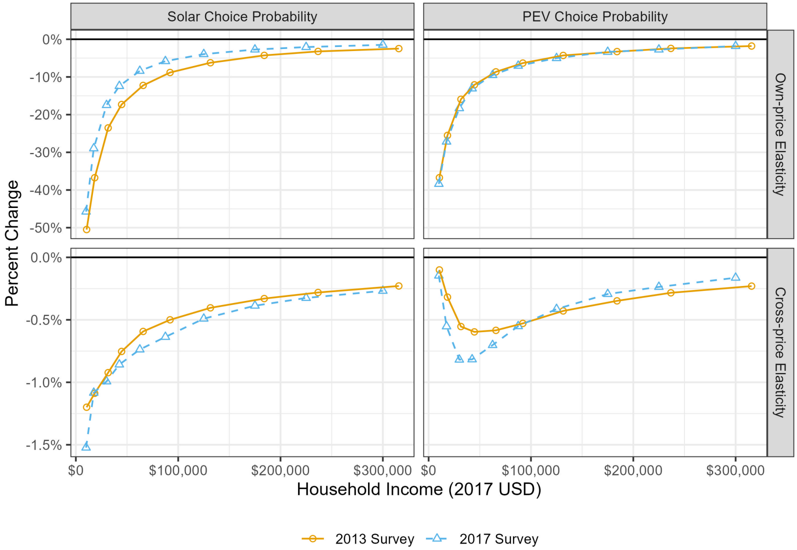
- Γ_b: bundle-specific complementarity term ($\Gamma_b = 0$ if $|b| = 1$)
- Identification:
  - α from experimental price/rebate variation in conjoint + PV-rebate variation
  - Γ_b from "one-shifters" that move utility of only one technology
    - HOV-lane access (ZEV-only)
    - Solar irradiance (PV-only)

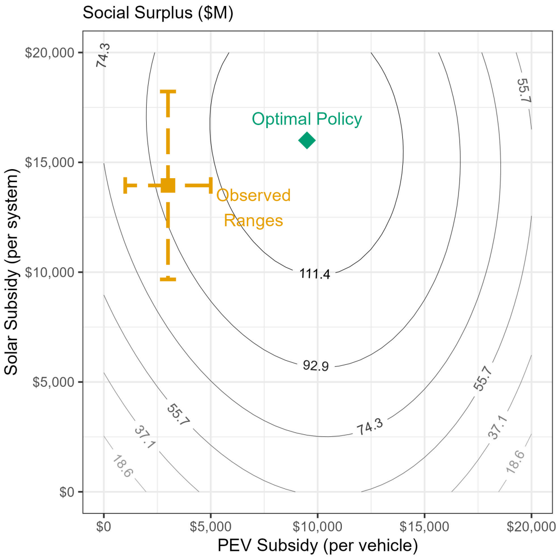
▸ Full estimates

Result: $\widehat{\Gamma} > 0$ and positive cross-price elasticities



▸ Full estimates

Ignoring complementarity leads to possible welfare loss



- Optimal (max Δ social surplus): **PEV $9K, Solar $16.5K**
- Observed CA subsidies less than the optimum on *both* axes $\Rightarrow$ welfare loss from ignoring Γ
- Validates theory takeaways #2 & #3
- Note: "Optimum" is

Outline

New: revealed-preference panel from Connecticut

SOLAR PV

CT state solar program

2005–2022

42,037

residential installations

VEHICLES

CT town property-tax records

2020–2024

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- Over 2020–2021: **1,277** households adopted both technologies

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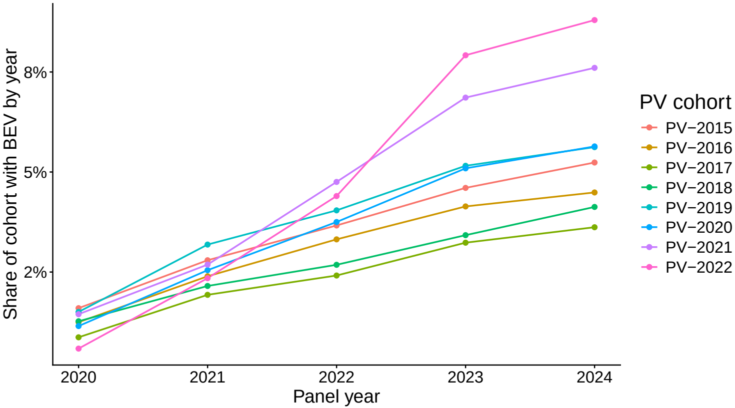
- Address-level merge ⇒ **798K-address panel**
- Over 2020–2021: **1,277** households adopted both technologies
- Additional data:
  - CoreLogic: CT solar building permits
  - DataAxle, L2: Household-level demographics

▸ Match details ▸ Panel composition

CT Fact 1: PV adopters are 3.2× more likely to have a BEV



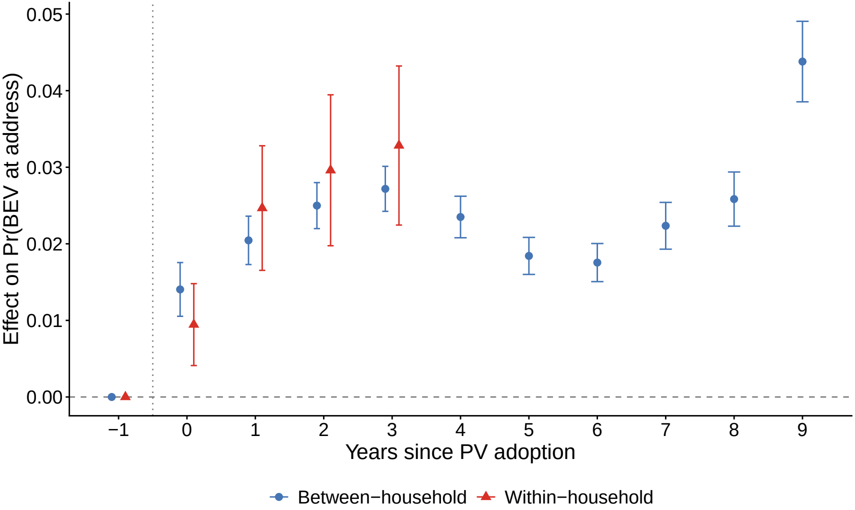
Unconditional rates:

- PV adopters: **5.92%** BEV
- Never-PV: **1.85%** BEV
- Ratio: **3.20**×

BEV co-adoption is accelerating:

- PV-2015 by year 9: 5.2%
- PV-2020 by year 4: 5.6%

CT Fact 2: PV adoption raises BEV adoption



- Also observe income gradient: 5× larger in top vs. bottom quartile ▸ Heterogeneity details

What the CT panel buys us: A dynamic Γ

- **Adoption is sequential, with very different durables.**
  - PV ($\sim$25-yr, near-irreversible) and EVs ($\sim$10-yr, more reversible) face different option values
  - $\rightarrow$ The *order* of adoption shapes the cross-elasticity

- **Welfare counterfactuals are inherently dynamic.**
  - E.g., "Phase out net-metering faster?" "Front-load EV credits?"
  - $\rightarrow$ Answering these requires modeling how anticipated subsidy paths shape adoption *timing*, not just whether to adopt.

- **Joint adoption is endogenously timed.**
  - Static Γ pools "intended both from day 1" with "PV today induces EV next year"
  - $\rightarrow$ These imply very different counterfactual responses to subsidy reform

Outline

Dynamic co-adoption model

- Household i chooses adoption sequence over $t = 1, \ldots, T$
  - state $s_{it} \in \{(0,0), (\text{PV},0), (0,\text{EV}), (\text{PV},\text{EV})\}$
  - Each period choose $a_{it} \in \{\text{wait, add PV, add EV, add both}\}$; PV and EV are absorbing

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- Flow utility from state s:

$$\pi_i(s_{it}; a) = \sum_{j \in s_{it}} \left[\alpha(p_{jt} - r_{jt}) + \theta' X_{it} + \xi_j\right] + \Gamma \cdot \mathbf{1}[s_{it} = (PV, EV)] + \varepsilon_{ia}$$

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- Bellman: $V_t(s_{it}) = \max_a \left\{\pi_i(s_{it}; a) + \beta\, \mathbb{E}\left[V_{t+1}(s_{i,t+1}) \mid s_{it}, a\right]\right\}$

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- **Targets:**
  - Γ: bundle complementarity, now *dynamic* (forward-looking adopters)
  - θ: rich household heterogeneity (income, urbanicity, etc.)
  - Recovers welfare counterfactuals over the entire CT subsidy regime

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- **Estimator:** ECCP / KSS (Kalouptsidi-Scott-Souza-Rodrigues) – linear IV regression on the ECCP equation; finite dependence eliminates continuation values

Identification: ECCP moments for (α, θ, Γ)

ECCP regression (KSS 2020): finite dependence in the $\{$none, PV, EV, both$\}$ state space eliminates continuation values; no dynamic program solution required.

- α **(prices):** CCP response to RSIP step-downs + CHEAPR + federal credit changes; lagged prices instrument unobserved demand shocks
- θ **(heterogeneity):** ACS cousub demographics in X (income, urbanicity, housing stock)
- Γ **(complementarity, dynamic Gentzkow):** residual co-movement of PV & EV adoption, conditional on roof visibility + Sunroof potential as PV-only shifters in X
  - Cleanest for PV $\rightarrow$ EV; EV $\rightarrow$ PV awaits longer post-2021 PV coverage

Joint observability window: 2020–2021 ($\sim$1,277 joint adopters); exploring CT building-permit data to extend PV coverage through 2024.

Outline

A Model of Optimal Second Best Subsidies

Evidence from California

New Evidence from Connecticut

Where We're Going

Wrap-up

Wrap-up

- **Today:**
  - Theory: optimal subsidy design depends on the full substitution matrix
  - CA: $\widehat{\Gamma} > 0$; observed subsidies over-subsidize both technologies
  - CT: $\sim$3pp PV $\rightarrow$ BEV effect; observe adoption timing; steep income gradient
- **Next:**
  - Identification: visibility + Sunroof as PV-only one-shifters?
  - Estimator: ECCP/KSS vs. MSM / Hotz-Miller / NFXP?
  - Counterfactuals: joint vs. separate subsidy design? NEM reform? Distributional impacts?

Thank you!

Backup Slides

CT match: tiered approach (full table)

Tier	**Method**	***N* matched**
1	Exact match on composite key (zip5, street #, street name, unit) after USPS suffix normalization	34,621
1b	Same key dropping unit, for multi-unit buildings	667
2	Within-ZIP Jaro-Winkler on full address ≥ 0.93; drop ties within 0.01 of best	2,496
3	Census-geocoded coordinates within 50m haversine; drop if multiple vehicles within 25m	485
4	100m radius using RSIP install lat/lon, for PV mailing-vs-physical mismatches (PO-box, dense-urban ZIPs)	330
5	250m spatial radius (town-restricted), select via Jaro-Winkler between RSIP *Host Customer* and vehicle *taxpayer* names (≥ 0.85, ≥ 0.05 above runner-up)	816
Total		**39,415 / 42,037 (93.8%)**

Coverage steps: Tiers 1–3 alone deliver 89.49%. `list_town` ZIP-blank recovery for 2023+ registrations adds ∼215K vehicle addresses; Tiers 4–5 cover the residual to a final **91.34%** of distinct PV addresses with a confidence-weighted match.

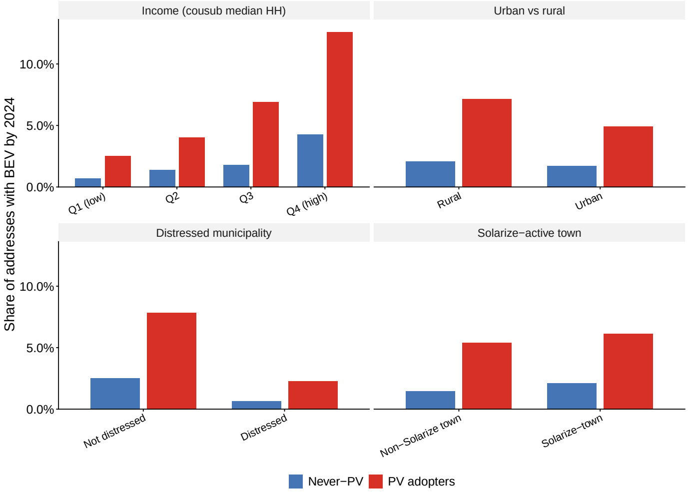
Panel composition and sample restrictions

Filter	N addresses
Universe (any vehicle reg., 2020–2024)	1,740,970
In CT, single-match	1,310,245
$\geq$ 3 years observed in vehicle panel	967,812
$\leq$ 8 vehicles per year (excludes fleets)	798,144
`sample_primary`	**798,144**
PV adopters (ever 2005–2022)	26,236
BEV adopters (ever 2020–2024)	15,812
Joint adopters (ever both)	2,265
Joint adopters in clean window (EV 2020–2021)	1,277

169 CT towns, 8 counties, 5 panel years (2020–2024). PV-side history extends to 2005, used for cohort identification and RSIP-side calibration in the structural model.

Go back

CT heterogeneity: steep income gradient



Per-stratum coefficient:

- Q1 (\$66K): 1.84pp
- Q2 (\$85K): 2.74pp
- Q3 (\$98K): 5.31pp
- Q4 (\$123K): **9.08pp**

Other dimensions:

- Rural > urban (+56%)
- Distressed muni: 3.6× smaller

→ *Disciplines preference heterogeneity in the dynamic model and drives distributional welfare counterfactuals.*

Go back

Toy model: Household's problem

- The representative household maximizes:

$$U = u(x_1, x_2, y_1, y_2) - N[e_x x_2 + e_y y_2] + \mu$$

where $u(\cdot)$ is a concave, C^2 function; subject to the following budget constraint:

$$(p_1^x + \tau_1^x)x_1 + (p_2^x + \tau_2^x)x_2 + (p_1^y + \tau_1^y)y_1 + (p_2^y + \tau_2^y)y_2 + \mu = m$$

- Assume that N is sufficiently large such that households do not internalize their impact on aggregate consumption of the dirty goods:

$$x_1\left(\frac{\partial u}{\partial x_1} - p_1^x - \tau_1^x\right) = 0 \qquad x_2\left(\frac{\partial u}{\partial x_2} - p_2^x - \tau_2^x\right) = 0$$

$$y_1\left(\frac{\partial u}{\partial y_1} - p_1^y - \tau_1^y\right) = 0 \qquad y_2\left(\frac{\partial u}{\partial y_2} - p_2^y - \tau_2^y\right) = 0$$

- FOCs imply demand functions:

$$x_1 = x_1(\boldsymbol{p}, \boldsymbol{\tau}) \qquad x_2 = x_2(\boldsymbol{p}, \boldsymbol{\tau}) \qquad y_1 = y_1(\boldsymbol{p}, \boldsymbol{\tau}) \qquad y_2 = y_2(\boldsymbol{p}, \boldsymbol{\tau})$$

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Toy model: Social planner's problem

- Government chooses a portfolio of per-unit taxes or subsidies, $\boldsymbol{\tau} = (\tau_1^x, \tau_2^x, \tau_1^y, \tau_2^y) \in \mathbb{R}^4$, with tax revenues: $N[x_1\tau_1^x + x_2\tau_2^x + y_1\tau_1^y + y_2\tau_2^y]$

- Assuming lump-sum revenue recycling, government problem is

$$\begin{aligned} W(\boldsymbol{\tau}) = u(x_1, x_2, y_1, y_2) &- N[e_x x_2 + e_y y_2] + m \\ &- (p_1^x + \tau_1^x)x_1 - (p_2^x + \tau_2^x)x_2 - (p_1^y + \tau_1^y)y_1 \\ &- (p_2^y + \tau_2^y)y_2 + \tau_1^x x_1 + \tau_2^x x_2 + \tau_1^y y_1 + \tau_2^y y_2 \end{aligned}$$

- Government's FOC:

$$\underbrace{\begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & \frac{\partial x_2}{\partial p_1^x} & \frac{\partial y_1}{\partial p_1^x} & \frac{\partial y_2}{\partial p_1^x} \\ \frac{\partial x_1}{\partial p_2^x} & \frac{\partial x_2}{\partial p_2^x} & \frac{\partial y_1}{\partial p_2^x} & \frac{\partial y_2}{\partial p_2^x} \\ \frac{\partial x_1}{\partial p_1^y} & \frac{\partial x_2}{\partial p_1^y} & \frac{\partial y_1}{\partial p_1^y} & \frac{\partial y_2}{\partial p_1^y} \\ \frac{\partial x_1}{\partial p_2^y} & \frac{\partial x_2}{\partial p_2^y} & \frac{\partial y_1}{\partial p_2^y} & \frac{\partial y_2}{\partial p_2^y} \end{bmatrix}}_{\equiv \Omega} \begin{bmatrix} \tau_1^x \\ \tau_2^x \\ \tau_1^y \\ \tau_2^y \end{bmatrix} = e_x N \begin{bmatrix} \frac{\partial x_2}{\partial p_1^x} \\ \frac{\partial x_2}{\partial p_2^x} \\ \frac{\partial x_2}{\partial p_1^y} \\ \frac{\partial x_2}{\partial p_2^y} \end{bmatrix} + e_y N \begin{bmatrix} \frac{\partial y_2}{\partial p_1^x} \\ \frac{\partial y_2}{\partial p_2^x} \\ \frac{\partial y_2}{\partial p_1^y} \\ \frac{\partial y_2}{\partial p_2^y} \end{bmatrix}$$

Toy model: "Naive" constrained policy

- Naive constrained policy: Government sets policy ignoring all interactions between the electricity and transportation goods

- In this case, the government's problem becomes

$$\begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & 0 \\ 0 & \frac{\partial y_1}{\partial p_1^y} \end{bmatrix} \begin{bmatrix} \tau_1^x \\ \tau_1^y \end{bmatrix} = e_x N \begin{bmatrix} \frac{\partial x_2}{\partial p_1^x} \\ 0 \end{bmatrix} + e_y N \begin{bmatrix} 0 \\ \frac{\partial y_2}{\partial p_1^y} \end{bmatrix}$$

- The government sets the following policies:

$$\tilde{\tau}_1^x = e_x N \left(\frac{\partial x_2}{\partial p_1^x} \right) \left(\frac{\partial x_1}{\partial p_1^x} \right)^{-1} \qquad \tilde{\tau}_1^y = e_y N \left(\frac{\partial y_2}{\partial p_1^y} \right) \left(\frac{\partial y_1}{\partial p_1^y} \right)^{-1}$$

Go back

Toy model: Second-best policy

- Second-best policy: Government sets policy accounting for all interactions between the electricity and transportation goods

- In this case, the government's problem becomes

$$\underbrace{\begin{bmatrix} \frac{\partial x_1}{\partial p_1^x} & \frac{\partial y_1}{\partial p_1^x} \\ \frac{\partial x_1}{\partial p_1^y} & \frac{\partial y_1}{\partial p_1^y} \end{bmatrix}}_{\equiv \tilde{\Omega}} \begin{bmatrix} \tau_1^x \\ \tau_1^y \end{bmatrix} = e_x N \begin{bmatrix} \frac{\partial x_2}{\partial p_1^x} \\ \frac{\partial x_2}{\partial p_1^y} \end{bmatrix} + e_y N \begin{bmatrix} \frac{\partial y_2}{\partial p_1^x} \\ \frac{\partial y_2}{\partial p_1^y} \end{bmatrix}$$

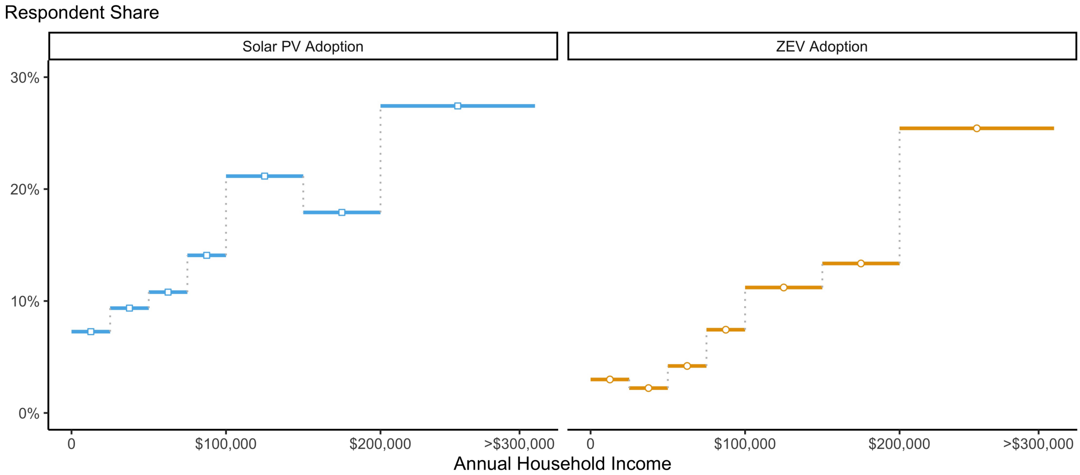
- The government sets the following policies:

$$\bar{\tau}_1^x = \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial x_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^x}\frac{\partial y_1}{\partial p_1^y} - \frac{\partial y_2}{\partial p_1^y}\frac{\partial y_1}{\partial p_1^x}\right)$$

$$\bar{\tau}_1^y = \frac{e_x N}{|\tilde{\Omega}|}\left(\frac{\partial x_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x} - \frac{\partial x_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right) + \frac{e_y N}{|\tilde{\Omega}|}\left(\frac{\partial y_2}{\partial p_1^y}\frac{\partial x_1}{\partial p_1^x} - \frac{\partial y_2}{\partial p_1^x}\frac{\partial x_1}{\partial p_1^y}\right)$$

▸ Go back

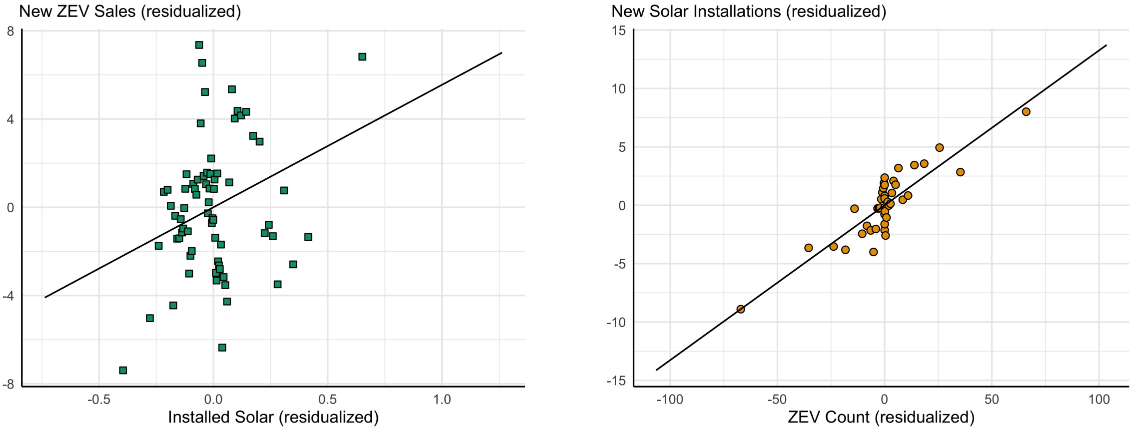
CA Fact #1: Adoption rises with income



Source: California Energy Commission, CA Vehicle Survey

Go back

CA Fact #3: Stocks and flows are correlated



▸ Go back ▸ 2SLS framework

CA: descriptive 2SLS on stocks vs. flows

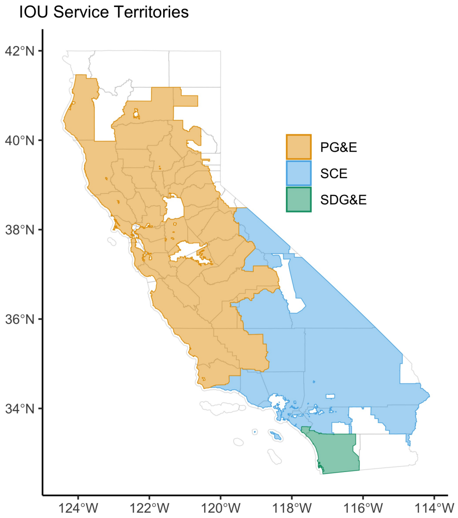
- Goal: Estimate likelihood of adopting one technology conditional on adopting the other
  - → Empirical challenge: unobservable factors affecting *both* PV and EV adoption
- Solution: Instrument adoption with relevant policy variation
  - PV: Spatial and temporal variation in solar rebates
  - ZEV: Temporal variation in EV rebate program × proximity to HOV lanes
- Estimate the following via two-stage least squares for ZCTA z in year t:

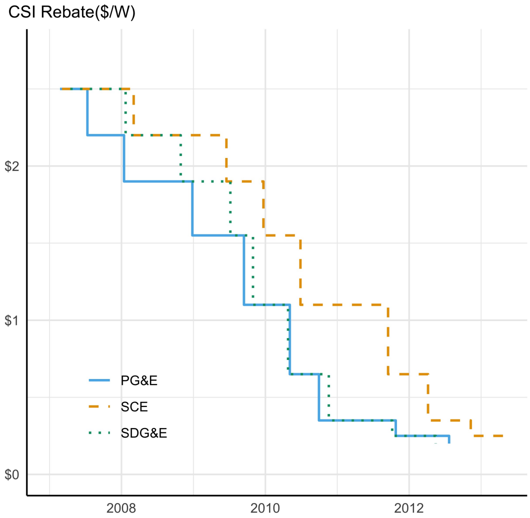
$$\Delta q^{EV}_{zt} = \alpha_1\, q^{PV}_{z,t-1} + \gamma_{c(z)t} + \lambda_z + \varepsilon_{zt}$$
$$\Delta q^{PV}_{zt} = \alpha_2\, q^{EV}_{z,t-1} + \eta_{c(z)t} + \mu_z + \epsilon_{zt}$$

  - $\gamma_{c(z)t}, \eta_{c(z)t}$ are county-by-year FE; λ_z, μ_z are ZCTA FE

▸ PV variation ▸ EV variation ▸ PV results ▸ EV results ▸ Go back

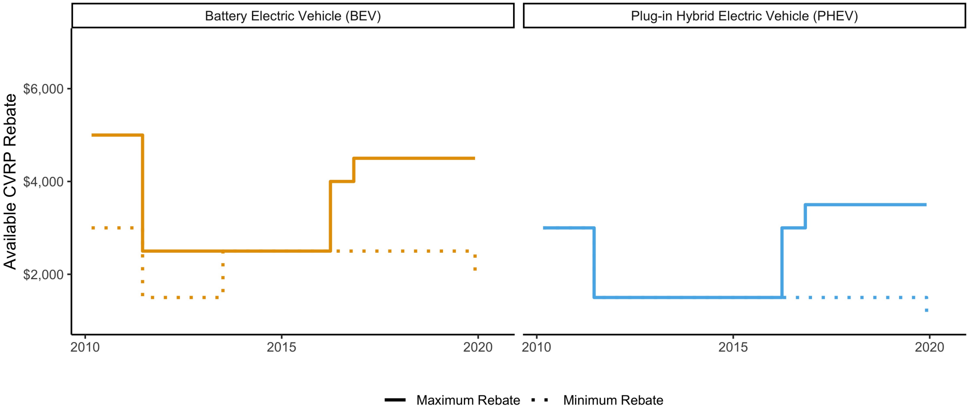
CA: PV policy variation (CSI step-down rebates)





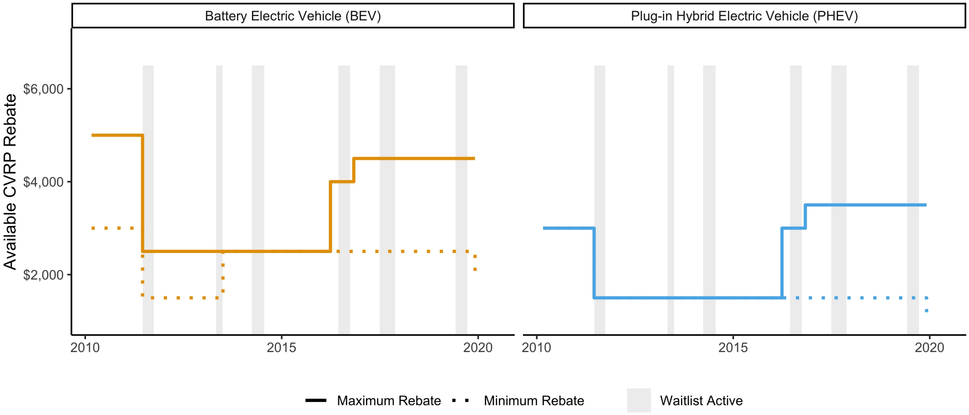
▸ Go back

CA: EV policy variation (CVRP rebates)



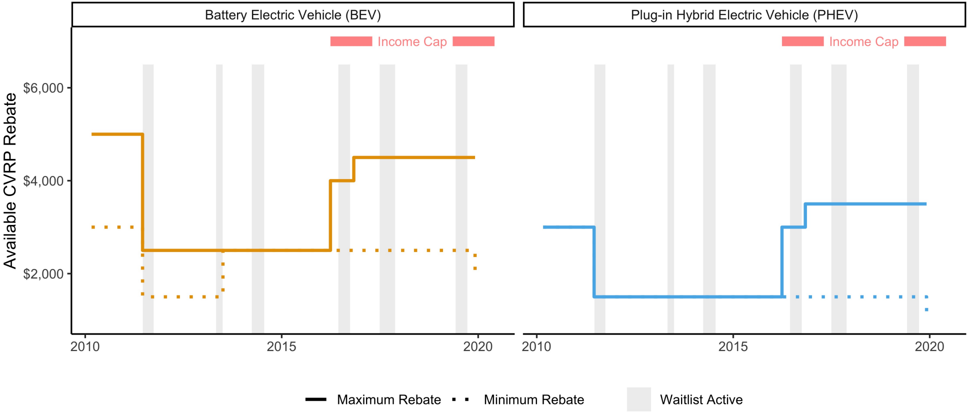
▸ Go back

CA: EV policy variation (CVRP rebates)



Go back

CA: EV policy variation (CVRP rebates)



▸ Go back

CA full results: PV adoption

	First Stage: ZEV Count (1)	Second Stage: PV Installations (2)
CVRP Waitlist Length × HOV Miles	-0.080 (0.009)	
CVRP Income Cap × HOV Miles	36.7 (3.99)	
Max CVRP Rebate × HOV Miles	-0.004 (0.0005)	
Gas Price × HOV Miles	-2.15 (0.378)	
ZEV Count		0.133 (0.019)
Observations	46,464	46,464
F-test (IV only)	177.45	86.374
ZCTA fixed effects	✓	✓
County-Year fixed effects	✓	✓

▸ Go back

CA full results: EV adoption

	First Stage: Installed Solar (1)	Second Stage: ZEV Sales (2)
$(\text{CSI Rebate})_t$	-21.4 (4.14)	
$(\text{CSI Rebate})_{t-1}$	-33.1 (3.25)	
$(\text{CSI Rebate})_t \times \log(\text{GHI})$	2.93 (0.553)	
$(\text{CSI Rebate})_{t-1} \times \log(\text{GHI})$	4.48 (0.435)	
Installed Solar		5.55 (2.20)
Observations	46,464	46,464
F-test (IV only)	58.444	22.564
ZCTA fixed effects	✓	✓
County-Year fixed effects	✓	✓

▸ Go back

CA Gentzkow model: full estimates

	Estimate (SE)		Estimate (SE)
Common Parameters		**Vehicle Attributes**	
(Price – Subsidy) / Income	-1.904 (0.033)	Acceleration Rate	-0.060 (0.002)
Complementarity Term (Γ)	0.771 (0.030)	Fueling Time	-0.139 (0.004)
		Fuel Cost/Mile	-0.047 (0.015)
Solar PV Attributes		Miles/Gallon	0.391 (0.018)
$\mathbb{1}\{\text{Solar PV}\}$	-6.374 (0.404)	Range	0.533 (0.012)
Solar Radiation	0.058 (0.018)	Trunk Space	0.198 (0.013)
Module Efficiency	0.205 (0.012)	Vehicle Age	-0.037 (0.004)
		$\mathbb{1}\{\text{Small Car}\}$	-0.157 (0.015)
Income Interactions		$\mathbb{1}\{\text{SUV}\}$	-0.039 (0.022)
Income $\times$ $\mathbb{1}\{\text{PEV}\}$	0.028 (0.002)	$\mathbb{1}\{\text{Truck}\}$	-0.692 (0.024)
Income $\times$ $\mathbb{1}\{\text{Solar PV}\}$	0.015 (0.002)	$\mathbb{1}\{\text{Van}\}$	-1.280 (0.036)
		$\mathbb{1}\{\text{PEV}\}$	-0.213 (0.032)
		$\mathbb{1}\{\text{Hybrid}\}$	0.130 (0.014)
Log Likelihood		$-85\,665.49$	
Individuals		6754	
Choices		54 032	

Go back

CA Gentzkow model: full estimates

	Estimate (SE)		Estimate (SE)
Common Parameters		**Vehicle Attributes**	
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References I

Bollinger, B., Darghouth, N., Gillingham, K., & Gonzalez-Lira, A. (2023, December). Valuing Technology Complementarities: Rooftop Solar and Energy Storage.

Borenstein, S. (2017).Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates. *Journal of the Association of Environmental and Resource Economists*, *4*(S1), S85–S122.

Crawford, G. S., Lee, R. S., Whinston, M. D., & Yurukoglu, A. (2018).The Welfare Effects of Vertical Integration in Multichannel Television Markets. *Econometrica*, *86*(3), 891–954.

Crawford, G. S., & Yurukoglu, A. (2012).The Welfare Effects of Bundling in Multichannel Television Markets. *American Economic Review*, *102*(2), 643–685.

De Groote, O., & Verboven, F. (2019).Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems. *American Economic Review*, *109*(6), 2137–2172.

Dubé, J.-P. (2004).Multiple Discreteness and Product Differentiation: Demand for Carbonated Soft Drinks. *Marketing Science*, *23*(1), 66–81.

Fenichel, E. P., & Horan, R. D. (2016).Tinbergen and tipping points: Could some thresholds be policy-induced? *Journal of Economic Behavior & Organization*, *132*, 137–152.

Gentzkow, M. (2007).Valuing New Goods in a Model with Complementarity: Online Newspapers. *American Economic Review*, *97*(3), 713–744.

Gillingham, K., & Tsvetanov, T. (2019).Hurdles and steps: Estimating demand for solar photovoltaics. *Quantitative Economics*, *10*(1), 275–310.

Grzybowski, L., & Verboven, F. (2016).Substitution between fixed-line and mobile access: The role of complementarities. *Journal of Regulatory Economics*, *49*(2), 113–151.

Hendel, I. (1999).Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns. *The Review of Economic Studies*, *66*(2), 423–446.

Hicks, J. R., & Allen, R. G. D. (1934).A Reconsideration of the Theory of Value. Part I. *Economica*, *1*(1), 52–76.

Iaria, A., & Wang, A. (2020, January). Identification and Estimation of Demand for Bundles.

Kwak, K., Duvvuri, S. D., & Russell, G. J. (2015).An Analysis of Assortment Choice in Grocery Retailing. *Journal of Retailing*, *91*(1), 19–33.

Lee, S., Kim, J., & Allenby, G. M. (2013).A Direct Utility Model for Asymmetric Complements. *Marketing Science*, *32*(3), 454–470.

Liu, H., Chintagunta, P. K., & Zhu, T. (2010).Complementarities and the Demand for Home Broadband Internet Services. *Marketing Science*, *29*(4), 701–720.

Lyu, X. (2023).Are Electric Cars and Solar Panels Complements? *Journal of the Association of Environmental and Resource Economists*, *10*(4), 1019–1057.

Manski, C. F., & Sherman, L. (1980).An empirical analysis of household choice among motor vehicles. *Transportation Research Part A: General*, *14*(5), 349–366.

Muehlegger, E., & Rapson, D. S. (2022).Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *Journal of Public Economics*, *216*, 104752.

Muehlegger, E. J., & Rapson, D. S. (2023).Correcting Estimates of Electric Vehicle Emissions Abatement: Implications for Climate Policy. *Journal of the Association of Environmental and Resource Economists*, *10*(1), 263–282.

Nevo, A., Rubinfeld, D. L., & McCabe, M. (2005).Academic Journal Pricing and the Demand of Libraries. *American Economic Review*, *95*(2), 447–452.

References II

Samuelson, P. A. (1974).Complementarity: An Essay on The 40th Anniversary of the Hicks-Allen Revolution in Demand Theory. *Journal of Economic Literature*, *12*(4), 1255–1289.

Sandmo, A. (1975).Optimal Taxation in the Presence of Externalities. *The Swedish Journal of Economics*, *77*(1), 86–98.

Theil, H. (1956).On the Theory of Economic Policy. *The American Economic Review*, *46*(2), 360–366.

Tinbergen, J. (1952). *On the Theory of Economic Policy*. North-Holland Publishing Company.

Wijkander, H. (1985).Correcting externalities through taxes on/subsidies to related goods. *Journal of Public Economics*, *28*(1), 111–125.