Heterogeneous Diffusion of Electric Vehicles in China

Demand, Cost, Product Entry, and the Sources of Adoption Growth

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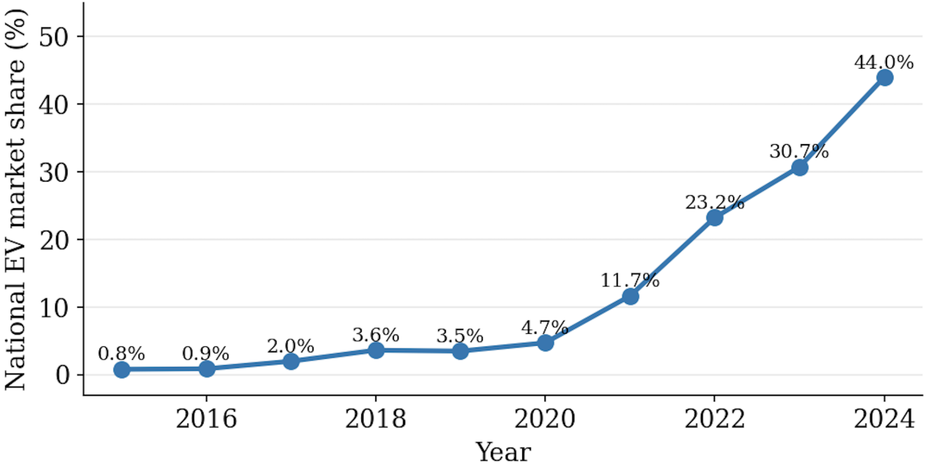
SUFE Empirical IO Conference, June 2026

Motivation: China's EV Market Share Took Off Almost Vertically



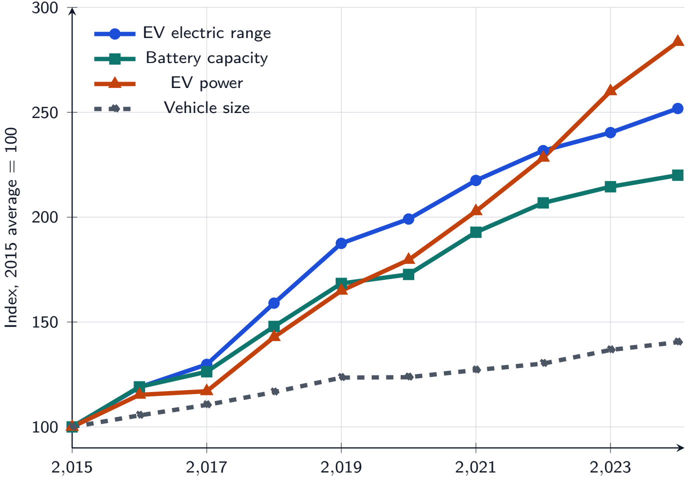
- The EV share of new vehicle sales rose from less than 1% in 2015 to about 45% in 2024.

Motivation: EV Growth Coincided with Massive Product Entry

Year	Total Products	EV Products	ICE Products
2015	452	35	417
2020	656	177	479
2024	784	398	386

- EV product offerings expanded more than tenfold between 2015 and 2024.
- ICE product variety stagnated and eventually declined.
- Most EV products available in 2024 did not exist in 2015.

Motivation: EV Products Also Became More Capable



EV electric range
153 → 386 km

EV battery capacity
24 → 53 kWh

EV maximum power
60 → 169 kW

- Average EV electric range increased from 153 km to 386 km, while battery capacity and power also rose sharply.

Motivation: Many Explanations Moved Together

Technology

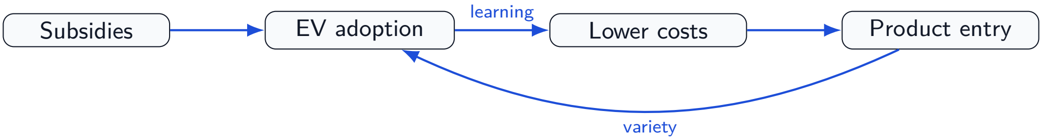
- Battery costs fell.
- Driving range improved.
- EV quality increased.

Policy

- Purchase subsidies expanded.
- Demand increased.
- Scale economies emerged.

Market structure

- New EV products entered.
- Domestic brands expanded.
- Product variety increased.



Research Question

What drove China's EV adoption boom?

0.96% $\longrightarrow$ 45.3% in ten years

Endpoint attribution

- Which 2015–2024 changes explain the observed rise?
- How much comes from entry, battery costs, attributes, subsidies, income, and residual demand/supply shifts?

Historical counterfactual

- Would the same 2024 market exist without the subsidy history?
- Did early policy help create the scale behind later learning?

This Paper

1. Estimate BLP demand + Bertrand supply → **2. Decompose** Shapley attribution → **3. Simulate** no-subsidy history

Market data

- China passenger vehicles, 2015–2024
- City × model × fuel × year
- 476,787 observations in 79 markets
- Sales, prices, attributes, subsidies, battery costs

Static attribution

- Explain the 2015–2024 rise in EV share
- Separate entry, battery costs, attributes, subsidies, income, and residual shifts
- Use order-invariant Shapley decomposition

Dynamic counterfactual

- Remove the full subsidy history
- Let battery costs evolve through Wright's Law
- Ask whether the 2024 market would still emerge

▸ model details

Main Findings

Static decomposition

Channel	Contribution
Entry	**+16.7%**
Battery learning	**+15.3%**
Residual demand/supply drift	**+9.8%**
Observed attributes	+3.8%
Subsidy phase-out	**-3.0%**
Income and macro	-1.3%

Dynamic subsidy counterfactual

Scenario	2024 EV share
Actual path	**45.1%**
No subsidies, full history	**3.1%**

Interpretation: static says what explains the observed endpoint change; dynamic says subsidies were load-bearing in the historical path.

static vs dynamic

Literature

- **Technology diffusion and clean-technology adoption**

  Griliches (1957); Jaffe and Stavins (1995); Comin and Hobijn (2010); Acemoglu et al. (2012); Aghion et al. (2016); Muehlegger and Rapson (2022)

  ⇒ Focus on adoption, policy incentives, and technology diffusion.
  ⇒ **We decompose EV diffusion into demand, cost, product-entry, and policy channels.**

- **Automobile demand and product differentiation**

  Berry, Levinsohn and Pakes (1995); Petrin (2002); Berry, Levinsohn and Pakes (2004); Fan (2013); Grieco et al. (2024)

  ⇒ Estimate substitution patterns and pricing in differentiated vehicle markets.
  ⇒ **We use a structural demand-supply model to study a decade-long market transition.**

- **Electric vehicle policy and market complementarities**

  Li et al. (2017); Springel (2021); Xing, Leard and Li (2021); Holland et al. (2021); Li et al. (2023); Remmy et al. (2025)

  ⇒ Study EV subsidies, charging infrastructure, and local policy incentives.
  ⇒ **We distinguish static subsidy effects from dynamic policy effects through scale and learning.**

Overview

Model

Demand Model

Indirect utility for household i choosing product j in market m in year t is:

$$u_{ijmt} = \beta_{\log p} \log p_{jmt} + \pi_p \left(\frac{1}{\bar{Y}_{mt}} \right) \log p_{jmt} + \beta' x_{jmt} + \sigma \nu_i \mathbf{1}\{EV_j\} + \xi_{jt} + \varepsilon_{ijmt}$$

where

- x_{jmt} includes vehicle attributes, EV-policy interactions, city demographics, and fuel, body, year, and firm fixed effects.
- Consumers differ in their preferences for EVs through a random coefficient on the EV indicator.
- Price sensitivity varies with market income:

$$\alpha_{mt} = \beta_{\log p} + \pi_p \left(\frac{1}{\bar{Y}_{mt}} \right).$$

- Higher-income markets are less price sensitive.

Demand Estimation and Identification

Identification comes from variation in prices, income distributions, and product differentiation.

Estimation

- Random-coefficients logit estimated using PyBLP.
- Two-step GMM with Berry contraction mapping.
- 25 simulated income draws per market.
- Demand estimated on 79 city markets from 2015–2024.

Identification

- BLP differentiation instruments.
- EV-vintage instrument captures model maturity.
- Income heterogeneity identifies price sensitivity.
- Policy control function addresses policy endogeneity.

Demand Estimates

Consumers value EVs, but remain responsive to prices.

Parameter	Estimate (SE)‡	Interpretation
EV taste heterogeneity (σ_{EV})	0.59^{***} (0.05)	Substantial heterogeneity in EV preferences
Mean price coefficient (β_p)	-0.085 (0.06)	Demand slopes downward
Income × price (π)†	-0.200^{**} (0.08)	Higher-income buyers are less price sensitive
Mean own-price elasticity	-4.0	Consistent with automobile literature
Median Lerner index	0.29	Moderate market power

‡ Two-step efficient GMM SE, market-clustered ($\widehat{V} = (G'\hat{S}^{-1}G)^{-1}$, pyblp default). † π at the interior boundary $\pi \leq -0.20$; Wald SE is the interior-point approximation, so inference on π is one-sided. Bottom two rows are implied moments from the multi-product Bertrand MC backout — analytical SE not reported. Stars: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

- EV-specific demand becomes increasingly favorable after 2021.
- Estimated elasticities are similar to previous studies of vehicle demand.

Supply and Marginal Cost

Estimated demand derivatives recover marginal cost from multi-product Bertrand pricing.

$$p_{jmt} - mc_{jmt} = -\left[\Omega(p,s) \odot \mathbf{1}\{\text{same firm}\}\right]^{-1} s_{jmt}.$$

$$\log mc_{jmt} = \gamma_{\text{size}} \log size_j + \gamma_{\text{power}} \log power_j^{GV} + \gamma_{\text{range}} \log range_j^{EV} \\ + \gamma_{\text{bat}\times\text{EV}} B_t \mathbf{1}\{\text{EV}_j\} + \gamma_{FT}' FT_j + \gamma_{BT}' BT_j + \gamma_t' Year_t + \gamma_{FG}' FG_j + \xi_{jt}^{mc}.$$

- The ownership matrix restricts cross-price terms to products owned by the same firm.
- The MC projection separates attributes, fuel/body/year/firm effects, and the BNEF battery-cost interaction.
- The residual ξ_{jt}^{mc} becomes part of the residual block in the Shapley decomposition.

Subsidy Measurement

Observed prices are consumer-net prices, so subsidy must not be counted twice.

$$p_{jmt}^{net} = p_{jt}^{msrp} - subsidy_{jmt} \qquad mc_{jmt}^{eff} = mc_{jmt}^{true} - subsidy_{jmt}.$$

- Consumers face the net price.
- Firms optimize with the effective marginal cost wedge.
- Counterfactual subsidy schedules move through equilibrium prices and shares.

Static Decomposition

Static Decomposition: Object

Ask what explains the observed 2015-to-2024 change.

- Each block is toggled from its 2015 value to its 2024 value.
- The model recomputes equilibrium prices and shares.
- Shapley values average each block's marginal contribution across all orderings.

▸ formula

The Six Blocks

Block	Mechanism toggled from 2015 to 2024
A_attrs	Attribute upgrade: size, power, EV range, battery capacity, and associated costs.
Battery	Wright's-Law battery cost decline, BNEF $373/kWh to $115/kWh.
Subsidy	National plus local purchase subsidy schedules.
Entry	Choice-set expansion plus entrant identity in the headline six-block specification.
ξ	Demand and supply residual drift, including EV-year and brand/firm trajectories.
Income	City market size, income distribution, and macro environment.

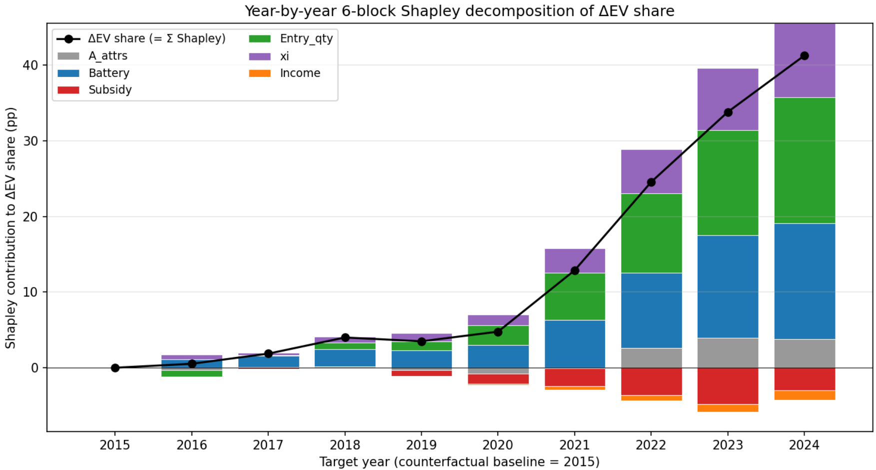
Entry quality is logically nested inside entry, so the clean headline specification treats entry as one block.

Main Static Result

Block	Contribution to EV share	Share of model Δ
Entry	**+16.66%**	40.4%
Battery	**+15.28%**	37.0%
ξ	**+9.77%**	23.7%
A_attrs	+3.81%	9.2%
Subsidy	**-2.97%**	-7.2%
Income	-1.26%	-3.1%
Total model decomposition	**+41.29%**	100%
Observed EV-share change	+44.30%	–

Entry and battery learning explain most of the endpoint growth.

Year-by-Year Decomposition



Cumulative

Shapley contributions relative to 2015.

Interpretation: A Regime Shift

2016–2017

- small total EV-share gains;
- battery and residual demand shifts matter;
- entry not yet dominant.

2018–2020

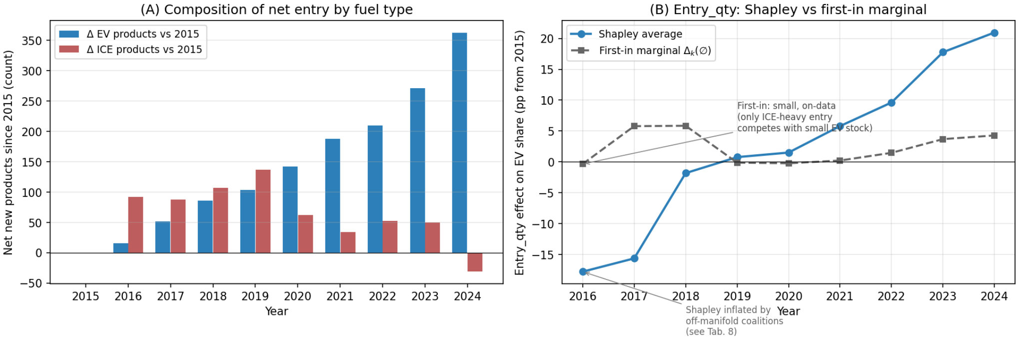
- EV entry catches up;
- subsidy retrenchment starts;
- adoption remains below 6%.

2021–2024

- entry and battery learning dominate;
- EV share jumps to 45%;
- ICE product count falls below 2015.

▸ entry details

Why Entry Flips Sign



Early product-set expansion is ICE-heavy; later product-set expansion is EV-heavy.

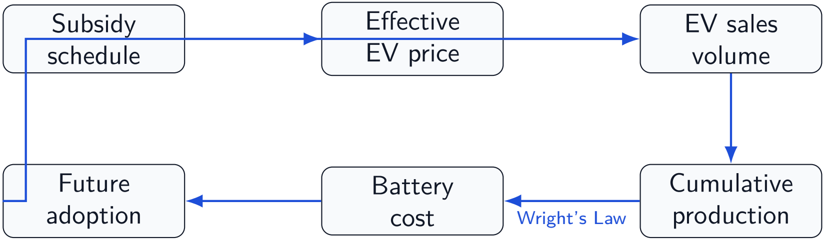
Dynamic Counterfactual

Why Static Subsidy Is Not Enough

Static subsidy compares endpoint subsidy generosity. Dynamic subsidy asks about policy history.

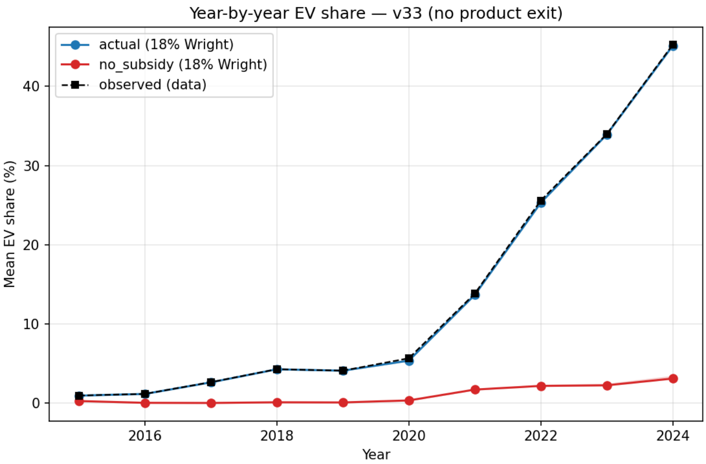
Static Shapley subsidy	Dynamic no-subsidy counterfactual
2015 subsidy schedule vs 2024 subsidy schedule.	Subsidies removed throughout 2015–2024.
Holds the realized market history mostly fixed.	Lets production, learning, and future prices move.
Finds **-2.97%**.	Finds about **-42%**.

Dynamic Feedback Loop



The policy object is dynamic: early subsidies affect state variables that later appear as battery learning and market scale.

Dynamic Result



No-subsidy counterfactual with Wright-endogenous battery cost.

Dynamic Result in Numbers

Wright learning rate	Actual all	No-subsidy 2024 EV share 18%	 22%	 28%
2024 EV share	**45.13%**	**3.11%**	**3.22%**	**3.42%**
Effect vs actual	–	-42.02%	-41.91%	-41.71%

- The actual scenario matches observed adoption closely.
- Removing subsidies reduces 2024 EV share by about **42%**.
- Wright-slope sensitivity is modest.

dynamic assumptions

Interpretation

What We Learn

1. **EV diffusion was a market-creation process.** Product entry and battery learning were the dominant endpoint drivers.
2. **Subsidies were historically load-bearing.** Static subsidy is small because it is an endpoint wedge; dynamic subsidy is large because it changes the path.
3. **The transition was sequential.** Early policy helped build scale; scale helped lower battery cost; lower cost and entry sustained adoption.

The same policy can be small at the margin and large in history.

Conclusion

The transition was built in layers.

1. EV share rose from 0.96% to 45.3%.
2. Static Shapley attributes the endpoint gain mainly to entry and battery learning.
3. Year-by-year decomposition shows a regime shift from early demand/technology growth to later entry-led diffusion.
4. Dynamic subsidy removal shows policy was load-bearing: no-subsidy 2024 EV share is about 3%.

China's EV diffusion was not just adoption. It was market creation.

Thank you

Questions and comments

Research question	What drove China's EV diffusion?
Main static answer	Entry + battery learning.
Main dynamic answer	Subsidies built the early scale.

Backup

Details and Robustness

Backup: Demand and Supply Details

Demand utility

$$u_{ijmt} = \alpha_{imt} \log p_{jmt}^{net} + x_{jmt}'\beta + \sigma_{\mathrm{EV}}\nu_i \mathbf{1}\{\mathrm{EV}_j\} + \xi_{jt} + \varepsilon_{ijmt}, \qquad \alpha_{imt} = \beta_{\log p} + \pi_p (y_{imt}/\bar{y}_t)^{-1}.$$

Demand share

$$s_{jmt}(\delta, \theta) = \int \frac{\exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{k \in J_{mt}} \exp(\delta_{kmt} + \mu_{ikmt})} dF_i.$$

Supply FOC

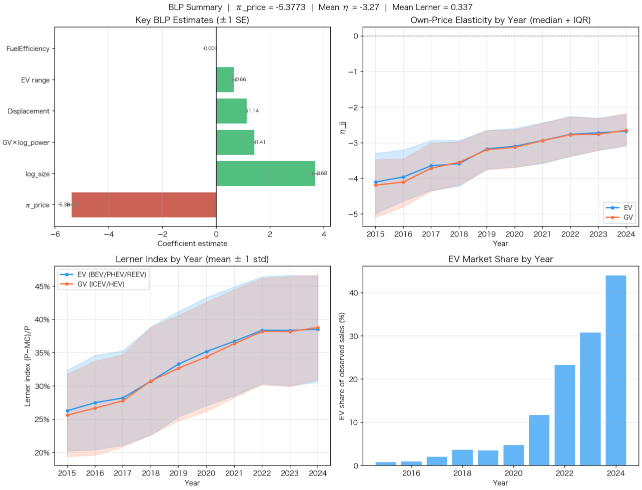
$$p_{jmt} - mc_{jmt} = -\left[\Omega(p, s) \odot \mathbf{1}\{\text{same firm}\}\right]^{-1} s_{jmt}.$$

Stacked moments

$$Q(\theta) = g_{\mathrm{EV}}' W_{\mathrm{EV}} g_{\mathrm{EV}} + g_{\mathrm{GV}}' W_{\mathrm{GV}} g_{\mathrm{GV}}.$$

◂ main

Backup: BLP Summary Figure



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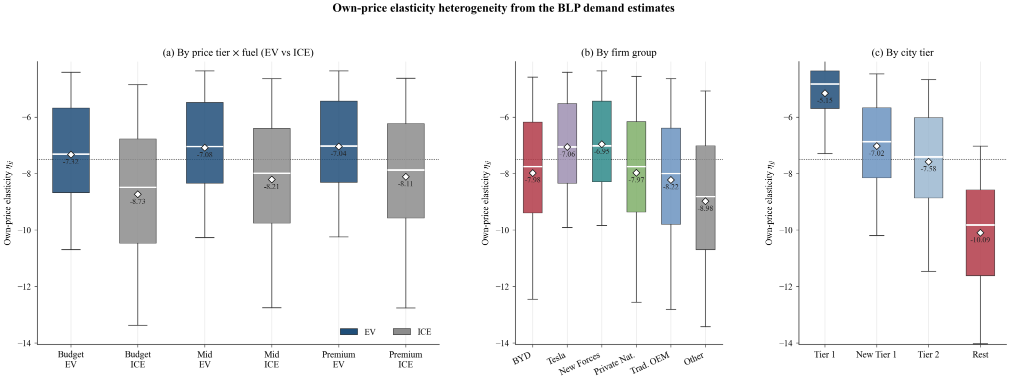
Backup: Elasticity Heterogeneity



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Backup: Shapley Formula

For blocks $K = \{1, \ldots, 6\}$ and outcome $V(S)$:

$$\phi_k = \sum_{S \not\ni k} \frac{|S|!(K - |S| - 1)!}{K!} \left[V(S \cup \{k\}) - V(S) \right].$$

- S is a coalition of blocks already switched to 2024.
- The weight averages over all possible orderings.
- The sum of Shapley values equals the total model-implied change.

main

Backup: Full Decomposition Table

Block	Shapley	First-in	Last-in	Std	p25	p75
A_attrs	+3.81	-0.26	+19.89	10.41	-4.38	-0.02
Battery	+15.28	+0.85	+41.61	16.19	+0.31	+17.90
Subsidy	-2.97	-0.30	-11.27	2.72	-2.13	-0.21
Entry	+16.66	+4.24	+40.95	15.98	+2.18	+21.13
ξ	+9.77	+0.55	+35.74	12.71	+0.33	+1.54
Income	-1.26	-0.20	-4.57	2.03	-0.57	+0.33

Wide first-in/last-in gaps indicate complementarity with other blocks.

main

Backup: Product-Set Composition

Year	EV products	ICE products	ΔEV	ΔICE	Entry effect
2015	35	417	0	0	–
2016	51	509	+16	+92	-0.83%
2018	121	524	+86	+107	+0.89%
2020	177	479	+142	+62	+2.57%
2022	245	470	+210	+53	+10.47%
2024	398	386	+363	-31	+16.66%

- Early entry is partly ICE-heavy.
- Later entry becomes EV-heavy.
- By 2024, product variety itself is an EV advantage.

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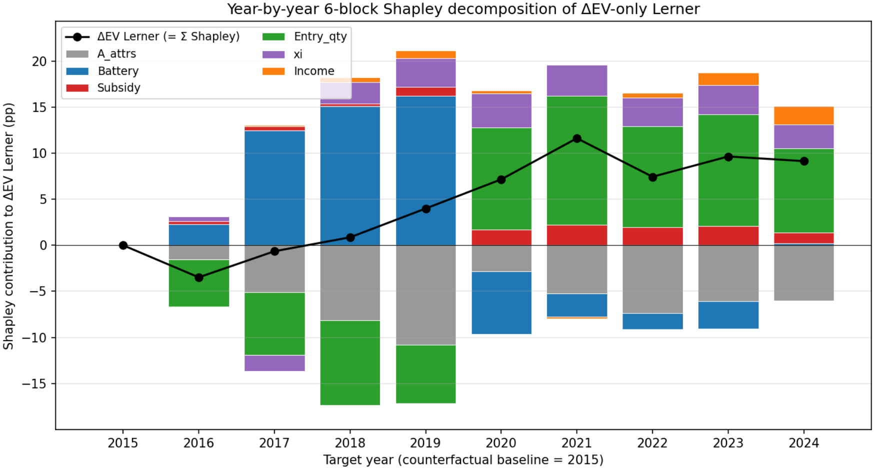
Backup: Markup and Lerner Decomposition



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Backup: Income Substitution Pattern

Year	Quintile	ICEV	BEV	PHEV	EV total
2015	Q1 low	99.59	0.37	0.03	0.39
2015	Q5 high	96.66	1.55	1.54	3.09
2024	Q1 low	49.88	30.42	16.33	48.12
2024	Q5 high	49.82	28.81	12.25	45.58

By 2024, BEV/PHEV adoption is mass-market, while high-income demand also goes to HEV, REEV, and ICE luxury.

◂ main

Backup: Static vs Dynamic Subsidy

Static Shapley subsidy	Dynamic no-subsidy counterfactual
Compares 2015 and 2024 subsidy schedules. Treats realized 2024 entry and scale largely as given. Answers endpoint attribution.	Removes subsidies over the entire history. Lets cumulative production and battery learning respond. Answers historical policy counterfactual.

Static: small at the endpoint. Dynamic: large in the history.

◂ main

Backup: Dynamic Assumptions

- Actual scenario uses observed annual BNEF battery costs.
- No-subsidy scenario uses counterfactual cumulative EV production to update battery cost.
- Product exit is treated in sensitivity checks; the main displayed grid is no-exit.
- Demand and marginal cost are held to the estimated v33-consistent specification.
- The simulation reproduces observed baseline shares closely before interpreting counterfactuals.

main

Backup: Why Wright Sensitivity Is Small

- The actual scenario is pinned to observed battery costs.
- Wright's Law operates only in the no-subsidy path.
- Across 18%–28% learning rates, no-subsidy EV share remains near 3%.
- The direct price-wedge loss and early quantity collapse dominate the precise learning slope.

main

Backup: Literature Positioning

- Technology diffusion: Griliches; Comin and Hobijn.
- Automobile demand and product differentiation: BLP; Petrin; Grieco et al.
- EV policy and industrial policy: Allcott and Wozny; Li et al.; Muehlegger and Rapson.
- Decomposition: Shapley/Shorrocks attribution adapted to structural counterfactuals.

main

Backup: Discussion Points

- How should we interpret entry when entry is exogenous but historically policy-influenced?
- Are residual EV demand shifts brand trust, charging convenience, software quality, or unexplained demand?
- How much of China's result depends on industrial capacity rather than consumer subsidies alone?
- What would be needed to export the framework to the US or Europe?

◂ main