Innovation Path Choices in China's Electric Vehicle Battery Industry

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Abstract

Technologies that are equally green can yield very different gains in social welfare. I examine whether market-driven innovation in green industries follows the socially optimal technological path when firms face competing options with distinct cost structures, and explore policies that can correct potential inefficiencies in path choices. I estimate a dynamic structural model of Chinese electric vehicle (EV) battery suppliers choosing how much to innovate along two competing paths: Lithium-Ion–Ferro–Phosphate (LFP) and Nickel–Cobalt–Manganese (NCM). The analysis shows that a social planner would undertake about four times as much innovation as the market in LFP, which involves higher innovation sunk costs but delivers lower marginal costs in production. By contrast, the market innovates about twice as much as the social planner in NCM, which has the opposite cost structure. I attribute this divergence primarily to vertical separation between battery suppliers and EV makers, competition between EVs, and limited demand for EVs in early years, rather than to innovation spillovers or environmental benefits that firms fail to internalize. Finally, I demonstrate how R&D subsidies could help correct the path choice inefficiency and shift innovation toward the socially preferred path.

JEL Codes: L52, O31, O25, L65, O38, L22, D24

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"The issue with battery investment lies in the choice of technology path: whether to go with NCM or LFP, cylindrical or prismatic cells. Choosing the wrong direction could result in a 10 billion RMB (˜1.4 billion USD) investment going to waste, along with three years of lost time."

—Chuanfu Wang, Founder and Chairman of the BYD Company

1. Introduction

Acemoglu (2002; 2023) and Acemoglu et al. (2012) show that the market innovates less than the socially optimal level, and also makes suboptimal choices about which technologies to develop. Green industries often face competing technological paths that differ in performance, innovation difficulty, and production costs, and thus may provide very different welfare benefits.[1] I ask in this paper: when such competing green-tech paths exist, can the market alone direct innovation to the socially optimal one, or is policy intervention necessary? I answer this by estimating a dynamic model of Chinese EV battery firms choosing between two alternative paths for increasing energy density of batteries, quantifying the distortions in path choices and evaluating how far different policies can correct them.

In EV batteries, energy density, the amount of energy stored per unit weight (Wh/kg), is a key performance metric because it directly determines driving range.[2] Innovation in this paper is defined as pushing the energy density frontier, the highest level a firm has achieved at scale.[3] There are two battery technology paths dominating for over a decade: Lithium-Ion–Ferro–Phosphate (LFP) and Nickel–Cobalt–Manganese (NCM). LFP batteries are built using relatively cheap raw materials (e.g., Iron), yielding lower marginal costs of production, but are harder to improve in energy density, implying higher sunk costs of

[1] Beyond EV batteries, examples include solar panels (Ali et al., 2025) and wind turbines (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2019).

[2] https://about.bnef.com/insights/clean-energy/new-lithium-battery-technology-set-to-disrupt-storage-market/; https://www.bloomberg.com/news/articles/2017-12-26/autonomous-cars-need-tougher-batteries-lithium-ion-pioneer-says

[3] In some cases, an extremely high energy density can be achieved in labs but has no commercial values due to the difficulty in mass-production.

innovation. NCM batteries use expensive rare earth elements, leading to higher marginal costs in production, but their superior electrochemical properties allow energy density to be increased with lower innovation costs (Hu et al., 2013; Zhang et al., 2023).

To analyze firms' choices across these paths, I develop a dynamic model where battery suppliers[4] make innovation decisions every period and then supply batteries, with bargained prices, to EV makers, who compete *à la Bertrand* for consumers. This framework allows me to examine why firms' preferred technology path may diverge from that of a social planner: firms must share innovation gains with EV makers through bargaining,[5] operate in a market with limited demand for EVs,[6] pass through the marginal cost savings to consumers under competition, and fail to internalize the social benefits of innovation spillovers.

In my sample period from 2017 to 2023, China's EV industry has experienced a rapid growth, with EV's market share rising from less than 5% in 2017 to over 25% in 2023. Policy-wise, the Chinese government provided a generous energy-density-based consumer subsidy from 2017 to 2019, later the subsidy started to drop substantially in 2019 and eventually exited in 2022. From 2017 to 2023, I made two observations: first, innovation concentrated on NCM from 2017 to 2019, which was then followed by a major switch to LFP in the later period. Second, for most battery suppliers, innovations that catch up with the industry-wide frontier of energy density[7] account for over 80% of a given firm's total innovations.

Building on these stylized facts and institutional details, I develop and estimate a dynamic model of battery suppliers' innovation game. To estimate the model, I compile a comprehensive dataset covering each EV model's battery attributes (e.g., energy density, supplier, and type), non-battery attributes, vehicle sales, retail prices, and policy variables. The model has two key elements. First, each supplier decides how much to improve the energy density frontier for both LFP and NCM. Second, many studies have confirmed the importance of

[4] I include the vertically integrated BYD who supplies almost all of its batteries to its own EVs during my sample period from 2017 to 2023.
[5] The exception is BYD because of the vertical integration.
[6] Total EVs demand is the product of the vehicle market size and EV's market share. The limited demand for EVs can be a result of either a small overall market size or a small market share of EVs.
[7] The industry-wide frontier refers to the highest energy density frontier across all firms for a given type of battery.

spillovers from leading innovation (Romer, 1990; Goettler and Gordon, 2011; Bloom et al., 2013; Lensman, 2025). In my model, innovation that catches up with the industry-wide frontier within a path (e.g., LFP) can incur a different (potentially lower) cost from innovation that advances the industry-wide frontier. Firms' incentives to innovate on LFP or NCM depend crucially on the relative difference in innovation costs and the future payoff.

The estimation proceeds in three steps. First, I estimate a nested logit demand model for consumers, addressing price and nesting-parameter endogeneity with instruments suggested by the literature including Gandhi and Houde (2019). The mean own-price elasticity is -2.95. Consumers prefer cheaper, larger vehicles; ICEs with higher fuel efficiency; and EVs with longer range. Second, I estimate a bilateral bargaining model between EV makers and battery suppliers to recover battery marginal costs. Exploiting a 2016–2019 policy favoring Chinese battery suppliers, I identify the bargaining parameter and find that suppliers capture slightly more of the gains from trade than EV makers. Consistent with industry views, NCM batteries entail higher marginal costs than LFP, translating into a 12.9% price premium.

Finally, I estimate innovation cost parameters for battery supplier CATL, BYD, and GuoXuanGaoKe (GX). Identification comes from battery suppliers' innovation responses to changes in the industrial frontier, downstream demand, and policies. Results show that advancing NCM's energy-density frontier is 71% cheaper than advancing LFP's for the same step size, consistent with NCM's superior electrochemical properties. All else being equal, catch-up innovation within a path costs 37% less than frontier-pushing innovation, indicating a large spillover across firms within a technological path.

With the estimated model, I conduct two sets of counterfactual analyses to evaluate the distortion of market-driven innovation outcomes and the effects of alternative policy instruments. The first compares the equilibrium innovation choices of a social planner with those of battery suppliers operating in a market without subsidies. The social planner selects innovation to maximize total surplus, which encompasses consumer surplus, producer surplus, and environmental benefits, whereas firms pursue innovation solely to maximize profits. The second set examines how battery suppliers' innovation behavior changes under

two alternative subsidy regimes: the energy-density-based consumer subsidies and the R&D subsidies.[8]

The counterfactual results reveal a clear divergence between the social planner and the market. The planner places more weight on the LFP path, which requires higher sunk costs of innovation but offers lower marginal costs in production. In contrast, firms innovate too little on LFP and too much on NCM. Given the same fiscal budget, R&D subsidies are more effective than consumer subsidies in stimulating LFP innovation. Without innovation spillovers, overall innovation intensity declines slightly on both paths, but the gap between technological leaders and laggards widens, as leaders innovate more while laggards disengage. Further exploration of market conditions shows that stronger EV demand, more bargaining power for battery suppliers or higher integration between battery suppliers and EV makers, and softer competition among EVs help narrow the divergence.

Related Literature—I contribute to three strands of literature. First, it is situated within the long-standing literature on endogenous technological change. Among many studies on innovation direction choices (Dosi, 1984; Acemoglu, 2002; Moscona, 2021; Lensman, 2025), increasing attention has been paid to the environmental dimension of innovation, particularly how pricing mechanisms or targeted subsidies can shift innovation toward cleaner technologies (Acemoglu et al., 2012; Aghion et al., 2016; Pless and Srivastav, 2022; Acemoglu et al., 2023; Dugoua and Gerarden, 2025). These studies examined firms' choices between "old" and "new" technologies, with the former benefiting from historical knowledge or investment accumulation (e.g., fossil fuels) and the latter involving higher uncertainty and cost (e.g., wind).

Two among them are close to my work: Lensman (2025) examines the role of market structure and R&D concentration in sustaining technology diversity, while Pless and Srivastav (2022) compare the directional impact of carbon pricing and R&D subsidies on firms' adoption of clean technologies over dirty technologies. I depart from them by studying firms' choice between two emerging clean technologies, neither with historical knowledge/capital

[8]Governments in the U.S., Europe, and China have increasingly turned to industrial policies to shape green innovation. Two common tools are consumer subsidies, often tied to product performance, and R&D subsidies, which reduce the cost of technological development.

accumulation but differing in innovation and production costs, and show empirically, in line with Acemoglu (2023), why the market may not yield the socially optimal direction and how governments can help. Methodologically, I explicitly solve the equilibrium of a dynamic innovation game, which enables me to quantify the path distortion and the welfare implications of different policies.

Second, I contribute to the growing literature on the determinants of innovation direction. Prior work has highlighted the role of relative energy prices (Newell et al., 1999; Popp, 2002; Aghion et al., 2016; Acemoglu et al., 2023), market size (Acemoglu and Linn, 2004; Aghion et al., 2024), environmental conditions (Moscona, 2021; Moscona and Sastry, 2023, 2025), regulations (Finkelstein, 2004; Acemoglu et al., 2006), global politics and trade policies (Alfaro et al., 2025; Flynn et al., 2025), exposure to automation (Cong et al., 2024), and labor market conditions (Acemoglu and Restrepo, 2022; Hémous et al., 2025) on the direction of innovation. I add by showing how cost structure differences, vertical separation, and competition jointly generate divergence between the market and the social planner's choices, and I demonstrate that R&D subsidies accelerate alignment more effectively than attribute-based consumer subsidies. Relatedly, Gerarden (2023) studies how solar panel consumer subsidies stimulate upstream innovation, but he focuses on cost reductions rather than technological path choices.

Third, this study contributes to the literature on industrial policies in the electric vehicle sector (Li et al., 2019; Springel, 2021; Holland et al., 2021; Allcott et al., 2024). The rapid growth of China's EV industry has drawn extensive attention (Li et al., 2017, 2022; Wang and Xing, 2023; Kwon, 2023). Two closely related studies are particularly relevant: Barwick et al. (2024) highlight how the interaction between market power and driving-range-based consumer subsidies shapes EV product design, while Barwick et al. (2025) show how policy-induced learning-by-doing reduces battery production costs. My paper complements this line of research by analyzing potential distortions in firms' choices between alternative battery innovation paths and evaluating the role of industrial policies in correcting these distortions.

The remainder of the paper is organized as follows: Section 2 provides industry and policy

background. Section 3 describes the data and highlights key stylized facts. Section 4 outlines the empirical model. Section 5 details the identification and estimation of model parameters, and Section 6 presents the estimation results. Section 7 analyzes counterfactual outcomes, and Section 8 concludes.

2. EV Battery Industry and Policy Background

In this section, I will first provide an overview of the industry, with emphasis on the diversity of battery innovation paths. Then, I review the consumer subsidy policies that the Chinese government has implemented during my sample period.

2.1. EV Battery Industry, Innovation Definition, and Technology Fork

EV sales in China have grown tenfold from 2017 to 2023.[9] As one of the most important upstream industries for EV, China's EV battery industry is relatively concentrated, with CATL and BYD being the top 2 battery suppliers and persistently commanding 60-70% market share collectively. BYD is vertically integrated, producing nearly every EV component in-house, including batteries. Near the end of my sample period, it had begun supplying batteries to other brands, but external sales accounted for less than 3% of its production. For a given EV model, it is very rare that the EV maker changes the model's battery supplier.

The key performance metric in my paper is the energy density frontier, the maximum energy density (Wh/kg) achieved in mass production. Driving range rises with battery capacity but falls with vehicle weight, and capacity (kWh) equals energy density (Wh/kg) times battery weight (kg). Higher energy density allows more energy to be stored without increasing battery size or weight, enabling longer travel per charge. I define innovation as raising the energy density frontier, consistent with how major battery suppliers frame their battery

[9] https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars

development progress.[10]

Measuring innovation in an accurate and sensible way by the industry standard is challenging, as proxies such as patents or composite indices have well-known limitations (Griliches, 1979; Griliches et al., 1986; Griliches, 1998; Hall et al., 2001). A key advantage of my setting is that I can observe this battery-industry-acknowledged innovation metric directly in the data.[11]

The main constraint on improving lithium-ion batteries' energy density lies in the cathode material. Two technological paths dominate: Lithium-Ion–Ferro–Phosphate (LFP) and Nickel–Cobalt–Manganese (NCM), with combined market share above 90% over the years. Although there have been attempts to try other technological paths, like NCA (Nickel-Cobalt-Aluminum), they have never become mainstream nor achieved a comparable scale of commercial production.

NCM uses rare metals with superior electrochemical properties, enabling higher densities but at a much higher cost: its raw materials are about three times as expensive as those for LFP. LFP relies on cheaper inputs like iron and phosphate, making it cheaper to produce[12] but intrinsically harder to improve in density due to its relatively inferior properties (Chakraborty et al., 2020; Yang et al., 2021). In the empirical model presented later, I allow both the marginal production costs of LFP and NCM and the costs of improving their respective energy density frontiers to differ, capturing the heterogeneity in their innovation challenges and production costs.

[10] https://www.reuters.com/technology/new-catl-m3p-batteries-can-improve-energy-density-by-10-20-chairman-2022-08-27/; https://www.reuters.com/business/autos-transportation/exclusive-tesla-supplier-panasonic-eyes-20-jump-battery-density-by-2030-2022-07-13/

[11] I abstract from another form of innovation, cost-reduction efforts for NCM batteries, because these attempts were largely unsuccessful. Battery suppliers initially sought to lower NCM's marginal cost by reducing the use of cobalt and manganese and by adjusting the nickel–cobalt–manganese ratios from 5-2-3 to 6-2-2 and then to 8-1-1. However, higher nickel content increased the risk of thermal runaway and fires, leading suppliers to revert to the original 5-2-3 composition.

[12] https://36kr.com/p/1664125266008064.

2.2. Government Policies

China introduced consumer subsidies for EV purchases in 2009, with eligibility criteria revised over time. Early subsidies were uniform and broadly inclusive. Beginning in 2013, amounts were tied to driving range, awarding higher subsidies to longer-range vehicles. Yet industry experts emphasized that battery energy density, not range alone, is the key marker of technological progress. Without targeting energy density, firms could simply scale up the quantity of batteries rather than pursue genuine improvement on batteries' quality to boost driving ranges.[13]

To "promote high-performance batteries" and "encourage technological advancement,"[14] the subsidy formula was revised in 2017 to depend on both the driving range and pack energy density, the first time a battery attribute directly determined subsidy size. Government statements stressed that this attribute-based design aimed to catalyze innovation, enhance competitiveness along the EV supply chain, and shift the growth from fiscal-incentive-driven to technology-driven.[15]

From 2017 onward, the subsidy amount equaled a base amount (step function of range) multiplied by an adjustment factor (step function of pack energy density[16]). As shown in Figure 1, subsidies were substantial in 2017–2018, covering over 25% of retail prices for high-range, high-density EVs. In 2019, however, a sharp phaseout began: subsidies were slashed, and support for low-range, low-density vehicles was eliminated. Thereafter, even top-performing EVs saw steadily declining support, which eventually ended in 2022. The details of EV purchase subsidies from 2017 to 2022 can be found in Table 7 in the Appendix.

The reduction schedule, announced in 2016 and implemented in 2019, gave firms clear

[13] auto.people.com.cn/n1/2018/0720/c1005-30158926.html

[14] https://www.gov.cn/xinwen/2016-12/31/content_5155087.htm; https://industry.people.com.cn/n1/2017/1123/c413883-29663317.html

[15] https://www.gov.cn/zhengce/2019-03/27/content_5377064.htm

[16] For brevity, I will use "energy density" to refer to pack energy density in the rest of the paper. Pack energy density refers to the amount of energy stored per unit mass of the entire battery pack, including cells, casing, cooling systems, wiring, and other structural components. In contrast, cell energy density measures only the energy per unit mass of the battery cells themselves, excluding packaging and auxiliary systems and is therefore always higher than pack energy density. The policy and my paper share the common focus on the pack energy density, which has more practical implications for driving ranges.

Figure 1: The Ratio of Consumer Subsidy to EV Prices by Different EV Specifications

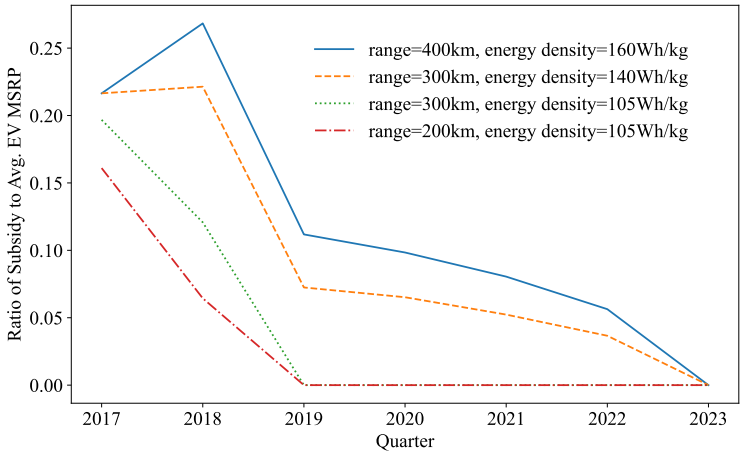


FIGURE NOTES: The y-axis in the figure above calculates the ratio of subsidies to the average Manufacturer's Suggested Retail Price of EVs, which is 22.36 (10000 RMB) in Table 1. Different lines indicate EV models of different energy density and driving range.

expectations. Although subsidies were originally slated to end in 2020, they were extended to 2022 due to COVID-19. By then, however, subsidy levels were already minimal, and the extension likely had little effect on firm decisions. The program was fully phased out by the end of 2022.

When consumer subsidies were reduced, I observe that the sales-weighted average energy density fell.[17] This pattern suggests that the earlier rise in energy density was driven by a shift toward costly NCM batteries, not by lasting innovation. Until very recently the Chinese government has shifted toward other industrial support measures, including a 6 billion RMB (≈$830 million USD) allocation in 2024 for R&D on solid-state batteries, a next-generation technology.[18]

[17] Details can be found in Figure 13 in the Appendix.
[18] https://www.wsj.com/business/autos/china-and-u-s-both-eye-breakthrough-ev-technology-597903ce

Table 1: Summary Statistics

Fuel Type	Battery		Plug-in Hybrid		Gasoline/Diesel	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: Vehicle Information						
MSRP (10000RMB)	22.36	19.52	31.96	23.61	24.29	24.82
Subsidy (10000RMB)	0.88	1.11	0.22	0.29	0.00	0.00
Sales	818.40	2984.82	1445.25	3778.98	1249.81	3196.55
Size(m^3)	12.67	2.64	14.82	1.65	13.87	2.06
Horsepower	169.72	110.88	190.27	89.22	184.48	77.03
Driving Range (km)	408.17	139.68	93.83	53.80	0.00	0.00
# of Unique Models	1267		279		6098	
# of Unique Brand-Series	421		141		1230	
# of Unique Vehicle Manufacturer	74		27		62	
Panel B: Battery Information						
Battery Capacity (KWh)	55.32	23.60	18.52	9.67	-	-
Energy Density (Wh/kg)	148.03	22.51	113.91	24.36	-	-
Type: LFP	0.76	0.43	0.21	0.41	-	-
Type: NCM	0.20	0.40	0.59	0.49	-	-
Supplier: CATL	0.34	0.47	0.20	0.40	-	-
Supplier: BYD	0.08	0.27	0.22	0.42	-	-
Supplier: GX	0.07	0.26	0.03	0.18	-	-
# of Unique Supplier	104		28		-	
# of Obs. (Model-Quarter)	7513		1438		44733	

TABLE NOTES: Each observation in my sample is a vehicle model in a given quarter. The sample period is from 2017Q1 to 2023Q4.

3. Data and Stylized Facts

In this section, I start by introducing the datasets that are used in this paper. Then, I highlight some stylized facts that will motivate my empirical model later.

3.1. Data and Sample

I draw on three primary datasets covering 2017–2023, supplemented with additional policy and battery input price data. The analysis focuses on passenger vehicles, excluding buses and other non-passenger types.

Vehicle sales data, covering both ICE and EV models, comes from proprietary records of China's statutory automobile liability insurance, which track every newly purchased vehicle. The same data is also used in Guo and Xiao (2023). This dataset provides quarterly national sales at the vehicle model level.

Vehicle attributes and retail prices are collected from AutoHome.com. This website reports detailed model-level information, including Manufacturer's Suggested Retail Price (MSRP). For EVs in particular, the website identifies battery capacity (kWh), battery supplier, battery chemistry (e.g., LFP vs. NCM), and pack energy density.

I also collect some supplementary datasets: the annual consumer subsidy schedule for 2017–2022, and quarterly prices of lithium carbonate Li_2CO_3, a key input for both LFP and NCM, from https://cn.investing.com/.

EVs in this paper include both battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). Summary statistics are presented in Table 1. A vehicle model is defined by make, brand, series, fuel type, driving range, engine displacement size, vintage, if imported, e.g., Tesla Model Y 2021, Battery EV, 594 km, Chinese version. A market is defined at the quarter national level.

To keep the state space tractable in the dynamic estimation, I concentrate on the innovation decisions of three leading battery suppliers, CATL, BYD, and GX, while treating other suppliers' innovations as given throughout the estimation and counterfactuals. These three provide good representativeness. Together they account for more than 75% of China's market in 2023, and according to SNE Research (2025), CATL, BYD, and GX rank 1st, 2nd, and 7th globally. Importantly, all three have long innovation records in both LFP and NCM, unlike smaller rivals that typically specialize in a single path.[19]

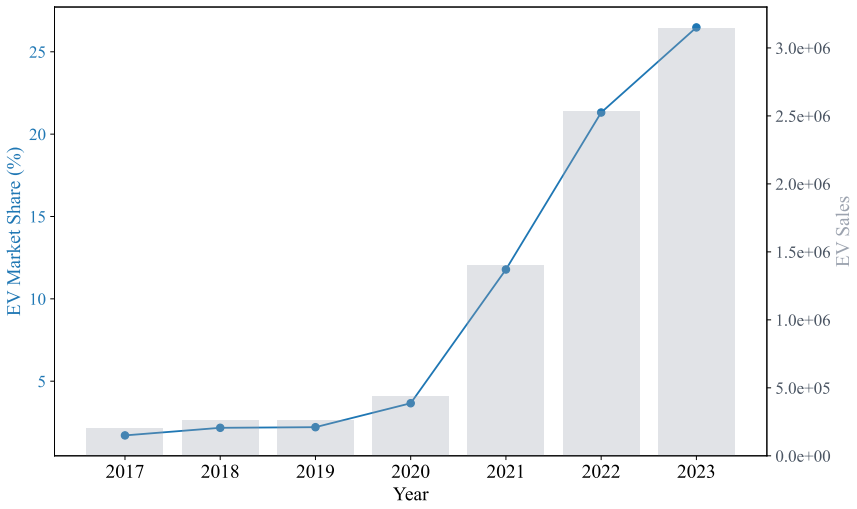
3.2. Stylized Facts

In this subsection, I highlight three empirical observations that motivate my research question and modeling choices.

[19] https://finance.sina.com.cn/roll/2022-09-08/doc-imqqsmrn8273893.shtml

Figure 2: EV Sales and Market Shares of LFP and NCM

(a) Share of EV



(b) Share of LFP and NCM

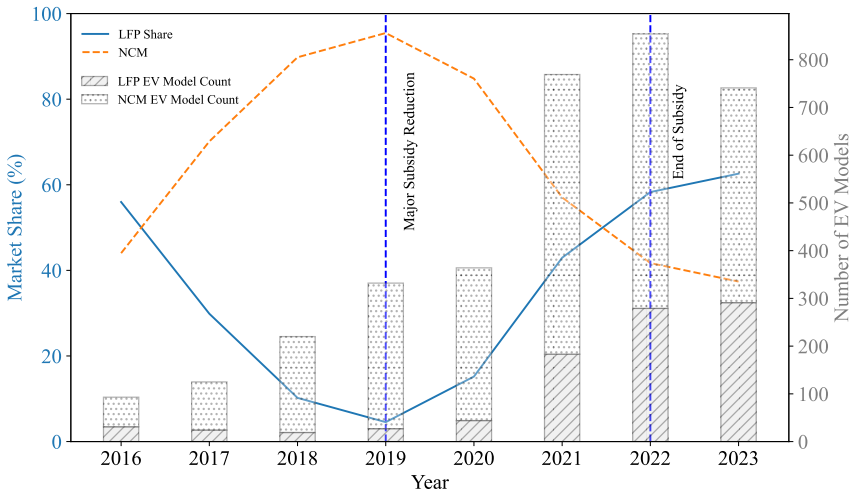


FIGURE NOTES: The figure in the upper panel shows the share of EV and the sales of EV over time. The figure in the bottom panel displays the market share of LFP (blue solid line) and NCM (orange dashed line) batteries from 2016 to 2023. The market share is calculated based on the installed battery capacity (sales $\times$ capacity per EV) on EVs. A complementary battery installation data is used to compute the number in 2016. The vertical blue dashed lines indicate the timing of major policy changes. The sum of LFP and NCM's market shares is close to but not necessarily 100% because there are other types of battery, e.g., NCA, which accounts for a trivial share in the market.

Figure 3: Innovation Size by LFP and NCM

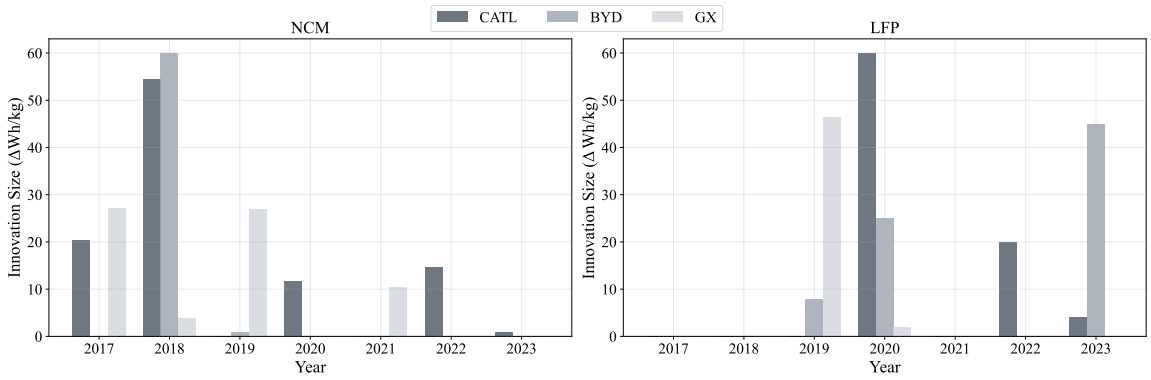


FIGURE NOTES: The figure displays the year-to-year change in energy density frontier at firm-type level for three battery suppliers: CATL, BYD, and GX. For example, the highest energy density that CATL has ever produced for LFP batteries until 2019 is 150 Wh/kg and in 2020 the number increases to 180 Wh/kg. Then the year-to-year change in energy density frontier for CATL's LFP type battery in 2019 is 30Wh/kg, which will be viewed as the innovation step size in my empirical model.

First, Figure 2a shows EV market share rising from under 3% to over 25% between 2017 and 2023, with annual sales growing from fewer than 0.3 million to more than 3 million. This pace underscores that EV and the related battery industry cannot be viewed as mature or stationary. Figure 2b shows a dramatic shift in battery dominance over the same period. During the years when generous subsidies were available (2017–2019), EVs pivoted sharply to NCM, while LFP stagnated. After subsidies began phasing out in 2019, LFP regained ground and eventually overtook NCM. Model counts in bars reinforce this pattern: NCM was represented in more EV models throughout, but the number of LFP models did not rise significantly until after 2020.

Second, Figure 3 highlights that innovation targeted NCM before 2019, with large jumps in energy density frontiers. After the subsidy retreat and EV market expansion in 2019, the focus shifted: NCM progress slowed to small incremental gains, while LFP innovation accelerated, especially in 2020 and 2023. This abrupt switch suggests that policy changes and market dynamics reshaped innovation direction in a short time.

Third, following earlier work on innovation spillovers (Goettler and Gordon, 2011; Pless

Figure 4: Distribution of the Percentage of Leading Innovation of a Battery Supplier

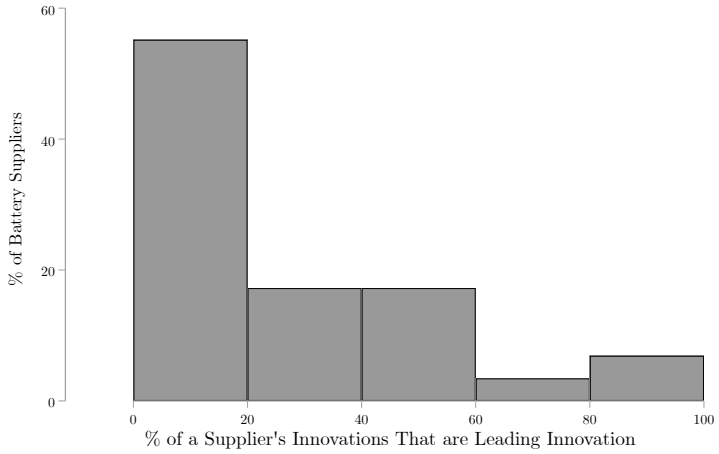


FIGURE NOTES: The x-axis in the figure above calculates the percentage of leading innovation in a battery supplier's total innovation, e.g., 20 means that out of 10 innovations that a battery supplier committed during 2017 and 2023, 2 of them are leading innovation that pushed the industry-wide energy density frontier forward. In this plot, I only keep the battery suppliers that have made more than one innovation in my sample period.

and Srivastav, 2022; Lensman, 2025), I distinguish leading innovations, those pushing the industry-wide energy density frontier, from catch-up innovations, those only close a firm's gap to the industry-wide frontier. Figure 4 shows the distribution of the percentage of leading innovation in a battery supplier's total innovations. Most suppliers rarely push the industry-wide frontier: fewer than 20% of their innovations are leading, and many contribute nothing to the industry-wide frontier. CATL is the outlier, with 54% of its innovations advancing the frontier, compared with 17% for BYD and none for GX. This pattern suggests that raising the industry-wide frontier is much more costly than incremental catch-up, consistent with reports of CATL's efforts to defend its technological lead, including lawsuits against competitors accused of poaching engineers.[20]

[20] https://finance.sina.com.cn/tech/it/2022-10-13/doc-imqmmthc0770701.shtml; https://news.qq.com/rain/a/20220412A0BMRH00

4. Model

I develop a dynamic model of battery suppliers' innovation problem, namely the step-size of improvement on energy density frontier for both LFP and NCM. Battery suppliers make their innovation decisions based on the innovation cost and their expectation of future returns. Upon the realization of innovation on energy density frontier, the driving range and eligible subsidy, if any, of all the relevant EV models will be updated. Battery suppliers will bargain with EV makers over battery prices and EV makers set prices for their EV models simultaneously. Facing the prices and updated EV attributes, consumers will decide on which vehicle model to purchase or leave the market without buying any vehicles. I assume that time t is discretized at the quarterly level. i, j denotes a battery supplier and a vehicle model respectively.

4.1. EV Demand

I assume a nested logit demand model where EVs are in one nest and ICEs are in the other nest. I define the market at the quarter level and take the whole country as an integrated market, which is suitable for my purpose because what really matters for the battery innovation decision is the sum of profits nationwide instead of regional profits. The utility of consumer c choosing vehicle j is modeled as follows:

$$u_{cjt} = \xi_j + \boldsymbol{\beta}^{car}\mathbf{x}_j^{car} - \alpha(p_j - s_{jt}) + f_j^{\text{fuel}} + f_t^{\text{quarter}} + f_j^{\text{segment}} + f_j^{\text{brand-series}} + \zeta_{c,g} + (1-\sigma)\varepsilon_{cj} \tag{4.1}$$

$$s_{jt} = b_j \mathbf{1}(R_j > \underline{R}) \cdot (1 + (\iota_j - 1)\mathbf{1}(d_j > \underline{d})) \tag{4.2}$$

where ι_j is the adjustment factor and b_j is the subsidy base. R_j is the driving range while d_j is the energy density. $\underline{R}, \underline{d}$ are the subsidy threshold of driving range and energy density stipulated by the government as in Table 7. ξ_j is the unobserved characteristic and $\mathbf{x}_j^{car}$ denotes the observed car characteristics, including vehicle size, log of curb weight, log of horsepower, log of driving range, fuel consumption rate (how many liters of gasoline or

diesel are consumed per 100 kilometer).[21] p_j is the MSRP and s_{jt} is the subsidy available in period t for model j. $\zeta_{c,g}+(1-\sigma)\varepsilon_{cj}$ follows the Type-I Extreme Value distribution where $g \in \{\text{EV}, \text{ICE}\}$. The parameter $\sigma \in [0, 1]$ denotes correlation in preferences within the nest and is assumed to be the same for two nests. I also incorporate a set of fixed effects in the model: fuel-type fixed effect, quarter fixed effect, segment fixed effect, and brand-series fixed effect.

4.2. EV Marginal Cost and Battery Marginal Cost

$$\begin{aligned} c_{jt}^E \;=\; p_{jt} - \mu_{jt}^E =\; & \mu_{jt}^B + n_{jt} c_{jt}^B + c_{jt}^{\text{non-battery-related}} \\ =\; & \mu_{jt}^B + n_{jt} \underbrace{\Big(\varphi_1 \mathbf{1}(\text{NCM}) + \varphi_2 d_{jt} + \varphi_3 log(p_t^{\text{Li}_2\text{CO}_3}) + \text{Year Fixed Effect}\Big)}_{\text{battery marginal cost per kWh}} \\ & + \underbrace{\gamma_1 \text{size}_{jt} + \gamma_2 log(\text{Horsepower}_{jt}) + \text{Fixed Effects}}_{\text{non-battery-related cost}} + \omega_{jt} \end{aligned} \tag{4.3}$$

The marginal cost of an EV model j in market t is modeled in a similar way to Barwick et al. (2025), which is equal to price less EV markup, can be decomposed into battery-related cost and non-battery-related cost. The battery-related cost is equal to the sum of the battery markup charged by the battery supplier (μ_{jt}^B) and battery production cost. The battery production cost for an EV is the product of battery capacity (n_{jt} in kWh) in the EV and battery marginal cost (10000 RMB per kWh).[22] Battery capacity n_{jt} is equal to battery energy density (kWh/kg) times the battery weight (kg). Note that n_{jt} stays fixed during my static estimation of marginal cost but is allowed to vary with updated energy densities in solving the dynamic innovation game in counterfactuals.

I explicitly model the battery marginal cost c_{jt}^B as a function of chemical type (i.e. if it is

[21] The specification of $\mathbf{x}_j^{car}$ follows prior studies modeling Chinese EV demand (Wang and Xing, 2023; Barwick et al., 2024) and aligns with the behavioral literature examining factors that influence Chinese consumers' EV purchase decisions (Li et al., 2017; Nie et al., 2018; Li et al., 2020; Guo et al., 2023). None of these studies finds evidence that battery chemistry (LFP vs. NCM) directly affects consumers' vehicle choice.

[22] Measuring battery cost in the unit of RMB per kWh is consistent with the industry practice: Https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/.

NCM), energy density (d_{jt}), input price ($log(p_t^{Li_2CO_3})$),[23] and year fixed effects which captures the industry-wide technology development. For batteries of the same energy density d_{jt}, $\varphi_1 n_{jt}$ captures the total additional cost of using the NCM type instead of LFP for an EV model j. In the non-battery-related part, I include the vehicle size, log of horsepower, year fixed effects, vehicle manufacturer fixed effects, battery supplier fixed effects, fuel type fixed effects, and year fixed effects.

As discussed in Barwick et al. (2025), a key benefit of consumer subsidies is their role in stimulating EV sales, which in turn allows battery suppliers to accumulate experience and reduce costs through learning-by-doing (LBD). However, the current model does not explicitly incorporate a firm-specific LBD mechanism, namely a supplier's cumulative production level affecting its battery and EV marginal costs. This omission is necessary here to make the estimation feasible: modeling LBD along with dynamic innovation decision would significantly expand the state space and render the model computationally intractable.

4.3. Bilateral Bargaining Over Battery Price r_{ij}

In each period, for an EV product j, its manufacturer E chooses EV price p_j and bargains with battery supplier i over the battery price (r_{ij}) simultaneously. In other words, p_j, r_{ij} are optimal with respect to one another in equilibrium, as in Crawford et al. (2018). Note that vertically-integrated BYD won't have the bargaining process and the battery markup is zero.

The bilateral bargaining framework in my paper follows Barwick et al. (2025) and the battery price r_{ij} is assumed to maximize the Nash product of two parties' surpluses from bargaining:

$$r_{ij}^* = \text{argmax} \left(\underbrace{\Delta\pi_i^B(r_{ij})}_{\text{battery supplier's gain from trade}} \right)^{\tau} \left(\underbrace{\Delta\pi^E(r_{ij})}_{\text{EV maker's gain from trade}} \right)^{1-\tau} \tag{4.4}$$

where τ indicates the bargaining power of battery suppliers. If bargaining fails, I assume

[23] Li_2CO_3 is a raw material that is used in both types of batteries.

product j will not be produced and consumers shift to other products or the outside option. In other words, there are no alternative suppliers for a given EV product. The first-order condition with respect to price r_{ij} will imply that the battery markup μ_j can be expressed as:

$$\mu_{ij} = \frac{\tau}{1-\tau}\bar{\mu}_{ij} \tag{4.5}$$

where $\bar{\mu}_{ij}$ refers to the battery markup when the bargaining parameter is fixed at 0.5 and $\bar{\mu}_{ij}$ is known to us as I can learn about sales change and vehicle markup from the demand estimation. Details about how I derive (4.5) can be found in Appendix C.

4.4. EV Pricing

Take the battery price r_{ij} as given, EV maker E chooses prices p_j for each EV in its product offering set $\mathcal{J}_E$ to maximize its profit:

$$\max_{\{p_j\}_{j\in\mathcal{J}_E}} \pi_E = \sum_{j\in\mathcal{J}_E}(p_j - c_{ij}^E)q_j(\widetilde{\mathbf{p}}) \tag{4.6}$$

where $\widetilde{\mathbf{p}}$ denotes the vector of retail prices less the subsidy.

The first-order condition with respect to price is:

$$p_j : \; q_j + \sum_{j'\in\mathcal{J}_E}(p_{j'} - c_{ij'}^E)\frac{\partial q_{j'}}{\partial p_j} = 0 \tag{4.7}$$

4.5. Innovation on Energy Density Frontier

I model innovation choices as the equilibrium of a finite-horizon dynamic game. I use a finite horizon framework because the market growth shown in Figure 2a implies a non-stationary environment and both LFP and NCM technologies are expected to be replaced by solid state technologies in the medium run. For battery suppliers, the state variable vector will be the energy density frontiers of LFP and NCM batteries and expressed as

$\mathbf{s}_t \equiv [z^{NCM}_{CATL,t}, z^{LFP}_{CATL,t}, z^{NCM}_{BYD,t}, z^{LFP}_{BYD,t}, z^{NCM}_{GX,t}, z^{LFP}_{GX,t}]$ where z^b_{it} indicates the highest energy density that the battery supplier i has ever produced for type b up to period t. The action space for battery supplier i in period t is characterized by vector $\mathbf{a}_{it} = [a^{NCM}_{it}, a^{LFP}_{it}]$. a^{NCM}_{it} is the step size for innovation on NCM batteries. Note that a firm can innovate on both LFP and NCM at the same time.[24]

It is crucial to clarify the timing of the dynamic game first. Entering a period with the state vector being $\mathbf{s}_t$, EV's battery type, energy density, and driving range will be updated.[25] Then, each battery supplier bargains with EV makers over battery prices and EV makers set prices for their EVs at the same time. Upon the realization of the demand, battery supplier i earns the flow profit $\pi^i_t(\mathbf{s}_t)$ from all the EVs that it supplies. After the realization of the flow profits in period t, battery supplier i draws an i.i.d. cost shock vector $\boldsymbol{\varepsilon}_{it} \equiv [\varepsilon^0_{it}, \varepsilon^1_{it}, \cdots, \varepsilon^K_{it}]$ which is private to itself and drawn from Type I Extreme Value distribution. Each entry (e.g. ε^K_{it}) in the private cost shock vector corresponds to one possible step-size option (e.g. K-th action). Facing their own private cost shocks, battery suppliers simultaneously choose $\mathbf{a}_{it}$, their step sizes of innovation for both LFP and NCM batteries respectively.

After battery suppliers made their choices $\mathbf{a}_{it}$, state variables transit from $\mathbf{s}_t$ to $\mathbf{s}_{t+1}$ at the beginning of the next period $t+1$. Throughout the finite horizon game, I take the energy density frontier evolution of other battery suppliers as given.[26]

When a battery supplier i chooses step size a^b_{it} for battery type b in period t, the innovation

[24] I assume that there is no uncertainty about the available technological paths for two reasons: First, LFP and NCM have been the primary paths chosen by battery suppliers for over a decade. According to IEA and SNE, the combined market share of LFP and NCM is persistently over 90%. Second, although there have been attempts of other technologies like NCA, these attempts never made it to the phase of massive commercial production.

[25] The update process will be explained shortly in Section 4.6.

[26] Two assumptions in my paper warrant caution. First, policies are assumed not to affect the entry or introduction of new EV models. Second, I abstract from learning-by-doing in EV and battery production. While these assumptions are necessary to make the dynamic innovation problem-solving computationally feasible, it does limit the flexibility of the counterfactuals, potentially understating the effect of consumer subsidies on model introduction and cost reduction.

cost is defined as follows:

$$h_{it}^{b}(a_{it}^{b}) = \begin{cases} exp(Aa_{it}^{b}+B) & if\ a_{it}^{b}>0 \\ & ,b\in\{\text{LFP},\text{NCM}\} \\ 0 & if\ a_{it}^{b}=0 \end{cases} \tag{4.8}$$

$$\begin{aligned} \text{where } A &= \phi_2 \\ B &= \phi_1+\phi_3\mathbf{1}(b=\text{NCM})+\phi_4\mathbf{1}(i=\text{CATL}) \\ &\quad +\phi_5\mathbf{1}(i=\text{BYD})+\phi_6\mathbf{1}(a_{it}^{b}+z_{it}^{b}<max\{z_{it}^{b}\}_i)+\phi_7 t \end{aligned} \tag{4.9}$$

In the innovation cost function, I allow the cost to be different between improving NCM and improving LFP. Inspired by the data observation in Section 3, I include the term $\phi_6\mathbf{1}(a_{b,t}^{i}+z_{b,t}^{i}<max\{z_{b,t}^{i}\}_{i,b})$ to capture potential within-path positive spillover effect.[27] If the innovation won't push the industry-wide frontier to a new height, $\mathbf{1}(a_{b,t}^{i}+z_{b,t}^{i}<max\{z_{b,t}^{i}\}_{i,b})$ will equal to 1, otherwise, 0. A negative ϕ_6 will imply that it is cheaper to do catch-up innovation than leading innovation. ϕ_7 captures the industry-wide time trend of innovation cost as the industry matures.

With the innovation cost explained, firms' innovation problem can be formalized as follows:

$$\max_{\mathbf{a}_{it}} -h(\mathbf{a}_{it})-\lambda\varepsilon_{it}^{a}+\beta E[V_{i,t+1}(\mathbf{s}_{t+1},\boldsymbol{\varepsilon}_{it+1})\mid \mathbf{s}_t,\boldsymbol{\varepsilon}_{it},\mathbf{a}_{it}] \tag{4.10}$$

$$\text{where } \mathbf{a}_{it}=[a_{it}^{NCM},a_{it}^{LFP}] \tag{4.11}$$

$$\text{innovation cost } h(\mathbf{a}_{it})=h(a_{it}^{NCM})+h(a_{it}^{LFP}) \tag{4.12}$$

ε_{it}^{a} is the private cost shock with respect to action a and drawn from Type I Extreme Value distribution. λ is the scaling parameter of the private cost shock.

Suppose battery supplier i faces a set of step sizes being $\{0,\delta,2\delta,...,K_i\delta\}$, the value function

[27] As implied by the introductory quotation from BYD's founder, there hardly exists cross-path spillover.

$V_t(\mathbf{s}_t, \boldsymbol{\varepsilon}_{it})$ can be expressed as:

$$V_{i,t}(\mathbf{s}_t, \boldsymbol{\varepsilon}_{it}) = \pi_{it}(\mathbf{s}_t) + \max_{\mathbf{a}_{it}} \{-h(\mathbf{a}_{it}) + \beta E[V_{i,t+1}(\mathbf{s}_{t+1}, \boldsymbol{\varepsilon}_{it+1}) \mid \mathbf{s}_t, \boldsymbol{\varepsilon}_{it}, \mathbf{a}_{it}] - \varepsilon^a_{it}\} \tag{4.13}$$

The expectation in the equation above is taken over the realization of private cost shocks and other firms' innovation step-sizes.

In period T, no one will innovate. Each firm will receive the flow profit in period T plus a terminal value as follows:

$$V_T(\mathbf{s}_T, \boldsymbol{\varepsilon}_{iT}) = \pi_{iT} + \frac{\beta - \beta^{19}}{1-\beta} \frac{1}{4} \sum_{t=T-3}^{T} \pi_{it}(\mathbf{s}_t) \tag{4.14}$$

The terminal value is the product of the average quarterly flow profit in 2023 ($\frac{1}{4}\sum_{t=T-3}^{T} \pi_{it}(\mathbf{s}_t)$) and a scalar $\frac{1-\beta^{19}}{1-\beta}$. I use the average here instead of the flow profit from last period to avoid the bias due to the seasonality. The scalar $\frac{1-\beta^{19}}{1-\beta}$ implies the terminal value is a discounted sum of the repeated averages for 18 quarters.[28] In this finite-horizon framework, I solve the finite-horizon game by backward induction and the equilibrium concept is finite-horizon Markov perfect equilibrium.

The innovation cost in the model is assumed to be deterministic up to an i.i.d. private shock. While innovation is generally uncertain in both its costs and outcomes, this simplification is also used in Igami (2017) and more importantly, appears to be largely consistent with some industry anecdotal evidence.

In terms of improving EV battery's energy density, reports from the flagship investment bank in China,[29] China International Capital Corporation, indicate that recent advances have primarily relied on optimizing internal space utilization rather than exploring unknown materials. Space optimization is a more predictable and replicable engineering practice, which supports the modeling assumption of relatively predictable innovation outcomes.

[28] The payoff of innovation on LFP and NCM may drop drastically when the solid-state battery becomes available. The prediction of the mass-production of solid-state battery varies around 2027 and 2028. I take the average and assume that solid-state battery won't become available until 18 quarters after 2023, namely 2027Q2.

[29] https://research.cicc.com/frontend/recommend/detail?id=3157

This viewpoint is also echoed by industry leaders such as the chairman of the China Automotive Power Battery Industry Innovation Alliance (CAPBIIA)[30] and analysts at Plug and Play Tech Center,[31] an American venture capital firm focusing on mobility and clean tech startups.

4.6. Implications of a Change in Energy Density Frontier

When the energy density frontier is changed due to firms' innovation action, the change will have two implications in my model: First, any change in the energy density frontier may change the relative frontier difference between LFP and NCM. The relative difference between LFP's energy density frontier and NCM's within a supplier has an impact on which type of battery is more capable of supporting some performance-demanding EVs. For example, if NCM's energy density frontier is higher than LFP, then heavy and driving-range demanding EVs are more likely to use NCM batteries. Therefore, I need to consider the composition effect of energy density frontiers on EV's choice of battery type.

Battery Type

The energy density frontier reflects a technological path's capacity to meet an EV's (high) performance requirements and thus influences the likelihood that an EV adopts NCM rather than LFP batteries. To quantify this relationship, I run a logit regression to predict the probability that EV model j chooses NCM using the following specification:

$$\mathbf{1}(\text{choose NCM})_{jt} = \beta_0 + \beta_1 z_{it}^{LFP} + \beta_2 z_{it}^{NCM} + \beta_3 s_{jt} + \beta_4 \mathbf{x}_{jt} + \beta_5 s_{jt}\mathbf{x}_{jt} \tag{4.15}$$

The set of explanatory variables draws on factors highlighted in industry reports (Roland Berger, 2024),[32] including the energy density frontier of NCM and LFP. Specifically, suppose

[30] https://www.cpnn.com.cn/news/xny/202312/t20231227 1664299.html
[31] https://www.pnpchina.com/resources/PNP20230420F
[32] https://www.questmobile.com.cn/research/report/1892112377266147329

Table 2: Battery Type Choice Estimation

Y=1(NCM)	Coefficient	S.E.
LFP Frontier (Wh/kg)	-0.050	0.003
NCM Frontier (Wh/kg)	0.051	0.003
Subsidy Index (10000 RMB)	17.064	2.679
Size (m^3)	-0.232	0.053
Electricity Efficiency (kWh/100km)	0.194	0.029
Log(non-battery curb weight) (kg)	2.268	0.442
SUV Dummy	0.696	0.086
Hybrid Dummy	-1.170	-.172
BYD Dummy	-1.806	0.125
CATL Dummy	-0.561	0.121
GX Dummy	-1.536	-.121
Subsidy Index×Size	0.259	0.047
Subsidy Index×Electricity Efficiency	-0.147	0.022
Subsidy Index×Log(non-battery curb weight)	-2.548	0.456
Pseudo-R2	0.415	
Observation	7579	

TABLE NOTES: The table above displays the results from the logit regression in which the dependent variable is the dummy of choosing NCM batteries. Each observation is an EV model in a quarter.

an EV model j sources its battery from supplier i.[33] z_{it}^{LFP} and z_{it}^{NCM} represent the energy-density frontiers of LFP and NCM batteries produced by supplier i.

The vector $\mathbf{x}_{jt}$ includes EV's key attributes: vehicle size, electricity consumption per 100 km, SUV and hybrid indicators, the log of non-battery curb weight, and dummies for whether the vehicle uses BYD, CATL, or GX batteries. s_{jt} represents a subsidy-intensity index that varies across models and policy regimes, reflecting the eligible subsidy amount for model j given its originally observed characteristics in the data under different policies in consideration. I also include interactions between the subsidy-intensity index and several vehicle characteristics, including vehicle size, electricity consumption per 100 km, and the log of non-battery curb weight, to capture heterogeneous effects of subsidy generosity across vehicle types.

The estimation results, presented in Table 2, show that an EV model is more likely to

[33] To keep the problem tractable, I assume the supplier choice is fixed.

adopt NCM when the NCM frontier is higher, the LFP frontier is lower, subsidies are more generous, electricity consumption per 100 km is higher, non-battery part is heavier, or the vehicle is an SUV. If LFP's (NCM's) frontier is increased by 30 Wh/kg, then, on average, there will be 14.78 percentage point decrease (15.02 percentage point increase) in the probability of an EV model choosing NCM.

Driving Range

After pinning down the choice of battery type, if BYD's LFP energy density frontier is changed from 150Wh/kg to 170 Wh/kg, for example, implying a change of $\check{d}$ =20Wh/kg, then for all the EV products equipped with BYD's LFP battery $\{j \mid j \in J^{LFP}_{BYD,t}\}$ in period t, their energy densities will be increased by the same amount: 20Wh/kg.[34]

In this way, I implicitly assume that change in the energy density frontier won't affect the shape of the distribution of energy density of all products for a given supplier-type-period but only shift the distribution horizontally, which is largely consistent with how the distribution of energy density changes over time in the data as in Figure 14 in the Appendix.

Then driving range, battery capacity, subsidy, battery marginal cost will be updated accordingly. Among updated attributes, driving range is the most relevant for consumers. Details about how to update driving range based on the new energy density can be found in Appendix F.

5. Estimation

In this section, I will explain my estimation of the model parameters in three steps. First, I estimate the system of demand for differentiated vehicle products and obtain the estimates for $\boldsymbol{\theta}^{demand} = \{\boldsymbol{\beta}^{car}, \alpha, \sigma\}$. Second, I uncover the parameters that govern the marginal costs of EV production and battery production, $\boldsymbol{\theta}^{battery} = \{\varphi_1, \varphi_2, \varphi_3\}$ and $\boldsymbol{\theta}^{EV} = \{\gamma_1, \gamma_2\}$. The estimation is assisted by the demand estimates, the first order conditions of EV maker's

[34] In some cases, $\check{d}$ can be so negative that $d^{observed}_{jt} + \check{d} < 0$. I set a lower bound for $d^{observed}_{jt} + \check{d}$ as 85Wh/kg, which is the observed lowest energy density in the data.

period profit maximization, and the first order conditions of the bilateral bargaining over battery prices.

With the assumption on how the energy density frontier affects EV's attributes in Section 4.6, estimates from the first two steps enable me to calculate the battery suppliers' period profits under different innovation levels. Lastly, I feed the period profits into the dynamic game of innovation and estimate the cost of innovation on energy density frontier, obtaining parameter $\boldsymbol{\theta}^{dynamic} = \{\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, \phi_6, \phi_7\}$.

5.1. Demand

$\boldsymbol{\theta}^{demand}$ can be estimated like in Berry (1994), which is independent of the estimation of supply-side parameters. There is endogeneity issue with estimating the price coefficient and the nesting parameter. I adopt several sets of instrument variables to help us address the problem. The first set of instruments is widely used BLP instruments like in Berry (1994) and Berry et al. (1995), i.e. average driving range of products from the same make, average horsepower of products from the same make, average driving range of products in the same market and nest but from rivals, average size of products in the same market and nest but from rivals. The second set of instruments follows the suggestion by Gandhi and Houde (2019) and includes the log sum of the distance in size, driving range, fuel efficiency, and curb weight between the focal product and other products in the same market and nest. The last instrument variable I use is the number of rivals in the same market, suggested by Town and Liu (2003). Then I use these instruments and exogenous attributes to construct moment conditions:

$$E[\xi_j \mid \mathbf{x}_j^{car}, \text{instruments}] = 0 \tag{5.1}$$

Given the moments above, I conduct two-step GMM to estimate the demand parameters.

5.2. The Marginal Cost of EV and Battery

$$p_{jt} - \mu^E_{jt} = \frac{\tau}{1-\tau}\bar{\mu}^B_{jt} + n_{jt}\underbrace{\left(\varphi_1 \mathbf{1}(\text{NCM}) + \varphi_2 d_{jt} + \varphi_3 log(p_t^{\text{Li}_2\text{CO}_3}) + \text{Year Fixed Effect}\right)}_{\text{battery cost per kWh}}$$
$$+ \gamma_1 \text{size}_{jt} + \gamma_2 log(\text{Horsepower}_{jt}) + \text{Fixed Effects} + \omega_{jt} \tag{5.2}$$

ω_{jt} in (5.2) stands for the residual unobserved cost shock, which may include not only EV production related cost shock but also battery production related cost shock. Battery markup $\bar{\mu}^B_{jt}$ can be endogenous because unobserved cost ω_{jt} may be correlated with battery markup $\bar{\mu}^B_{jt}$. For example, if the unobserved cost ω_{jt} captures some production efficiency of battery supplier b, then such production efficiency can be translated into firms' pricing decisions and therefore shapes the battery markup in the equilibrium.

To address this endogeneity issue, I construct an instrument introduced by Barwick et al. (2025), which is called predicted battery markup (Details can be found in Appendix E). The construction of the instrument leveraged a White-list policy in China during 2016 and 2019. The White-list policy imposes that only EVs using domestic battery suppliers can enjoy the consumer subsidy and thereby creates exogenous variation in the battery markup among battery suppliers of different origins. I use the predicted battery markup and other exogenous variables as supply-side instruments and construct the following moments:

$$E[\omega_{jt} \mid \text{supply-side instruments}] = 0 \tag{5.3}$$

Then I conduct GMM estimation to obtain the estimates of supply-side parameters $\boldsymbol{\theta}^{battery}$ and $\boldsymbol{\theta}^{EV}$ in the static part. The bargaining parameter τ is identified from by the exogenous shifts in battery markups (thereby vehicle prices) due to battery suppliers' white-list status, e.g., being on the battery supplier whitelist or not. Effectively my identification assumption requires that whether a battery supplier makes it onto the whitelist or not is unrelated to their unobserved production cost differences, which is justified by the whitelist's intention

to foster domestic battery suppliers (Gong and Hansen, 2023, S&P Global).[35]

5.3. Innovation Cost

In the data, the energy density frontier is observed to range from 100 to 200 Wh/kg and the observed innovation step size ranges from 0 to 51. To balance the computation burden and accuracy, I discretize the energy density level to be {99, 132, 165, 198} and discretize the innovation step size for a given battery type to be $a_{it}^{NCM}, a_{it}^{LFP} \in \{0, 33, 66\}$, so the total size of the state space is $4^6 = 4096$. Scaling parameter λ is set as 1.[36]

To obtain the value function for a given state, part of job is to calculate the flow profits. For a given quarter, I resolve the outcomes from EV pricing and battery bargaining and calculate the flow profits for 729 states spanned by $\{99, 165, 231\}^6$. In each state, there are nearly 2000 products' prices to be solved. To speed up the process, I will only solve for vehicles manufactured by major vehicle manufacturers,[37] whose combined sales account for over 97% of Chinese domestic passenger vehicle sales. Then I interpolate the per-period profit for the remaining states.

After obtaining the flow profits for all possible states in all periods, it is ready to estimate the dynamic parameters in an inner-outer loop procedure. In the outer loop, I search for the parameter $\boldsymbol{\theta}^{dynamic}$ to maximize the likelihood function. In the inner loop, given the guess of $\boldsymbol{\theta}^{dynamic}$, I solve the value function in each period and obtain the choice probability in each period-state.

In the inner loop, given the intermediate value function $\tilde{V}_{t+1}$,[38] for each state $\mathbf{s}_{t+1}$, I will search for the optimal choice probability $\mathbf{Y}^\star \equiv [\mathbf{y}^\star_{CATL}, \mathbf{y}^\star_{BYD}, \mathbf{y}^\star_{GX}]$ for a given state $\mathbf{s}_t$,

[35] https://www.spglobal.com/ratings/en/research/articles/240424-credit-faq-china-s-different-paths-to-driving-consumption-electric-vehicles-13082880

[36] I tried to estimate λ but the model fit gets worse. Results can be found in Appendix G.

[37] The selection of major vehicle manufacturers proceeds as follows: If a manufacturer has ever achieved top 10 ICE sales or top 10 EV sales in at least one quarter (e.g., manufacturer A ranked 7th in terms of ICEs sales in 2021Q1), then all of this manufacturer's vehicle models from 2017 to 2023 will be kept when I calculate the flow profit for a state. In this way, I keep the pricing solving problem manageable while preserving the representativeness of the sample.

[38] The intermediate value function is the value after taking the expectation of the value function over the private cost shock $\boldsymbol{\varepsilon}$, $\tilde{V}_t \equiv E_{\boldsymbol{\varepsilon_t}}(V_t)$. Details can be found in Appendix D.

which is a fixed point defined by (D.4) in the Appendix D. The derivation of $\mathbf{Y}^\star$ can be found in Appendix D. The choice probability will be consistent with the expectation of next period values because I assume rational expectations. Given the choice probability and the expected next period values, I can calculate the $\tilde{V}_t(\mathbf{s}_t)$. After repeating the same procedure for all states in period t. I will move on to the estimation of optimal choice probability in $t-1$.

I start with the final period T where firms won't make any decision and the value function is essentially the flow profit plus a Euler constant. The inner loop is completed when the choice probability and the intermediate values are computed for all states in all periods.

With the output from the inner loop, I can calculate the joint likelihood for the observed actions in the data:

$$\ell(\mathbf{a}_{it}^{obs.} \mid \mathbf{s}_t^{obs.}, \boldsymbol{\theta}^{dynamic}) \;=\; \prod_{i,t} y_{it}(\mathbf{a}_{it})^{\mathbf{1}(\mathbf{a}_{it}^{obs.}=\mathbf{a}_{it})} \tag{5.4}$$

The joint likelihood of observing actions in all periods is:

$$\prod_{i,t} \ell(\mathbf{a}_{it}^{obs.} \mid \mathbf{s}_t^{obs.}, \boldsymbol{\theta}^{dynamic}) \tag{5.5}$$

I search for the dynamic parameters that maximize the joint likelihood above. Throughout the process of dynamic estimation, I will take the observed frontier evolution of other battery suppliers as given.

6. Results

In this section, I will first present the results of demand estimation and the estimation of EV and battery's marginal cost. Then, I will show the estimation of parameters in innovation cost. Finally, I test the predictive power of innovation cost parameters by comparing the simulated energy density frontier path with the observed one.

Table 3: Demand Estimation

	Coefficient	S.E.
Price (10000RMB)	–0.022	0.003
Size (m^3)	0.114	0.022
log(Curb Weight)	-0.310	0.098
log(Horsepower)	0.325	0.042
log(Driving Range)	0.714	0.090
Fuel Consumption Rate (L/100km)	-0.046	0.005
Nesting Parameters	0.811	0.116
Fuel Type	Y	
Quarter	Y	
Segment	Y	
Brand×Series	Y	
Median Own Elasticity	-1.812	
Mean Own Elasticity	-2.950	

TABLE NOTES: The table above displays the estimated parameters in my demand model. The market is defined at quarter level, including all cities in China. All sold vehicles, whether it is EV or a gasoline/diesel vehicle, are included in the estimation. Standard Error is clustered at vehicle manufacturer level.

6.1. Demand Estimation

Table 3 presents the demand estimation results[39]. The coefficient signs align with intuition: conditional on the same segment (i.e., compact SUV), consumers prefer vehicles that are cheaper, larger, lighter, more powerful, more fuel-efficient, and with longer driving ranges. The estimated own-price elasticity is -2.95, consistent with prior findings(Li et al., 2017; Xing et al., 2021; Wang and Xing, 2023; Barwick et al., 2025).

6.2. EV and Battery Marginal Cost

Table 4 reports the cost parameter estimates for EVs and batteries. The battery cost rises with input prices and energy density. The bargaining parameter is estimated at 0.527,

[39]The way I define the market size can be explained by an example: For the 2018Q2 market, I obtain the highest quarterly vehicle sales in 2018 and multiply this number by 2 to get the market size for all 4 markets in 2018, including 2018Q2.

suggesting that battery suppliers on average hold slightly bigger bargaining power than EV makers. To validate my results, I cross-check two key findings. First, my estimate of bargaining parameter (0.527) is comparable to the counterpart (0.503) in Barwick et al. (2025). Second, the model predicted average battery unit price (RMB/Wh) and unit profit (RMB/Wh) are 1.17 and 0.17 respectively, which are consistent with the estimates of 1.02 and 0.19 in industry reports.[40]

The coefficient of the NCM dummy is 0.152. Using NCM rather than LFP technology to produce battery of same energy density would imply an 12.9% (0.152/1.17) premium of the battery price, which is consistent with reports on the cost disadvantage of the NCM technology.[41] All else equal, using LFP batteries would be significantly cheaper than using NCM batteries, which is a result of LFP's lower marginal cost. Note that innovation won't reduce the marginal cost, instread, it will elevate an EV model's energy density and increase its marginal cost.[42]

6.3. Innovation Cost

Table 5 presents the estimated dynamic parameters, which reveal innovation cost heterogeneity across battery types, firms, and relative positions to the industry-wide frontier. For a given step size, when the new firm-level frontier remains below the current industry frontier, innovation costs 37% less than industry-wide-frontier-raising innovation, supporting the hypothesis that catch-up innovation is less costly than leading innovation. The negative coefficient on the NCM dummy suggests that innovation on NCM is 71% cheaper than LFP, consistent with the chemical features of these two technologies.[43] A bigger step size

[40] Because battery suppliers treat unit-level profit as confidential business information, I cannot obtain these figures directly. Instead, I benchmark my results against estimates from industry reports published by Soochow Securities Co Ltd. These estimates are derived from firm-level financial disclosures and represent an industry-standard approach. Consistent with common practice in the battery sector, I measure unit profit in RMB per watt-hour (RMB/Wh)

[41] https://www.fastmarkets.com/insights/lfp-batteries-extend-dominance-over-ncm-batteries-china/#:~:text=LFP%20batteries%20accounted%20for%2065.81,38.77%25%2C%20according%20to%20CABIA.

[42] A higher energy density represents an upgrade in battery technology because it allows the same amount of energy to be stored in a lighter battery—much like how a smartphone upgrade enables greater memory capacity without increasing its physical size.

[43] A back-of-envelope calculation shows that for CATL to increase the frontier by 33Wh/kg as a follower in 2020Q2, innovation on NCM incurs 18 billion RMB less than innovation on LFP.

Table 4: EV and Battery Marginal Cost Estimation

	Coefficient
Bargaining Parameter	
τ	0.527
	(0.014)
Battery Cost Parameters (φ)	
log(price of Li_2CO_3)(10000RMB/ton)	0.034
	(0.0003)
1(NCM)	0.152
	(0.0001)
Energy Density (Wh/kg)	0.001
	(0.0002)
Year FE	Y
Vehicle Cost Parameters (γ)	
Size (m^3)	0.271
	(0.005)
log(Horsepower)	0.343
	(0.027)
Fixed Effects	
PHEV FE	Y
Battery Supplier = CATL	Y
EV Maker FE	Y
Year FE	Y
Observation	6548

Table Notes: The table above provides the estimates of the bargaining parameter, battery marginal cost parameters, and EV marginal cost parameters. The sample used for the estimation covers all EV models sold from 2017 to 2023. Given that BYD is vertically integrated and the implied battery markup is 0, I only use non-BYD models in the estimation above. Standard errors are clustered at the year level.

Table 5: Innovation Cost Estimation

		Coefficient	S.E.
Intercept	ϕ_1	0.5384	0.0256
Cost Per Unit of Innovation	ϕ_2	0.0222	0.0022
NCM Dummy	ϕ_3	-1.2326	0.0034
CATL Dummy	ϕ_4	-0.0000	0.0110
BYD Dummy	ϕ_5	2.1836	0.0440
Catch-up Innovation Dummy	ϕ_6	-0.4616	0.0268
Time Trend	ϕ_7	0.0090	0.0027

TABLE NOTES: The table above provides the estimated innovation cost parameters. The estimation is based on the observed energy density frontier improvement made by CATL, BYD, and GX during 2017Q1 and 2023Q3. 2023Q4 is dropped because firms in my model will receive a terminal value and won't do any innovation in the last period.

of energy density frontier improvement would incur a higher cost.

At firm level, BYD seems to face the highest innovation cost for the same step size of improvement while GX faces a similar level to CATL.[44] The positive coefficient in front of the time trend variables indicates that the innovation cost is increasing over time, everything else equal, which may imply that the higher the current frontier is, the more costly to move forward.

Figure 5 validates the innovation cost parameter estimates by comparing observed firm-type (e.g. CATL-NCM) specific energy density frontiers with simulated counterparts. Using parameters from Table 5, 1000 innovation paths were simulated for each battery type across the focal firms. Each plot displays the simulation mean (thick non-grey dashed line) and observed values (solid line), with thin grey dashed lines representing the 5th and 95th percentiles.

[44]The fact that BYD has higher innovation cost doesn't conflict with the view that vertical integration raises firms' incentive to innovate (Yang, 2020). In theory, integration boosts firms' innovation incentive mainly by reducing transaction costs and hold-up risks rather than reducing total research spending. BYD undertakes a broader range of innovation activities across chemistry, cell design, pack integration, and vehicle optimization, which raises its measured "innovation cost" in this model. The estimated parameter reflects BYD's observed innovation intensity and scope rather than pure engineering efficiency. In other words, integration reduced coordination frictions but allowed BYD to internalize a wider set of research tasks, leading to higher total observed costs.

There are two things to be noted when interpreting this figure. First, the observed frontier represents a single realization while the dashed line represents the mean of 1000 simulations; Second, zero constitutes a possible action choice, enabling flatness in one single realization. Consequently, the simulated mean naturally exhibits greater smoothness than the observed single realization. For better reference, I also plot the median across 1000 simulations with a dotted line. Figure 5 demonstrates that the simulated frontier path in general remains consistent with observed data patterns. Although the fit is not exact, the simulated averages (thick dashed lines) closely follow the trend of the observed values (solid lines), and nearly all data points lie within the 5th–95th percentile interval.

6.4. Potential Substitution Between LFP and NCM Innovation

Given the estimated demand, battery marginal cost, and probability of choosing NCM batteries, it is necessary to understand how innovation on LFP and NCM may substitute for each other. In this framework, potential substitution between innovation on two paths can arise at two levels.

At the consumer level, relative preferences between LFP-based and NCM-based EVs shape the relative payoffs to innovation on each path. Consumers value both lower prices and longer driving ranges in Table 3, and driving ranges depend on energy densities.[45] If innovation raises LFP's energy density to a level comparable to NCM's, LFP-based EVs would offer similar ranges. Between same-energy-density LFP and NCM batteries, LFP batteries can be cheaper because NCM uses more expensive rare earth elements and its marginal cost is higher than LFP's, as shown in Table 4. Therefore, innovation on LFP may help LFP-based EV steal NCM-based EV's market share.[46]

While NCM innovation also enhances energy densities and driving ranges, the use of expensive rare earth materials raises the cost of NCM batteries, making NCM-based EVs pricier than LFP-based ones. As a result, comparable energy-density improvements on NCM yield

[45] In my model, both battery weight and vehicle weight are taken as exogenous and fixed. The driving range is largely determined by the change in energy density.

[46] A back-of-envelope calculation shows that the sales-weighted average diversion ratio from an LFP-EV to an NCM-EV is 0.5% while the opposite direction is 0.8%.

Figure 5: Observed and Simulated Energy Density Frontier

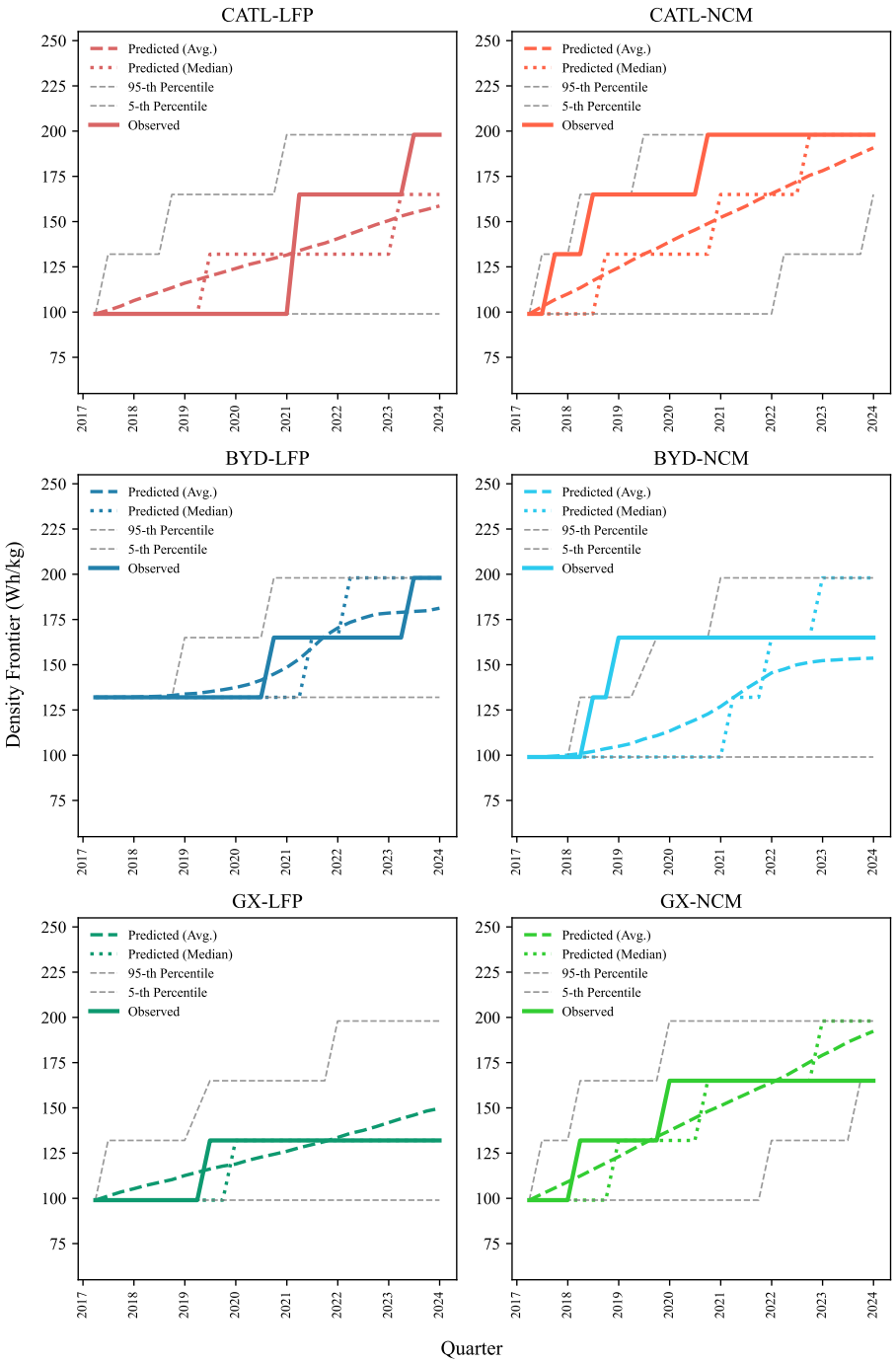


FIGURE NOTES: The figures above demonstrate the model fitness. The thick non-grey dashed line shows the average of predicted quarterly energy density frontier across 1000 simulations, which is surrounded by thin grey dashed lines indicating the 5th and 95th percentiles. The solid line displays the observed quarterly energy density path frontier in the data, which is discretized by 33. I also provide the median (the thick dotted line) from the 1000 simulations as reference.

smaller demand gains than LFP innovation.

At the model level, the battery type choice for each EV model is summarized in Table 2. When innovation expands the energy density frontier of one battery type, more EV models adopt that technology. Since the number of EV models is taken as exogenously given in my analysis, a larger share of models adopting LFP implies less models using NCM, therefore a smaller potential market for NCM innovation, and vice versa.

An empirical exploration of the substitution can be found in Figure 22 in the Appendix. I make one path of innovation unavailable and see how the innovation on the other path would change. Figure 22 implies that there exists certain degree of substitution between LFP innovation and NCM innovation for a given battery supplier.

7. Counterfactual Analysis

In this section, I compare the innovation magnitude of LFP and NCM across counterfactual scenarios.[47] To maintain computational tractability, I impose an upper bound of 198 Wh/kg on the energy-density frontier. Although this cap may slightly dampen measured innovation toward the end of the sample, it does not affect earlier dynamics.[48] I calculate each firm's cumulative improvement in the energy density frontier (Wh/kg) from 2017 to 2019 along a given path and then aggregate these cumulative changes across the three focal firms. For instance, the aggregated cumulative LFP innovation is the sum of all three firms' cumulative gains in its LFP energy density frontier over 2017–2019. The analysis therefore centers on the relative difference in this aggregated cumulative innovation between LFP and NCM during the period 2017–2019.

[47] Note that the timing assumption in the model, which allows firms to make innovation decision simultaneously, can lead to multiple equilibria when solving for counterfactual outcomes. To address this issue, I will focus on the average outcomes from a set of 1000 simulations for each counterfactual scenario.

[48] Figure 16 in the Appendix H shows the detailed evolution path of energy density frontiers and confirms that the imposed cap is not binding during 2017-2019.

Figure 6: Innovation: Social Planner vs. No-Subsidy

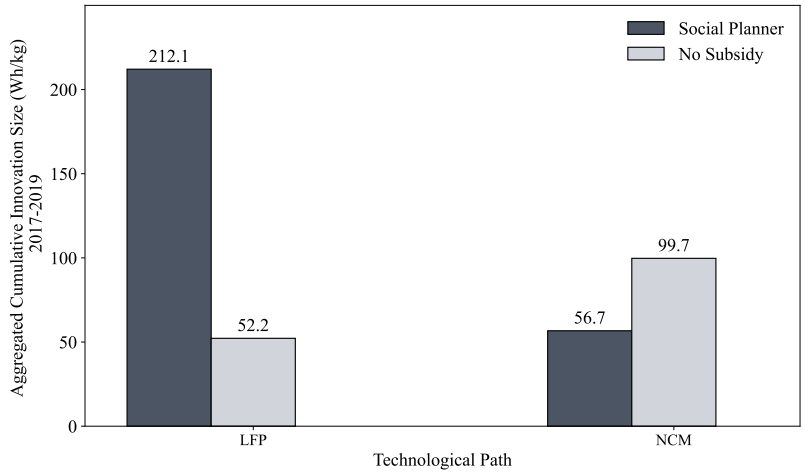


FIGURE NOTES: The figure above compares the aggregated innovation size on LFP and NCM from 2017 to 2019. Dark grey bars represent the social planner and light grey bars represent the no-subsidy case.

7.1. Divergence Between the Social Planner and the Market

In the first set of counterfactuals, I compare the social planner scenario with the no-subsidy scenario. In the social planner case, I remove the observed consumer subsidies and examine how the energy density frontier evolves when a social planner directs both the innovation decision for the 3 focal firms[49] and the prices[50] of all batteries and vehicles to maximize total surplus, which is a summation of consumer surplus, producer surplus, and environmental benefits.[51] Unlike private firms, the social planner internalizes the innovation spillovers and environmental benefits. In the no-subsidy case, any format of subsidies is excluded and firms take charge of both innovation and pricing decisions to maximize their own profits while ignoring spillovers and environmental benefits.

Figure 6 compares the innovation step sizes for LFP and NCM under the social planner

[49] Take the other battery suppliers' observed innovation as given.

[50] In the social planner case, EV prices will be marginal cost minus environmental benefits and battery markup will be zero.

[51] The calculation of environmental benefits from replacing an ICE vehicle with an EV is explained in Appendix J.

and no-subsidy cases. Dark gray bars represent the social planner case, while light gray bars correspond to the no-subsidy case. Firms in the no-subsidy scenario innovate almost twice as much as the planner on NCM, whereas the planner undertakes substantially more innovation on LFP, over four times the market level. These contrasting patterns indicate that the social planner generally favors the LFP path, while firms tend to significantly under-innovate on the socially preferred path.

For the social planner, innovation on both LFP and NCM enhances consumer surplus by extending driving range. However, because LFP batteries rely on cheaper raw materials, they lead to lower EV prices relative to NCM-based vehicles. The lower price of LFP-based EVs stimulates EV demand and amplifies environmental benefits. Compared with the social planner, battery suppliers capture a smaller share of the social benefits from innovation on the low-marginal-cost path, LFP.

First, a supplier's innovation on its lower-marginal-cost technology (i.e., LFP) will create competitive pressure that promotes rivals' innovation on LFP , resulting in more competitive LFP-based EV products. Then, fierce competition in the vehicle market will drive down overall prices and limit the supplier's private returns from innovation. In contrast, the social planner sets prices equal to marginal costs net of environmental benefits and fully accounts for the resulting increase in consumer surplus when EVs become more affordable.

Second, battery suppliers can extract only a fraction of the total trade surplus through the bargaining with EV makers, regardless of the technology path. In addition, because the social planner internalizes both innovation spillovers and environmental benefits, the planner perceives higher social returns to innovation and therefore exhibits greater willingness to bear LFP's higher sunk costs of innovation.[52]

7.2. Consumer Subsidy vs. R&D Subsidy

In the second set of counterfactuals, I examine how alternative subsidy schemes influence innovation intensity along the two technology paths. Specifically, I compare a hypothetical

[52] Figure 21 shows that internalizing the environmental benefits will lead to only a very small increase in the innovation size on both LFP and NCM by the social planner.

energy-density-based consumer subsidy with a hypothetical R&D subsidy. The hypothetical consumer subsidy is set at 2.5 times the observed subsidy to EV buyers. For the R&D subsidy to battery suppliers, I consider two cases. In the first, both technology paths receive a subsidy that covers a fixed share $\varphi \in [0, 1]$ of the deterministic component of the innovation cost, $\varphi h(\mathbf{a}_{it})$, with the rate set at $\varphi = 0.0575$.[53] In the second case, the subsidy applies only to the LFP path, reimbursing a fraction $\varphi^{LFP} = 0.0715$ of its deterministic innovation cost. Both R&D subsidies are available only from 2017 to 2019, matching the phaseout period of consumer subsidies to facilitate direct comparison. The subsidy rates, 2.5, 0.0575, and 0.0715, are picked so that all three schemes impose approximately the same fiscal cost (˜152 billion RMB) on the government.[54]

The Effect of Alternative Subsidies on Innovation

To assess which subsidy format narrows the gap between the social planner's choice and private firms', I solve the dynamic game under the three almost equally costly hypothetical subsidies policies and simulate the innovation step size for LFP and NCM: Results in Figure 7 show that R&D subsidies in general promote more LFP innovation than consumer subsidies. Since the uniform version of R&D subsidies lowers innovation costs for both paths, NCM innovation also experiences an increase, but to a smaller extent than LFP. It is not surprising that LFP-only R&D subsidies lead to more LFP innovation. Consumer subsidies, by contrast, lead to a much smaller increase in LFP innovation and a decline in NCM innovation.[55] Given Figure 6 shows that the social planner prefers LFP innovation more and the market tends to under-innovate on LFP, the R&D subsidy schemes do better in addressing the issue of under-innovating LFP than an energy-density-based consumer

[53] For reference, the R&D tax credit rate in the United States is 0.2.

[54] The numerical search for the R&D subsidy rate that yields an equivalent fiscal cost to the consumer subsidy is computationally demanding, as it requires resolving the dynamic game for each candidate rate.

[55] I plot the firm-level innovation size in Figure 20 and find that the decline in NCM innovation is driven by BYD. A much more generous consumer subsidy scheme will boost the demand for EVs and thereby the payoff to LFP innovation will be bigger and more likely to cover its high innovation cost. As the discussion on substitution between LFP and LFP innovation in Section 6.4, an LFP-based EV with equal energy density is more appealing to consumers than a NCM counterpart because of the lower marginal cost. As the leader in LFP innovation and the only vertically integrated firm, BYD has more incentives to innovate on its LFP batteries and the improvement in its own LFP-based EVs makes its own NCM-based EVs less competitive, therefore diminishing the payoff to its NCM innovation.

Figure 7: Innovation: Consumer Subsidy vs. R&D Subsidy

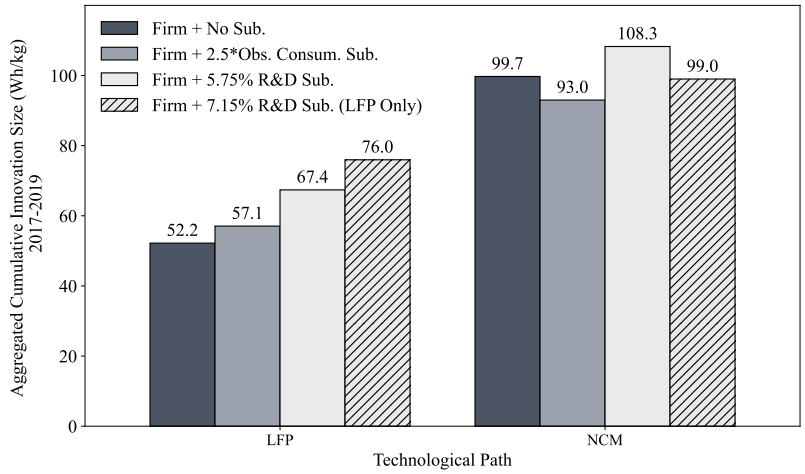


FIGURE NOTES: The figure above compares the aggregated innovation size on LFP and NCM from 2017 to 2019. The three subsidy schemes in the figure above incur a similar level of government expenditure (˜152 billion RMB).

subsidy scheme of similar fiscal costs.

Welfare Outcomes

Beyond innovation outcomes, it is important to evaluate the welfare implications of alternative policies. I focus on three metrics: consumer surplus, environmental benefits from EV adoption,[56] and producers' variable profits. Column (1) to (4) in Table 6 presents the relative difference to the no-subsidy scenario. Both consumer subsidy and R&D subsidy schemes raise consumer surplus, environmental benefits, and vehicle makers' profits, but the 2.5 times consumer subsidy generates substantially larger consumer and environmental gains than R&D subsidies. Battery suppliers' profits decline only modestly under either type of subsidy scheme.[57] The comparison between two R&D subsidy schemes shows that LFP-only R&D subsidies can generate more consumer surplus and environmental benefits than the almost equally costly uniform R&D subsidies.

[56]The calculation details can be found in Appendix J.

[57]For reference, the total battery suppliers' variable profits range from 19.24 to 21.31 billion RMB across the 4 scenarios in Table 6.

Table 6: Welfare Analysis 2017-2023 (in billion RMB)

Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to No Subsidy						Social Planner = 100	
	ΔConsum. Surplus	ΔEnviron. Benefits	ΔVehicle Maker Profit	ΔBattery Supplier Profit	Gov't Exp.	EV Sales (in million units)	Consum. Surplus+Environ. Benefits	Total Surplus
Obs. Consum. Sub.	39.14	5.39	4.41	0.05	49.41	64.04	83.8	92.62
5.75% R&D Sub.	9.26	1.29	1.09	-0.97	152.51	64.00	83.73	91.89
2.5*Obs. Cons. Sub.	226.88	31.83	25.91	-1.61	151.95	64.26	84.27	91.80
7.15% LFP R&D Sub.	30.7	4.19	3.47	-2.08	152.68	64.03	83.78	91.6

TABLE NOTES: Each number in the table above, measured in billion RMB unless indicated, is the summation of all markets during the sample period from 2017 to 2023. Again, to balance computation burden and model flexibility, 198 is set as the upper limit for state space, which may lead to an underestimation of R&D subsidy's benefits because innovation may push the frontier higher than 198 Wh/kg in later years. In Appendix L, I calculate the same group of welfare metrics using just 2017 to 2019 outcomes to avoid the potential binding effect of the 198 cap.

Fiscal Costs and the Role of Fuel Taxes

From the government's perspective, fiscal cost is a key concern. I list the subsidy expenditure for the government in Column (5) of Table 6. To finance these subsidy expenditures, I explore the effectiveness of the fuel consumption tax. Because fuel consumption taxes are often proposed as a proxy for carbon taxes (Aghion et al., 2016),[58] I consider a modest increase, 2.2%, in China's existing fuel consumption tax rate, 29%.[59] For reference, the percentage of fuel consumption tax in retail fuel prices is 15% in the United States.[60] Raising the existing fuel consumption tax rate in China by 2.2 percentage points (from 29% to 31.2%) can result in an over 155 billion RMB increase in fuel tax revenue,[61] which fully

[58] Carbon taxes on ICE emissions are rarely seen due to administrative difficulties. While fuel taxes are not equivalent to carbon taxes, they target fuel consumption and therefore emissions, making them a reasonable proxy in this context.

[59] In China, gasoline and diesel consumption are charged with a fixed tax: 1.52 RMB/liter and 1.2 RMB/liter. I calculate the tax rate based on the time-varying fuel prices across the sample period and take the average and obtain 29%.

[60] https://www.investopedia.com/gas-taxes-and-what-you-need-to-know-5118477

[61] Specifically, the increase in fuel tax revenue for the four scenarios from up to bottom in Table 6 is 155.76, 155.77, 155.71, 155.76 billion RMB respectively.

covers the subsidy schemes.[62]

7.3. Effect of Innovation Spillover

Figure 8: No-Subsidy vs. Social Planner: Without Spillover (ϕ_6=0)

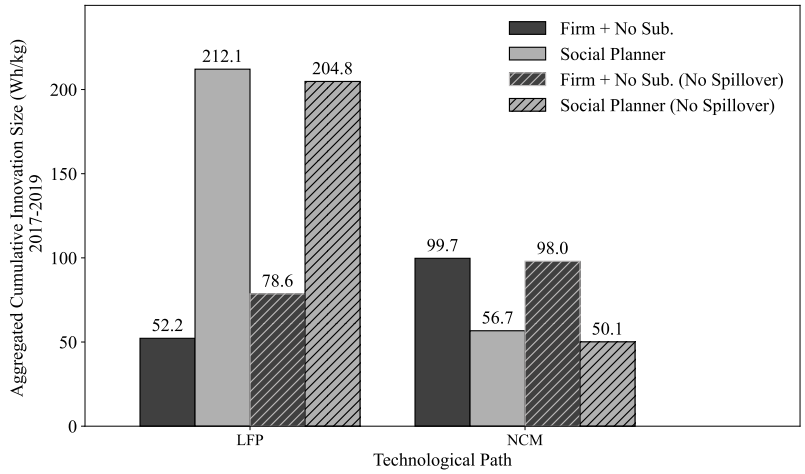


FIGURE NOTES: The figure above compares the aggregated innovation size on LFP and NCM from 2017 to 2019. Light grey bars represent the social planner while dark grey bars represent the no-subsidy case. Bars with hatches indicate the results in the absence of innovation spillover ($\phi_6 = 0$).

When spillovers are removed (ϕ_6=0), three main effects emerge. First, the social planner perceives lower social returns from innovation by technology leaders. Second, in the absence of spillovers, innovation leaders face weaker catch-up threats, making it more profitable for them to push aggressively in the technology where they hold an advantage, potentially beyond what the social planner would prescribe. Third, eliminating spillovers prevents early progress on NCM from further strengthening its innovation cost advantage over LFP.[63]

Figure 8 shows that the social planner will innovate less on both paths when there is no spillover, which is intuitive because the payoff to innovation is smaller due to the lack of

[62] Details of the fuel tax implementation are provided in Appendix K.

[63] This reinforcement can create a "lock-in" effect because of spillovers. Figure 19 in the Appendix breaks down the innovation by year and shows that firms devote less innovation to LFP in the early years when spillovers are present, consistent with the lock-in effect due to spillover-reinforced cost disadvantages.

Figure 9: Innovation by Firm: With vs. Without Spillover

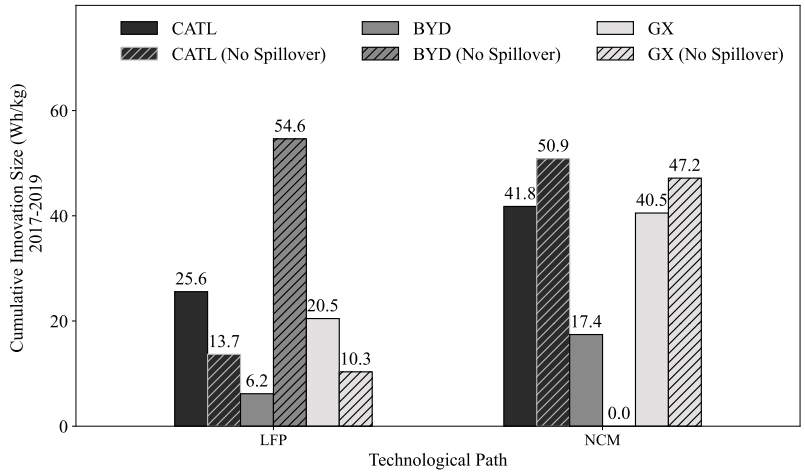


FIGURE NOTES: The figure above compares each firm's annual innovation size, measured in year-to-year energy density frontier change, on LFP and NCM. Dark, medium, and light grey represent CATL, BYD, and GX respectively. Bars with hatches indicate the results in the absence of innovation spillover ($\phi_6 = 0$).

the social benefits of spillovers. For firms, in the absence of innovation spillovers, while the total innovation on NCM is slightly lower, the aggregate size of innovation on LFP actually increases relative to the case when spillovers are present.

Figure 9 looks into the firm-level innovation and highlights the leader's aggressiveness: BYD, with an initial lead on LFP, doesn't innovate on NCM and expands its LFP lead even more aggressively. By contrast, CATL and GX, with early advantages on NCM, focus innovation on NCM and cut back sharply on LFP.

In summary, without innovation spillovers, the social planner's total innovation effort declines only slightly across both paths, while firms display a much wider gap in innovation intensity between frontier leaders and lagging competitors. The comparison between with and without innovation spillovers shows that while innovation spillovers incentivize laggard firms to make catch-up innovation, the presence of spillovers dulls the leader's incentive to push the industry-wide frontier forward.

7.4. Factors Affecting the Difference Between Planner and Market's Innovation Outcomes

Battery Suppliers' Bargaining Power

Given the vertical structure in my model, battery suppliers' innovation incentives can also be affected by how surplus is split between battery suppliers and EV makers. In Figure 10, I increased the bargaining weight for CATL from 0.52 to 0.8. I find that CATL innovates more on LFP than the status quo once it can split more surplus from the bargaining with downstream EV makers. Another interesting finding is that CATL will innovate significantly less on NCM once it can extract more surplus from the bargaining with EV makers, which is consistent with the expected substitution between LFP and NCM innovation that discussed in Section 6.4.

All these changes are consistent with the observed fact that BYD, a vertically integrated firm (bargaining weight is 1), is an initial leader on LFP innovation and innovates on LFP to a greater extent than other firms. The results of this counterfactual suggest that vertical integration can have significant implications not just for innovation levels (Yang, 2020) and lower product prices due to elimination of double marginalization (Crawford et al., 2018), but also for firms' innovation path choice. A higher level of integration between upstream innovators and downstream product seller can align upstream innovators' innovation path choice closer to the socially optimal one.

Market Size

The magnitude of the payoffs from EV battery innovation depends critically on the magnitude of downstream's market demand for EV. Figure 2a and Figure 3 show both growing EV sales and switching innovation path choices over time, which motivates the exploration of whether the market size has an effect on innovation direction.[64]

[64] Acemoglu and Linn (2004) studied a similar but different question: how the market size affects the rate of innovation.

Figure 10: CATL's Innovation After Having More Bargaining Power (τ_{CATL} from 0.52 to 0.8)

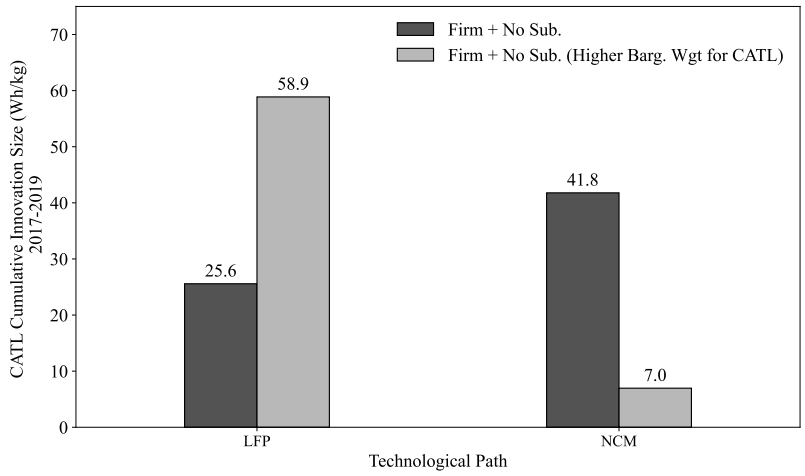


FIGURE NOTES: The figure above presents two no-subsidy cases. The difference lies in the bargaining weight τ for CATL. τ is 0.52 for CATL in the dark grey bars. In light grey bars, CATL's bargaining weight is 0.8 while the rest of battery suppliers' bargaining weight is still 0.52.

Figure 11: Innovation After Doubling Vehicle Market Size

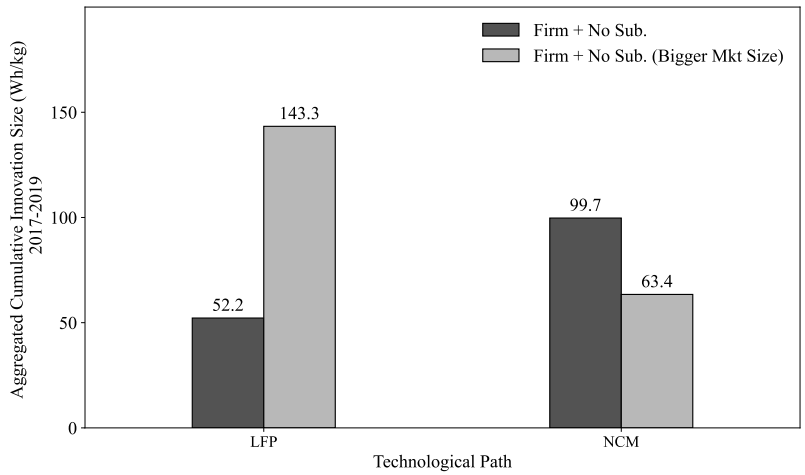


FIGURE NOTES: The figure above presents two no-subsidy cases. The difference lies in the market size of the vehicle market. The dark grey bars indicate the status quo. In light grey bars, the market size is doubled.

To quantify the effect of market size on innovation payoffs, I double the market size of the whole vehicle market in every sample period and resolve firms' innovation decisions. To be specific, I only elevated the level of total vehicle market size by the same extent through my sample period but didn't change the growing trend in EVs' total market share. Figure 11 shows that EV market size strongly shapes innovation step sizes, especially inducing more LFP innovation while less NCM innovation.

The rise in LFP innovation and the reduction in NCM innovation again confirms the substitution relationship between LFP and NCM innovation, as discussed in Section 6.4. The finding that a larger market size stimulates LFP innovation implies that policies expanding EV demand, particularly in the early years, can help narrow the gap between market and planner innovation outcomes.

Downstream Competition Among EVs

The innovation payoff to battery suppliers depends not only on how the gains from trade are divided between EV makers and battery suppliers, but also on the overall magnitude of these gains. Competition in the downstream vehicle market affects the total gains available for bargaining and thereby shapes how battery suppliers perceive the relative returns to LFP and NCM innovation.

If innovation on the LFP path raises the energy density and driving range of LFP-equipped EVs to match those of NCM-based EVs, one might expect that LFP's inherent low marginal cost[65] would translate into higher sales and larger profits to be shared. However, this need not be the case. As explained earlier in Section 7.1, under intense competition, most of the cost savings from LFP batteries are passed through to consumers as lower prices rather than captured by firms as higher markups.

To examine whether stronger competition exacerbates underinvestment in LFP innovation, I conduct a counterfactual that increases product market competition by expanding the

[65]Note that low marginal costs of LFP battery production arise from its use of inexpensive inputs such as iron rather than from innovation.

Figure 12: Innovation After Having More EV Models

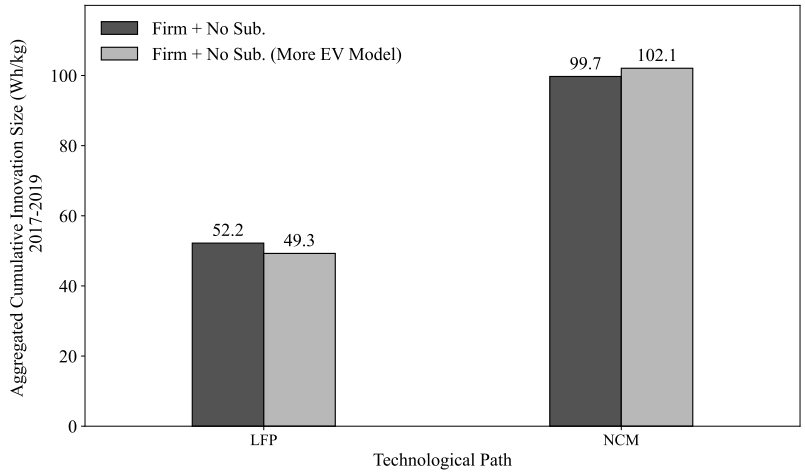


FIGURE NOTES: The figure above presents two no-subsidy cases. The difference lies in the number of EV models. The dark grey bars keep the same EV model portfolio in the market. In light grey bars, I add 100 extra EV models that are not supplied by the three focal battery suppliers to increase the competition among EVs.

number of EV models. In each market, I identify the top 100[66] EV models not supplied by CATL, BYD, or GX by sales and duplicate them. This approach intensifies competition, particularly among EVs, while holding constant the set of models supplied by CATL, BYD, and GX.

Figure 12 shows that as competition intensifies, innovation on the LFP path declines while innovation on the NCM path rises. This pattern supports the hypothesis that stronger downstream competition erodes the profits resulting from LFP's low-marginal-cost advantage and weakens firms' incentives to innovate on the LFP path.

Beyond bargaining power, market size, and downstream competition, I also discuss in Appendix N how other factors, such as differences in innovation cost and consumers' valuation of environmental benefits, shape the innovation gap between the social planner and the market.

[66]The average number of vehicle models and EV models in a market is 1918 and 320 respectively.

8. Conclusion

I use the Chinese EV battery industry to examine whether the market-driven innovation aligns with the social planner's preferred technological path and how policies can bridge their potential divergence. I develop and estimate a dynamic model of upstream battery suppliers' innovation decisions, which captures the trade-offs between two competing technologies, LFP and NCM.

The analysis shows that when green technologies differ in cost structures and involve a trade-off between high innovation sunk cost and low marginal cost in production, the social planner fully internalizes the benefits of marginal cost reductions, environmental gains, and innovation spillovers. As a result, the planner places greater weight on the low marginal cost path and is willing to bear its higher sunk costs for long-run welfare improvements.

By contrast, certain market conditions can lead upstream innovators to weight two paths in a way that is different from the social planner. A smaller market size, the vertical separation between upstream innovators and downstream product sellers, or a weaker bargaining power for upstream innovators discourages these upstream firms from investing in the path with high sunk costs in innovation. Intense downstream competition also discourages innovation on the low marginal cost path, since most cost savings are passed on to consumers as lower prices rather than retained by firms as higher markups, which gives rise to a smaller total trade surplus for the downstream firms (e.g., EV makers) and upstream firms (e.g., battery suppliers) to split. In addition, counterfactual exercises reveal innovation spillovers make leaders innovate less aggressively while encouraging laggards to make more catch-up innovation.

Policy experiments highlight the effectiveness of R&D subsidies in reducing the inefficiency in the market's innovation path choices. With the same fiscal budget, R&D subsidies narrow the innovation cost gap between the two paths and promote more balanced progress on both LFP and NCM, while attribute-based consumer subsidies generate much greater short-run consumer surplus and environmental benefits. A modest increase in the fuel consumption tax rate also emerges as an effective and fiscally sustainable financing source, capable of

restoring budget neutrality or even generating a surplus.

Although the empirical focus is on China's EV battery industry, the underlying mechanisms apply broadly to other green technologies characterized by high sunk cost and low marginal cost trade-offs, such as solar panels and wind turbines.[67] The results emphasize that even within two clean technologies, markets can deviate from the socially optimal path and highlights how carefully designed innovation policies can guide firms' innovation effort toward the socially desirable path, which is crucial for energy transition.

Finally, the analysis abstracts from two dimensions: policy induced entry of new electric vehicle models and learning by doing in production. It also assumes deterministic innovation costs aside from idiosyncratic shocks, which may not hold in industries with greater uncertainty. Future research could explore how the market-driven innovation direction and policy effectiveness would change when greater uncertainty, product entry, or learning-by-doing is factored in.

[67] The implications from this paper may apply beyond green technologies as long as the same trade-off exists.

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Online Appendices

Innovation Path Choices in China's Electric Vehicle Battery Industry

Qian Wang (U of Maryland)

A. Industry Patterns

Figure 13: Sales Weighted Average Energy Density by Price Range

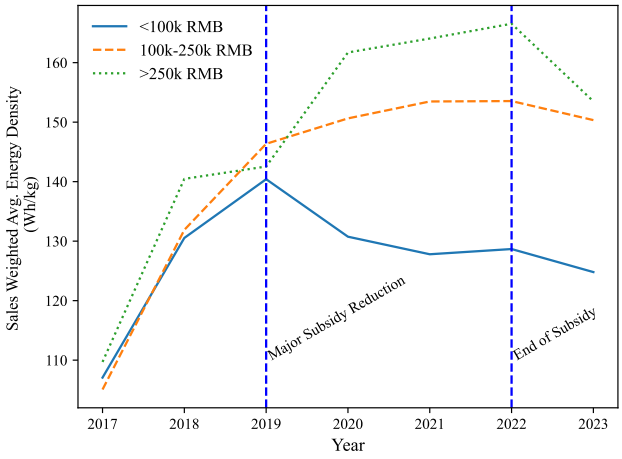


FIGURE NOTES: The figures above display sales-weighted energy density for EVs in different price ranges.

B. Subsidy Schedule

The details for the energy-density-based subsidy schedule can be found in Table 7.

Table 7: Overview of The Central Government's Subsidy Policy

(a) Base Amount (10000 RMB ≈ $1388) by Driving Range

Year	R=Range(km)						
	100≤R<150	150≤R<200	150≤R<250	200≤R<250	250≤R<300	300≤R<400	R≥400
2017	2	2	3.6	3.6	4.4	4.4	4.4
2018	/	1.5	1.5	2.4	3.4	4.5	5
2019	/	/	/	/	1.8	1.8	2.5
2020	/	/	/	/	/	1.62	2.2
2021	/	/	/	/	/	1.3	1.8
2022	/	/	/	/	/	0.91	1.26

(b) Adjustment Parameter by Energy Density

Year	D=Energy Density(Wh/kg)						
	threshold	90≤D<120	105≤D<120	120≤D<140	125≤D<140	140≤D<160	D≥160
2017	90	1	1	1.1	1.1	1.1	1.1
2018	105	/	0.6	1	1	1.1	1.2
2019	125	/	/	/	0.8	0.9	1
2020	/	/	/	/	0.8	0.9	1
2021	/	/	/	/	0.8	0.9	1
2022	/	/	/	/	0.8	0.9	1

Table Notes: The upper table documents the subsidy base for different driving ranges and the lower table documents the subsidy adjustment parameter for different energy density levels. Policy details are collected from announcements on government's websites. The energy density here refers to the battery pack's energy density. The subsidy I list here is for battery electric vehicle, the main target of policy, which is different from the subsidy scheme for plug-in hybrid electric vehicle.

C. Bilateral Bargaining Over Battery Prices

Consider battery supplier i bargains with product j's manufacturer over the battery price r_{ij}. The battery price r_{ij} is assumed to maximize the Nash product of two parties' surpluses from bargaining:

$$r_{ij}^{*} = \text{argmax} \left(\underbrace{\Delta\pi_i^B(r_{ij})}_{\text{battery supplier's gain from trade}} \right)^{\tau} \left(\underbrace{\Delta\pi^E(r_{ij})}_{\text{EV maker's gain from trade}} \right)^{1-\tau} \tag{C.1}$$

I define the payoff upon disagreement the same way as in Barwick et al. (2025): If bargaining fails, I assume product j will not be produced and consumers shift to other products or the outside option. In other words, there are no alternative suppliers. Therefore, the gain of trade is as follows:

$$\Delta\pi^E(r_{ij}) = \sum_{j' \in \mathcal{J}_E} \mu_{j'}^E \Delta q_{j'} = \sum_{j' \in \mathcal{J}_E} \mu_{j'}^E \big(q_{j'}(\mathbf{p}_{-j}) - q_{j'}(\mathbf{p})\big) \tag{C.2}$$

$$\Delta\pi_i^B(r_{ij}) = \sum_{j' \in \mathcal{J}_B} \mu_{j}^B \Delta q_{j'} = \sum_{j' \in \mathcal{J}_B} \mu_{j'}^B \big(q_{j'}(\mathbf{p}_{-j}) - q_{j'}(\mathbf{p})\big) \tag{C.3}$$

where $\big(q_{j'}(\mathbf{p}_{-j}) - q_{j'}(\mathbf{p})\big)$ denotes how the change in sales of all other products would be if product j won't be produced, which can be derived from demand estimation. $\mathcal{J}_B, \mathcal{J}_E$ denote the set of products that are supplied by battery supplier i and EV maker E respectively.

The first-order condition with respect to price r_{ij} is:

$$\tau \frac{\partial \pi_i^B}{\partial r_j} (\Delta\pi_i^B)^{\tau-1} (\Delta\pi^E)^{1-\tau} + (1-\tau) \frac{\partial \pi^E}{\partial r_j} (\Delta\pi_i^B)^{\tau} (\Delta\pi^E)^{-\tau} = 0 \tag{C.4}$$

For a given quarter t, I can rewrite the first-order condition in the vector form as follows:

$$(\mathbf{T}^B \circ \tilde{\mathbf{Q}}_1)\boldsymbol{\mu}^B = \frac{\tau}{1-\tau} (\mathbf{T}^E \circ \tilde{\mathbf{Q}}_2)\boldsymbol{\mu}^E \tag{C.5}$$

$$\boldsymbol{\mu}^B = \frac{\tau}{1-\tau} \Big(\mathbf{T}^B \circ \tilde{\mathbf{Q}}_1\Big)^{-1} (\mathbf{T}^E \circ \tilde{\mathbf{Q}}_2)\boldsymbol{\mu}^E = \frac{\tau}{1-\tau} \bar{\boldsymbol{\mu}}^B \tag{C.6}$$

where $J_{EV} \times J_{EV}$ matrix $\mathbf{T}^B$ is the co-supplier matrix, if EV i and EV j share the same battery supplier, then the (i, j)-th entry in $\mathbf{T}^B$ is one, otherwise it is zero. $J_{EV} \times J$ matrix $\mathbf{T}^E$ is the co-maker matrix whose (i, j)-th entry is equal to one if EV i and vehicle j are manufactured by the same maker, otherwise zero. The (i, j)-th entry in $J_{EV} \times J_{EV}$ matrix $\tilde{\mathbf{Q}}_1$ means the sales change in EV j if the bargaining fails to reach an agreement over the battery price for EV i. The (i, j)-th entry in $J_{EV} \times J$ matrix $\tilde{\mathbf{Q}}_2$ means the sales change in product j if the bargaining fails to reach an agreement over the battery for EV i. $\bar{\boldsymbol{\mu}}^B$ refers to the battery markup when the bargaining parameter is fixed at 0.5 and $\bar{\boldsymbol{\mu}}^B$ is known to us as I can learn about sales change and vehicle markup from the demand estimation.

D. Innovation Choice Probability

In period $T-1$, before the realization of private cost shocks, I define an intermediate value function as follows:

$$\tilde{V}_{T-1}(\mathbf{s}_{T-1}) \equiv E_{\boldsymbol{\varepsilon}_{T-1}}(V_{T-1}(\mathbf{s}_{T-1}, \boldsymbol{\varepsilon}_{iT-1})) \tag{D.1}$$

So

$$\begin{aligned}\tilde{V}_{T-1}(\mathbf{s}_{T-1}) = \pi_{iT-1}(\mathbf{s}_{T-1}) + \\ E_{\boldsymbol{\varepsilon}_{T-1}} \max\{-h(a_{iT-1}=0) + \beta E[\tilde{V}_T(\mathbf{s}_T) \mid \mathbf{s}_{T-1}, a_{iT-1}] + \lambda \varepsilon^a_{iT-1}\}\end{aligned} \tag{D.2}$$

Exploit the property of the distribution of $\boldsymbol{\varepsilon}_{T-1}$ and we have:

$$\tilde{V}_{T-1}(\mathbf{s}_{T-1}) = \pi_{iT-1}(\mathbf{s}_{T-1}) + \lambda\gamma + \lambda \ln\Big(\sum_{a_{iT-1}} exp(\frac{-h(a_{iT-1}) + \beta E[\tilde{V}_T(\mathbf{s}_T) \mid \mathbf{s}_{T-1}, a_{iT-1}]}{\lambda})\Big) \tag{D.3}$$

The expectation is taken over the state in the next period, which is governed by the probability of all firms' choices.

Now I can express the conditional choice probability as:

$$y_i(a \mid \mathbf{s}_{T-1}) = \frac{exp(\frac{-h(a)+\beta E[\tilde{V}_T(\mathbf{s}_T)|\mathbf{s}_{T-1},a]}{\lambda})}{\sum_{a'} exp(\frac{-h(a')+\beta E[\tilde{V}_T(\mathbf{s}_T)|\mathbf{s}_{T-1},a']}{\lambda})} \equiv F\Big(\mathbf{y}_i, \mathbf{y}_{-i}, \tilde{V}_T(\mathbf{s}_T) \mid \mathbf{s}_{T-1}\Big) \quad \text{(D.4)}$$

where $\mathbf{y}_i \equiv [y_i(a=0), y_i(a=\delta), \cdots, y_i(a=K_i\delta)]$.

E. Instrument Construction for Battery Markup

To address the endogeneity issue with the battery markup, $\bar{\mu}^B$, I construct the same instrument as in Barwick et al. (2025). First, I regress the observed price on a set of covariates exogenous to unobserved cost shocks ω_{jt}, including curb weight, size, driving range, horsepower, fuel efficiency, subsidy, whitelist status of the battery source, fuel type fixed effects, quarter fixed effects, segment effects, and brand-series fixed effects.

The whitelist status is determined by the Chinese government's list of approved battery suppliers from 2016 to June 2019. During this period, the Chinese government required EV models to use batteries exclusively from government-approved suppliers, all of which were domestic firms, to qualify for subsidies. Crucially, the selection process was driven by the nationality of the battery suppliers, ensuring its exogeneity. The predicted price from this regression is a function of exogenous variables alone. Using this predicted price, I recalculate market shares and derive the implied vehicle markup. Finally, the battery markup (assuming a bargaining parameter of 0.5) is computed based on (C.6).

F. Driving Range Technology

When calculating per-period profits for states that differ from the observed one, I need to determine how driving range would change. To estimate driving range for a given state, I first update the energy density for each EV model.[68] I then adopt an approach similar to Barwick et al. (2025), using regression analysis to recover the driving range technology.

[68] Specifically, Figure 14 provides evidence for the shape-preserving assumption on the energy density distribution, which is the key for the model-level energy density update.

Figure 14: Energy Density Distribution by Year

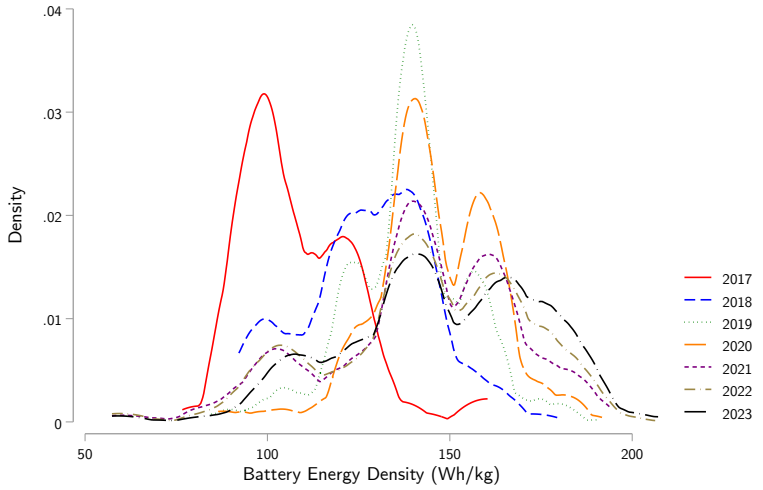


FIGURE NOTES: The figure above plots the distribution of the model-level energy density by year from 2017 to 2023.

Specifically, I regress driving range on a comprehensive set of regressors: second-degree polynomials of energy density, battery weight, curb weight, vehicle size, horsepower, and electricity consumption per 100 km. I perform this analysis separately for battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). The model demonstrates excellent predictive power in my setting: the R-squared exceeds 0.99, and the difference between actual and predicted driving ranges is negligible.

G. Alternative Dynamic Estimation Setting

In Figure 15, I present the model fit if λ is estimated rather than being fixed at 1. The fit in general gets worse, with all three firms' LFP frontier path inflated and GX's NCM frontier path deflated.

Figure 15: Observed and Predicted Energy Density Frontier (With λ Being Estimated)

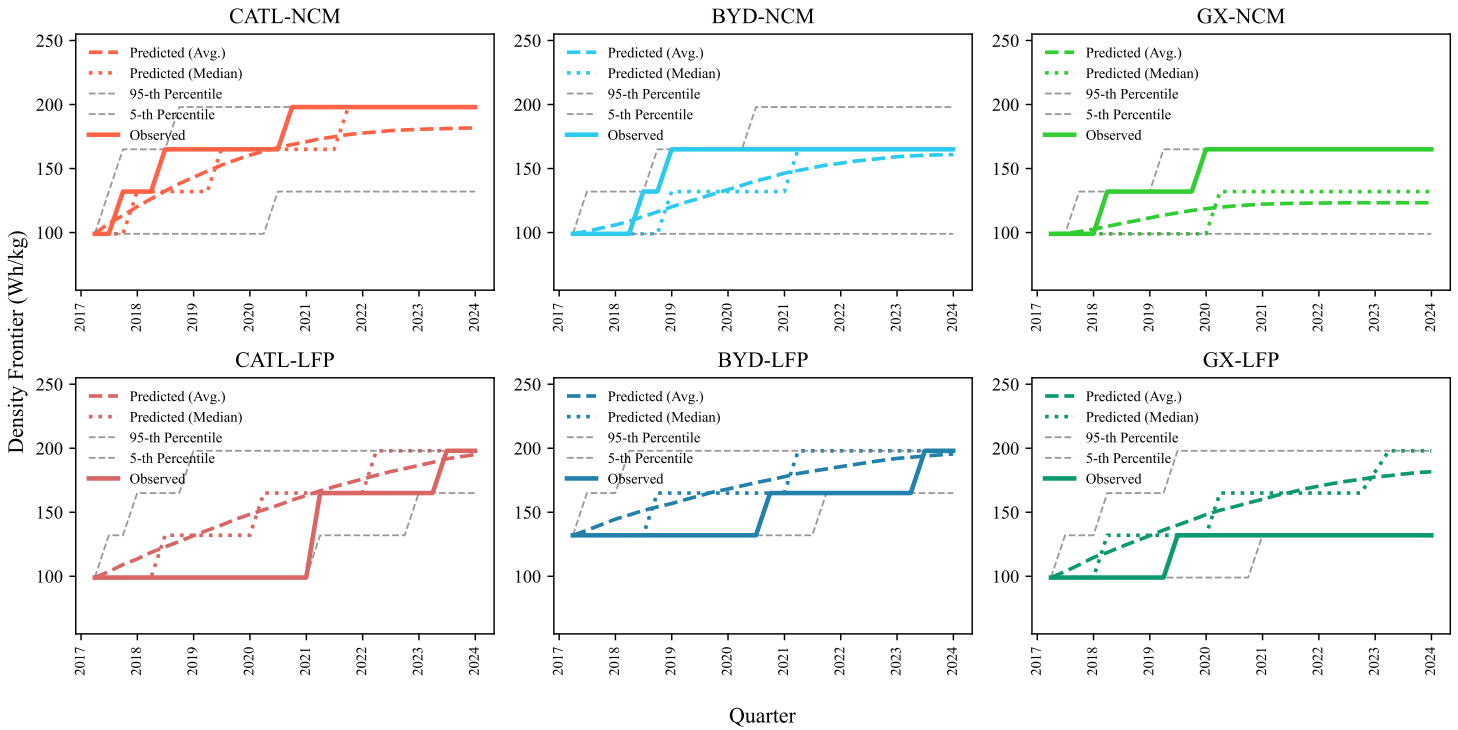


FIGURE NOTES: The figures above demonstrate the model fitness when the scaling parameter λ is also estimated. The thick non-grey dashed line shows the average of predicted quarterly energy density frontier across 1000 simulations, which is surrounded by thin grey dashed lines indicating the 5th and 95th percentiles. The solid line displays the observed quarterly energy density path frontier in the data, which is discretized by 33. I also provide the median (the thick dotted line) from the 1000 simulations as a reference.

H. Energy Frontier Evolution by Counterfactual

To provide a vivid illustration of the energy density frontier evolution, I plot the quarterly energy density frontier by firm by battery type in each counterfactual in Figure 16. The energy density frontier is the average of 1000 simulations.

I. Innovation Size by Path and Year

From Figure 17 to Figure 20, I break down the aggregate innovation size by year to illustrate the innovation dynamics over the years.

J. Environmental Benefits

Calculating the environmental benefits of replacing an ICE vehicle with EV is more complex, as it involves two widely recognized sources: reduced CO_2 emissions and diminished local air pollution such as $PM_{2.5}$, NO_x, and VOC (Holland et al., 2016; Xing et al., 2021; Barwick et al., 2025). Following Barwick et al. (2025)[69] who estimate lifetime environmental benefits of replacing a gasoline vehicle with an EV at \$19,506 in China, this analysis adopts their conservative approach of halving estimates to \$9,753 (70026.54 RMB[70]), accounting for EV's tendency to replace more fuel-efficient vehicles (Xing et al., 2021). In addition to creating revenue for the government, fuel tax implementation can also affect EB through reduced vehicle miles traveled (VMT). To reflect such behavioral response to higher fuel taxes, I set the elasticity of VMT to fuel price as 0.59, an estimates provided by Tan et al. (2019) using Chinese household panel data. A 10% fuel tax rate would imply that VMT will decrease by 5.9%. Figure 21 demonstrates the change in the social planner's innovation if the planner doesn't internalize the environmental benefits.

[69] Their estimates are based on Huo et al. (2013); Parry et al. (2014).

[70] The exchange rate for US dollar to Chinese yuan (RMB) is 7.18 as of July 21, 2025(https://www.google.com/finance/quote/USD-CNY?sa=X&sqi=2&ved=2ahUKEwi66Kripc-OAxUAFVkFHSohIkUQmY0JegQIIhAo).

Figure 16: Energy Density Frontier by Counterfactuals

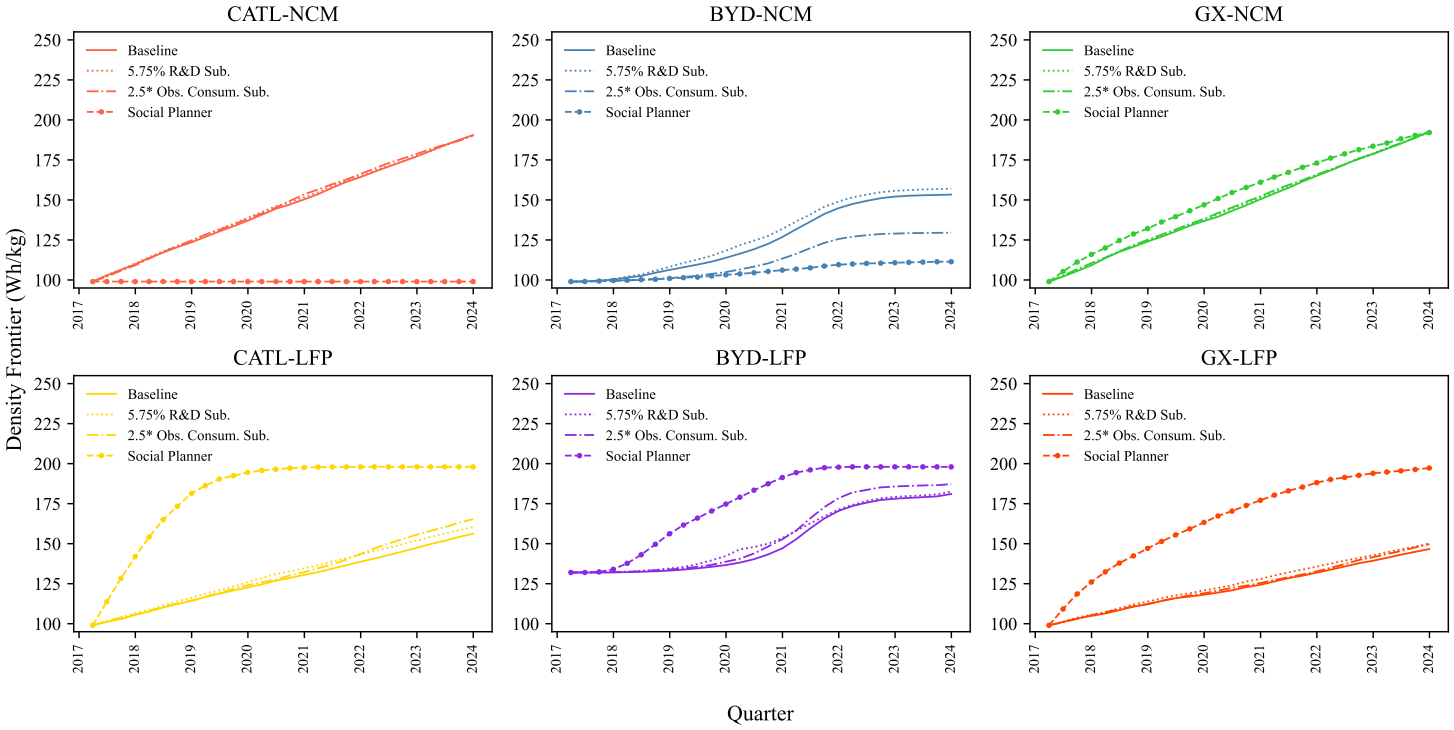


FIGURE NOTES: The figures above compare the energy density frontier evolution in LFP and NCM in the presence of within-path spillover. Different lines in a figure represent different counterfactuals. Each line represents the average of quarterly energy density frontier across 1000 simulations. The upper limit is set as 198 to rein in the state space size.

Figure 17: Social Planner vs. No-Subsidy: Innovation Direction

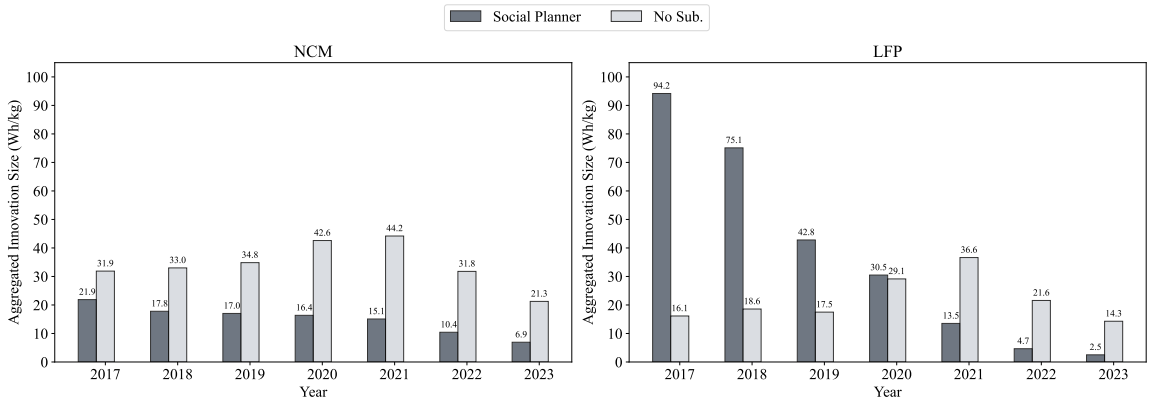


FIGURE NOTES: The figures above compare the annual aggregated innovation size, measured in year-to-year energy density frontier change, on LFP and NCM. Dark grey bars represent the social planner and light grey bars represent the no-subsidy case.

Figure 18: Innovation: Consumer Subsidy vs. R&D Subsidy

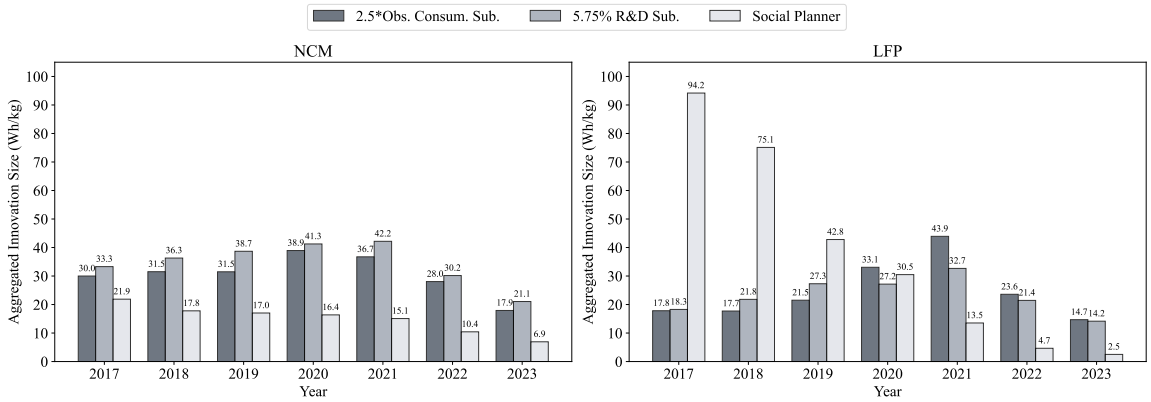


FIGURE NOTES: The figures above compare the annual innovation size, measured in year-to-year energy density frontier change, on LFP and NCM. Dark, medium, and light grey represent outcomes with the 2.5 times of the observed consumer subsidy only, with a 5.75% R&D subsidy only, and in the case of social planner respectively.

Figure 19: Market vs. Social Planner: Without Spillover(ϕ_6=0)

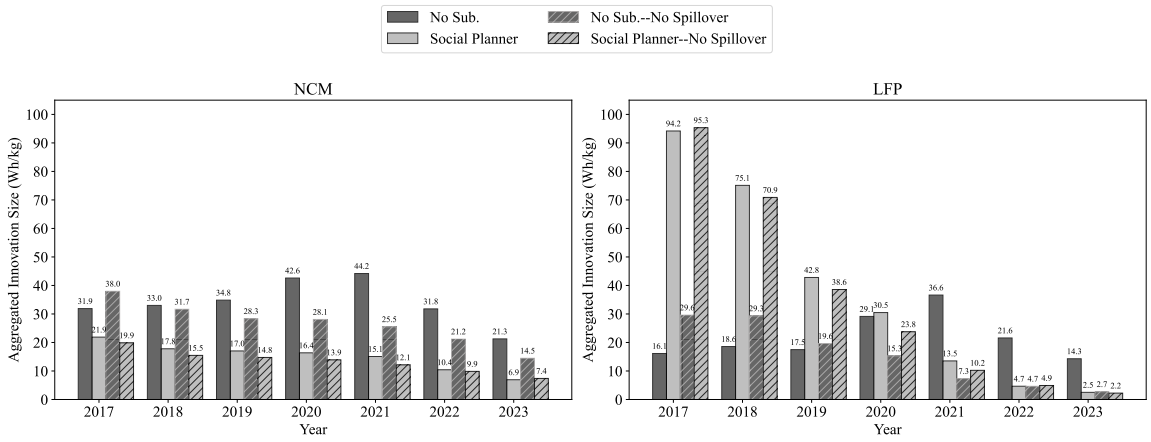


FIGURE NOTES: The figures above compare the annual aggregated innovation size, measured in year-to-year energy density frontier change, on LFP and NCM. Light grey bars represent the social planner while dark grey bars represent the no-subsidy case. Bars with hatches indicate the results in the absence of innovation spillover ($\phi_6 = 0$).

Figure 20: Firm-level Innovation: Baseline Consumer Subsidy vs. 2.5*Baseline Consumer Subsidy

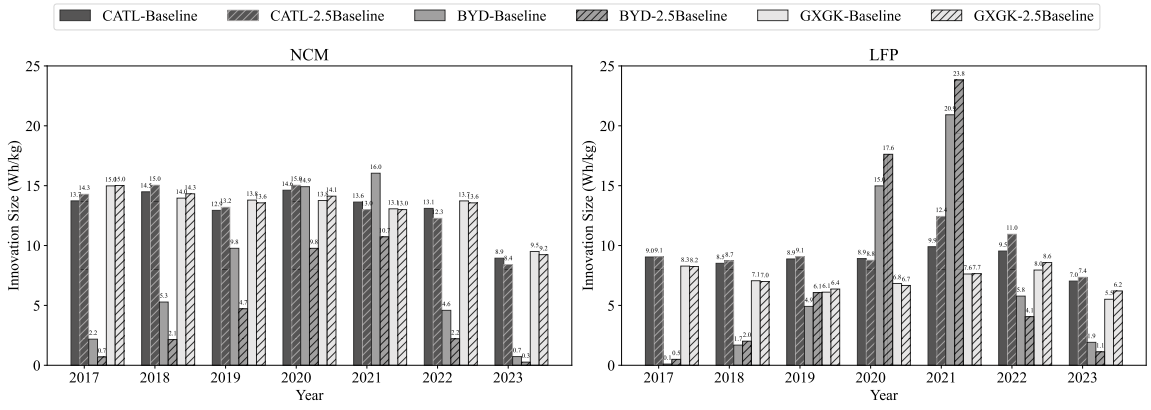


FIGURE NOTES: The figures above compare the annual innovation size at the firm level, measured in year-to-year energy density frontier change, on LFP and NCM.

Figure 21: Effect of Environmental Benefits on Social Planner Innovation

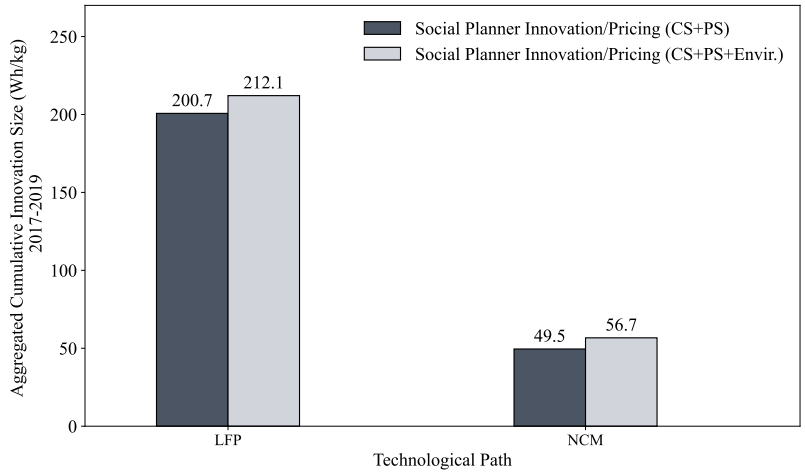


FIGURE NOTES: The figure above compares the aggregated innovation size, measured in year-to-year energy density frontier change, on LFP and NCM. Dark grey bars represent the case when the social planner doesn't internalize environmental benefits and light grey bars represent the case when the social planner does.

K. Fuel Consumption Tax

The fuel consumption tax level in my framework does not influence consumers' demand for gasoline and diesel vehicles in this framework but will be allowed to have an impact on VMT. Based on International Energy Agency (IEA) estimates in 2019 for China,[71] I assume 7.4 liters per 100 km for gasoline cars and 9.3 liters per 100 km for diesel cars. According to Barwick et al. (2025), the estimated average VMT for a vehicle in China is 10,000 miles/year. The fuel prices I use are the listed prices in Beijing for gasoline and diesel in the first quarter of each year.[72]

[71] https://www.iea.org/articles/fuel-economy-in-china
[72] https://data.eastmoney.com/cjsj/yjtz/default.html

Table 8: Welfare Analysis 2017-2019 (in billion RMB)

Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to No Subsidy						Social Planner = 100	
	ΔConsum. Surplus	ΔEnviron. Benefits	ΔVehicle Maker Profit	ΔBattery Supplier Profit	Gov't Exp.	EV Sales (in million units)	Consum. Surplus+Environ. Benefits	Total Surplus
Obs. Consum. Sub.	3.35	0.51	0.45	0.2	14	26.22	97.76	85.73
5.75% R&D Sub.	0.6	0.09	0.07	0.03	152.51	26.21	95.66	85.71
2.5*Obs. Cons. Sub.	44.73	6.79	5.19	0.44	45.33	26.27	94.93	85.99
7.15% LFP R&D Sub.	0.62	0.09	0.07	0.04	152.68	26.21	94.66	85.71

TABLE NOTES: Each number in the table above, measured in billion RMB unless indicated, is the summation of all markets during the sample period from 2017 to 2019.

L. Welfare Analysis from 2017 to 2019

To avoid the binding effect from the imposed 198 cap, I calculate the welfare outcomes only from 2017 to 2019 under different policiy schemes in Table 8.

M. Substitution Between LFP and NCM Innovation

To investigate if LFP innovation and NCM innovation are substitutes to each other, I make one path's innovation cost extremely high (10000 billion RMB per step size) and plot CATL's innovation size in 2017 on the other path. Results are shown in Figure 22 and confirms the existence of partial substibution.

N. Other Factors That Drive Divergence

Effect of Innovation Cost

To explore how the difference in innovation cost between LFP and NCM shapes firms' innovation effort allocation, I simulate innovation decisions between the social planner and

Figure 22: CATL's Innovation When One Path is Not Available

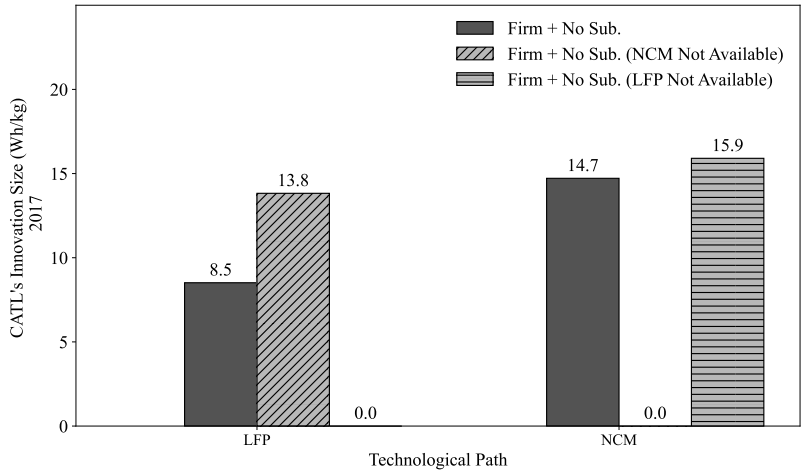


FIGURE NOTES: The figure above plots the innovation of CATL in 2017. Dark gray bars represent the no-subsidy case. Light gray bars depict two alternative scenarios: one in which LFP innovation is prohibitively costly (effectively unavailable) and another in which NCM innovation is prohibitively costly. The two scenarios are distinguished by different hatch patterns.

Figure 23: Social Planner vs. No-Subsidy: Different Innovation Cost Gap (ϕ_3=-1.23; 0; 10000)

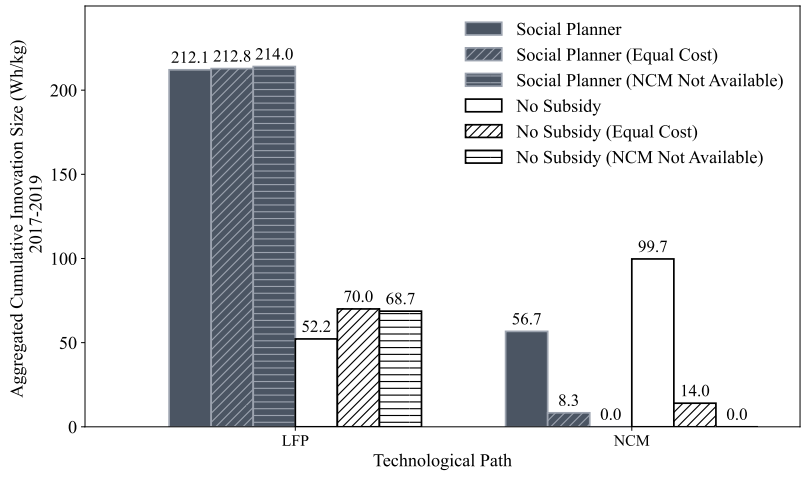


FIGURE NOTES: In the figures above, dark grey bars represent the social planner and light grey bars represent the no-subsidy case. Different hatches correspond to different gap levels between NCM and LFP's innovation costs. When $\phi_3 = 10000$, it is effectively making NCM not available to innovate.

Figure 24: Innovation When Consumers Care About Environmental Benefits

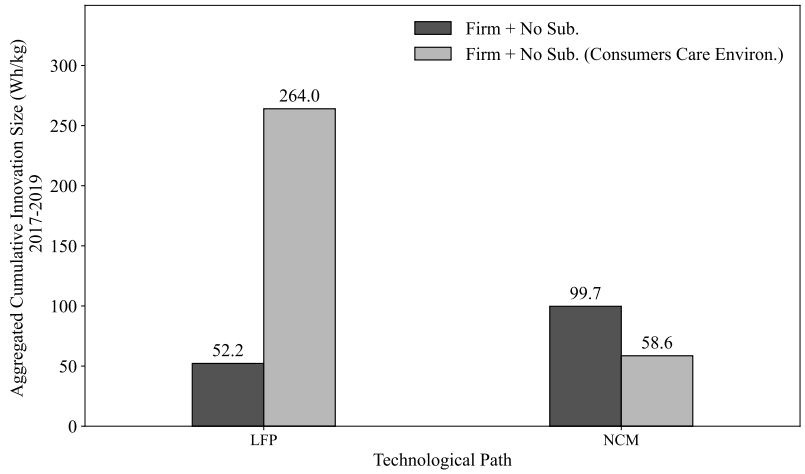


FIGURE NOTES: In the figure above, dark grey bars represent the no-subsidy case. For light grey bars, there is no subsidy but consumers fully internalize the environmental benefits of having an EV.

the market under three values for ϕ_3, the innovation cost gap between NCM and LFP: -1.23, 0, 10000, corresponding to NCM being cheaper than LFP to innovate, NCM as costly as LFP to innovate, and NCM is prohibitively costly to innovate and effectively not available.

As shown in Figure 23, eliminating the innovation cost gap leads firms to focus on LFP, aligning private choices more closely with the social planner. Nonetheless, the social planner continues to take larger LFP innovation steps in early years.

Consumers Care About Environmental Benefits

I explored how the innovation on LFP/NCM would be if consumers fully internalize the environmental benefits of buying EVs instead of ICEs. Figure 24 shows that when consumers care more about environmental benefits from EVs, firms will have more incentives to innovate on LFP and less so on NCM, which is consistent with Aghion et al. (2023).