Drive Down the Cost: Learning by Doing and Government Policies in the Global EV Battery Industry*

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Abstract

Electric vehicle (EV) battery costs have declined by over 90% in the past decade. This study investigates the role of learning-by-doing (LBD) in driving this reduction and its interaction with two major government policies – consumer subsidies and local content requirements. Leveraging rich data on EV models and battery suppliers, we develop and estimate a structural model of the global EV industry that incorporates heterogeneous consumer choices, EV manufacturers' pricing strategies, and bilateral bargaining between EV makers and battery suppliers. The model allows us to recover battery costs for each EV model and quantify the extent of LBD. Our findings suggest that battery production achieved a learning rate of 7.5% during our sample period after controlling for technological advancements, EV assembly experience, and economies of scale. LBD magnified the effectiveness of consumer subsidies on EV adoption by several folds and led to positive complementarity among subsidies across countries. It generated significant externalities not captured by upstream suppliers, with the associated cost reductions constituting much of the welfare gains from government subsidies. European and U.S. subsidies benefited other regions more than Chinese subsidies due to higher import shares and foreign sourcing. China's whitelist policy, which restricted EV subsidies to vehicles using domestically produced batteries, benefited domestic battery suppliers at the expense of foreign suppliers and domestic consumers. While China gained overall, delaying the policy by a few years would have resulted in net welfare losses for the country.

Keywords: Learning-by-doing, batteries, EVs, subsidies, local content requirement

JEL Classification: F13, L52, L62, Q48

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1 Introduction

Electrifying passenger transportation through the widespread adoption of electric vehicles (EVs) and simultaneously transitioning to a cleaner electricity grid is a crucial strategy to mitigate climate change. To achieve this, many countries have set ambitious targets for transportation electrification and implemented policies to promote EV adoption. Historically, the high upfront cost of EVs, primarily driven by expensive lithium-ion EV batteries, constituted a major barrier to widespread adoption. Over the past decade, however, EV battery costs have decreased by almost 90% between 2010 and 2020 (Bloomberg NEF, 2020). Industry experts attributed this substantial cost reduction largely to learning-by-doing (LBD), where production experience leads to lower unit production costs through reductions in scrap rates and improvements in production efficiency.[1] In addition, factors such as technological progress and increasing production scale might also have contributed to this dramatic decline in costs.

Despite the importance of battery costs in the diffusion of EV technology, there is a lack of credible causal evidence on the size and nature of LBD and a limited understanding of how LBD interacts with various government policies in the EV industry. This paper aims to address these gaps by: a) quantifying LBD and its contribution to the observed reduction in EV battery costs over time, and b) assessing how LBD interacts with the two prominent classes of government policies – consumer subsidies and local content requirements – on domestic and global EV diffusion, market shares dynamics, and social welfare.

Quantifying LBD is crucial for understanding the broad impacts of these policies. First, consumer subsidies have been widely adopted worldwide and amounted to $43 billion in 2022 (International Energy Agency, 2023). For example, the U.S. Inflation Reduction Act (IRA) of 2022 offers subsidies of up to $7,500 per EV for eligible purchases, while China provided generous subsidies to EV buyers between 2010 and 2022. LBD generates a positive "feedback loop": subsidies drive higher EV adoption, which increases experience in battery production, thereby reducing battery costs and EV prices. These cost reductions and lower EV prices, in turn, further accelerate EV adoption, amplifying the direct effects of consumer subsidies and other supportive policies.

Second, the preferential treatment of domestic battery producers has become part of a growing spectrum of industrial policies in recent years. During 2016-2019, China implemented a whitelist policy that restricted EV subsidies to vehicles using batteries from government-approved (domestic) producers. Similarly, to qualify for consumer subsidies, the U.S. IRA mandates EV models

[1]Theodore Wright, an aeronautical engineer, was among the first to attribute the observed decline in the labor requirement for airplane manufacturing to "learning by doing" (Wright, 1936). Wright's Law has since been commonly used to describe the reduction in unit production cost as a function of cumulative experience in manufacturing industries.

to source a certain fraction (in terms of value) of critical minerals and battery components from firms in North America or free-trade agreement partner countries. The broad implications of local content requirements hinge crucially on the size and scope of LBD. If LBD predominantly occurs within firms (i.e., internal LBD) and concentrates among industry leaders, these policies could accelerate LBD by consolidating production in a smaller set of firms. This would result in reduced EV battery prices but may come at the cost of increased market concentration. Conversely, if policies across countries erect regional barriers and redirect production toward domestic (and potentially less efficient) producers, they might slow down global LBD and hinder the further penetration of EVs. The overall impact on both domestic and global EV adoption is ambiguous and necessitates empirical investigation.

Third, the battery supply network is global, with EV producers worldwide sourcing from battery suppliers concentrated in three countries: China, Japan, and South Korea. The global nature of the battery supply network, an increasingly common phenomenon in many industries, implies that policies implemented in one country can create cross-border spillovers through the LBD channel, generating repercussions that extend well beyond country borders. Consequently, a global analysis is essential to accurately evaluate policy implications.

To that end, this paper takes advantage of a comprehensive database on the global EV and battery industries that have three key components. The first data set consists of annual EV sales from 2013 to 2020 in thirteen countries which collectively accounted for over 95% of global EV sales. The data report sales and vehicle and battery attributes by model by country for both battery EVs (BEVs) and plug-in hybrid EVs (PHEVs). The second data set contains information on battery suppliers including plant location and crucially the list of EV models supplied. The third data set contains financial incentives for EV purchases in each country over time. In addition, we have also collected socio-economic variables and household surveys on vehicle ownership across countries.

We develop a structural model of the global EV and battery industries featuring bargaining between battery suppliers and EV producers over battery prices as well as Bertrand-Nash price competition among EV producers. Estimating modeling parameters (e.g., the extent of LBD and bargaining weights) entails addressing two key empirical challenges. First, we do not observe systematic data on battery costs at the vehicle-model level, which are proprietary in nature. To address this challenge, we use the bargaining model to infer upstream and downstream markups and recover battery costs based on observed vehicle prices and estimated demand elasticity. We validate battery cost estimates using industry-level data and examine the robustness to alternative modeling assumptions.

Second, firm experience (i.e., cumulative production) that underlies LBD is potentially endogenous and correlated with unobserved marginal cost shocks in battery production. For example, efficient firms with favorable production cost shocks are more likely to sell a large quantity and accumulate more experience. We construct an IV for battery supplier experience by exploiting differences in suppliers' exposure to downstream EV subsidies, which vary over time and across vehicle models sold in different countries. The intuition is that suppliers selling batteries to countries with more generous EV subsidies will experience a larger increase in cumulative production than those selling in markets with lower subsidies. If LBD effects are present, battery costs for the former suppliers will decline more rapidly than for the latter group, ceteris paribus. We also construct a second set of IVs by leveraging China's whitelist policy, which generated arguably exogenous variation in production experience across battery suppliers.

Our empirical analysis delivers five key findings. First, the learning rate is estimated to be 7.5% after controlling for technological advancements, experience in EV assembly, and economies of scale. This implies that doubling battery production experience would reduce unit production costs by 7.5%. From 2013 to 2020, LBD accounted for a sizable 35.5% of the overall decline in battery costs. Technological advancements accounted for 39.9% of the cost reduction, with the remaining explained by changes in battery chemistry and plant capacity (economies of scale). On average, the learning benefit derived from one unit of other firms' production is 4.4% of that from their own experience (though the coefficient is insignificant). Smaller producers, constrained by limited production experience, derive 56% of their learning from other firms, whereas leading battery producers gain predominantly from their own experience.

Second, LBD greatly amplifies the sales impact of EV subsidies through positive feedback loops. In the absence of LBD, subsidies across different countries are estimated to increase cumulative global EV sales by 24.7% during the sample period, consistent with findings in existing studies (Springel, 2019; Li et al., 2021) that focus on the short-term effects of EV purchase subsidies. When both consumer subsidies and LBD were in effect, global EV sales surged by 231% relative to the baseline with neither subsidies nor LBD. Remarkably, LBD amplified the cumulative effect of subsidies by a factor of 8.45. As we discuss below, the welfare benefits of subsidies are also dramatically enhanced by LBD. These findings underscore the critical importance of accounting for LBD when evaluating the efficacy and cost-effectiveness of government policies designed to promote EV adoption. Ignoring LBD would lead to a substantial underestimation of the long-term benefits of such policies.

Third, consumer subsidies in one country generate global spillovers through LBD in battery production, but the magnitude of spillovers hinges critically on the supply chain network and trade patterns. For example, the estimated \$13.10 billion in U.S. subsidies generated \$16.47 billion in global welfare gains, measured as the sum of consumer surplus and firm profit on a global scale minus subsidy expenditure. U.S. (and Canada) captured 49% of these welfare gains, as the interaction between subsidies and LBD significantly lowered vehicle prices for domestic consumers and reduced input costs (batteries) for domestic EV producers. U.S. subsidies also benefited battery suppliers in Japan and South Korea, which captured 28% of the global welfare gains. EV producers and consumers in these countries also benefited from cheaper EV batteries, resulting in Japan and South Korea capturing a combined 34% of global welfare gains. Similarly, Europe and China benefit from U.S. subsidies, although China captured only 3% of the global gains. This modest share reflects China's limited trade in EVs with foreign countries and its minimal exports of EV batteries during our sample period, in contrast to Japan and South Korea, which export the majority of batteries produced.

In a similar manner, European governments invested \$16.44 billion in EV purchase subsidies, resulting in \$11.60 billion in global welfare gains, of which only 26% were captured by the EU. This relatively low capture rate is driven by Europe's higher import share of EVs and the widespread use of uniform subsidies, the latter of which was less effective in generating consumer surplus compared to the battery capacity-based subsidies in the U.S. (Barwick, Kwon, and Li, 2024). In contrast, China captured 92.6% of the global welfare gains from its subsidies due to China's limited EV imports and the fact that the majority of its EV producers source batteries domestically.

Fourth, LBD creates significant externalities through the supply chain, with upstream firms capturing only a small fraction of the economic benefits it creates. Our simulations indicate that CATL captures 13.5% of the total surplus generated by its increased LBD while Panasonic captures 14.7%. These externalities from LBD-driven cost reductions represent an important source of welfare gains from government subsidies; the other channel being subsidies mitigating deadweight losses from market power distortions. These findings suggest that the privately chosen experience level (and the degree of LBD) is unlikely to be socially optimal, and government subsidies have the potential to address the under-provision of LBD.

Lastly, China's whitelist policy benefited domestic battery suppliers at a cost to other countries. The EU, Japan and South Korea, and the U.S. and Canada collectively incurred \$5.88 billion in welfare loss. This was driven by a shift in global battery production from more efficient Japanese and South Korean battery suppliers to (at the time) higher-cost Chinese suppliers. Within China, while battery suppliers reaped gains, consumers bore the burden of higher EV prices, and EV firms initially suffered but eventually gained from faster domestic LBD as Whitelist facilitates sales concentration in top domestic suppliers. China's Whitelist was introduced at a strategically favorable time, when the learning curve for battery production was steep. Had the Whitelist policy been delayed to 2021-2024, China would have faced net losses, as consumer welfare reductions would have outweighed the gains to battery suppliers. The negative impact on other countries would become much smaller. These results highlight the important trade-offs inherent in protective policies that distort market forces. We believe that our analyses also offer valuable insights into the implications of the U.S. IRA and similar local content requirements considered in other countries.

Our study is related to several strands of literature. First, it adds to the growing economics literature to understand the adoption of EVs (Li et al., 2017; Li, 2023; Springel, 2019; Muehlegger and Rapson, 2022; Remmy, 2022; Barwick, Kwon, and Li, 2024). While these studies focus on understanding demand responses to consumer subsidies and the role of charging infrastructure, they do not account for LBD in the EV battery industry or the resulting feedback loop between reduced battery production costs and increased EV demand. Consequently, these studies may underestimate the impacts and cost-effectiveness of consumer subsidies and other supportive policies on EV adoption. Our study is the first in the literature to quantify LBD in the global EV battery industry and take it into account when assessing the broad impacts of EV policies. The results highlight that ignoring even moderate levels of LBD would significantly underestimate the impact of supportive government policies on EV adoption.

Second, this study contributes to the empirical literature on LBD that has been documented in a variety of industries (Argote and Epple, 1990; Head, 1994; Irwin and Klenow, 1994; Benkard, 2000; Thompson, 2001; Thornton and Thompson, 2001; Benkard, 2004; Ohashi, 2005; Covert and Sweeney, 2022). Except for Covert and Sweeney (2022), all the studies cited above relied on data on input requirements or costs associated with producing a product, but these data are often hard to obtain due to their proprietary nature. Our study develops a new methodology for estimating LBD without data on inputs and production costs. It exploits variations in prices and quantities of the final products (i.e., EVs) and information on the vertical links between final good producers and intermediate input suppliers. The methodology could be applied to estimate LBD in the production of intermediate inputs in other context.

Third, this paper contributes to the emerging literature that highlights the significant role of recent industrial and trade policies in the development and diffusion of new energy technologies such as EVs and solar panels (Allcott et al., 2024; Bollinger et al., 2024; Banares-Sanchez et al., 2024; Gerarden, 2023; Head et al., 2024). Our work is also related to Goldberg et al. (2024), which examines the role of industrial policies and LBD in the global semiconductor industry.[2] We add to this literature by quantifying the size and scope of LBD in the EV battery industry.

[2] The study shows that industrial policies, primarily in the form of subsidies, played a critical role in the development of the global semiconductor industry during 2004–2015, with learning rate estimates ranging from 3–8%, depending on whether cross-border spillovers are considered.

More importantly, our findings underscore that learning in the upstream sector not only provides a rationale for supportive policies, such as subsidies in the downstream sector, but also amplifies the impact of these policies on technology adoption and social welfare.

Lastely, this paper is related to studies that analyze vertical relationships between input suppliers and downstream producers as well as insurers and healthcare providers (Horn and Wolinsky, 1988; Chipty and Snyder, 1999; Crawford and Yurukoglu, 2012; Grennan, 2013; Gowrisankaran, Nevo, and Town, 2015; Ho and Lee, 2017; Fan and Yang, 2020). Our analysis builds on the methodology in these papers and develops a framework that leverages the vertical relationships to study LBD among the upstream suppliers.

2 Data and Descriptive Evidence

2.1 Battery Primer and Sources of LBD

We provide a primer on EV batteries and discuss how LBD arises in the battery production process. BEVs and PHEVs use lithium-ion batteries, which feature lithium as one of the key minerals in cathodes and graphite as the primary material in anodes. The chemical composition of the cathode is a major determinant of battery performance. There are three main types of lithium-ion batteries based on cathode chemistries: NMC (Nickel Manganese Cobalt), NCA (Nickel Cobalt Aluminum), and LFP (Lithium Iron Phosphate).[3]

Battery packs used in EVs consist of multiple interconnected modules, each made up of tens to hundreds of interconnected battery cells, which account for 70-80% of the battery pack's cost (Bloomberg NEF, 2023). Battery cell production has at least three key features that could contribute to LBD. First, the production process is highly complex and governed by hundreds of tuning parameters. The interconnected system needs to be constantly fine-tuned and optimized to achieve efficiency. Second, the production process is very sensitive to material purity and requires stringent clean-room standards. Tiny amounts of impurities can cause high scrap and low yield rates.[4] Third, the industry has been undergoing continuous technological advances in new chemistry composition and production techniques, which have important implications for production costs. All these

[3]NMC batteries, favored by American and European automakers, offer higher energy density but are more expensive due to costly manganese and cobalt. NCA batteries are mainly used by Tesla and sourced from Panasonic. Chinese automakers, like BYD, prefer LFP batteries for their lower cost and thermal stability. In 2020, NMC, NCA, and LFP batteries held 71%, 21%, and 6% of the global market share, respectively (International Energy Agency, 2021). By 2023, LFP's share surged to 40% globally due to its cost advantage, while NCA's share fell to 8%.

[4]Even industry leaders face challenges with high scrap rates. Tesla and Panasonic's Nevada Gigafactory, launched in 2017, initially had a scrap rate of 80–90%, which took years to reduce to 15%. Source: `https://www.autoweek.com/news/a46628833/early-production-battery-plant-scrap-rates/#`.

features suggest that production know-how by managers and engineers gained through experience could help improve production efficiency and reduce scrap, both leading to lower costs.[5]

The empirical literature on LBD has examined a variety of industries. In labor-intensive industries such as aircraft manufacturing and shipbuilding, learning is shown to occur as production workers become more efficient at performing tasks through repetition (Benkard, 2000; Thompson, 2001). In contrast, similar to semiconductors (Irwin and Klenow, 1994), battery production is more capital-intensive, where a key channel for learning involves the fine-tuning of production processes and techniques by engineers and managers.

2.2 Data Description

The empirical analysis relies on several rich data sets on global EV and EV battery industries.

EV Sales and Attributes The first data set, sourced from EV Volumes and IHS Markit, contains annual EV sales and vehicle price and attributes by model for each of the 13 countries that reported the largest EV sales from 2013 to 2020. These countries collectively accounted for 95% of global EV sales during the sample period.[6] Appendix Figure A1 shows the trend in EV sales by country/region in Panel (a) and the market share of EVs in the new vehicle market as well as the target for zero-emission-vehicles (ZEVs, which are primarily EVs) by country-year in Panel (b). Since the introduction of mass-market EV models in 2010, worldwide passenger EV sales have grown to 14.2 million units or 18.5% of the passenger vehicle market in 2023. There is a large variation in EV penetration across countries. China became the largest EV market in 2015 and accounted for 59% of global new EV sales in 2023. In terms of EV's market share in the new vehicle market, Norway has by far the highest share of 90.4% in 2023, while it was 34% in China, 21.4% in Europe, and 9.4% in the US, respectively.

Battery Suppliers The second data set from EV Volumes contains information on battery characteristics for each EV model (e.g., battery capacity and battery chemistry) and, crucially, the identity of battery suppliers. This data set allows us to establish vertical relationships between upstream battery suppliers and downstream EV producers. We construct the experience variable (i.e., cumulative production) for each battery supplier in each year based on the vertical supply relationships

[5] A 2018 report by Boston Consulting Group indicates that the most common challenges in battery production have to do with yield rate/scrap and efficiency/process time. Engineers need to rely on experience, rather than physical correlations, to adjust parameters in order to optimize the production process (Küpper et al., 2018).

[6] The 13 countries include Austria, Canada, China, France, Germany, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the UK, and the US.

and data on EV sales. We also collected data on the production plants owned by each battery supplier, including production capacity, start-up year, and plant location (see Appendix A).

Panels (a) and (b) of Figure A2 present the supply network in 2013 and 2020, respectively. The left side of the figure displays the top six battery producers, while the right side reports the eight largest EV producers. The thickness of the lines represents the battery sales volume in units. Both battery production and EV manufacturing are concentrated, illustrating a two-sided oligopoly market structure. In addition, EV producers often source from multiple battery suppliers, and battery suppliers sell to multiple EV producers. The only exceptions are BYD and AESC, which are vertically integrated firms in our sample period.[7] However, for any given EV model sold in a particular country, once a battery supplier has been chosen, it is rare for the EV producer to switch to a different battery supplier: only 4.3% of EV models switch battery suppliers. These features inform our use of a bargaining model to characterize the vertical relationship.

EV Incentives The third data set contains financial incentives for EV buyers at the country, year, and model levels as discussed in Barwick et al. (2023). The financial incentives are offered in a variety of forms, including direct consumer subsidies, acquisition tax credits, and ownership tax credits. For consistency across countries, we focus on EV incentives offered by the central government.[8] Subsidies for EV purchases vary across countries and over time. In addition, there is considerable cross-model variation within a given country and year due to the fact that the amount of subsidies is often based on vehicle attributes. For example, subsidies in the U.S. are based on an EV's battery capacity, with a minimum capacity of four kWh and a maximum subsidy of $7500.[9] EV subsidies in China are based on vehicle driving range with a notched design (Barwick, Kwon, and Li, 2024). These wedges in EV subsidies serve as a crucial source of exogenous variation in the experience of different battery suppliers (those supplying to countries with generous subsidies would sell more units).

Figure A3 reports the average EV subsidy (from the central government) by country during 2013-2020 in Panel (a) and the subsidy schedule over time in China in Panel (b). Norway has the most generous subsidies, consistent with its high penetration of EVs. China's attribute-based subsidy from the central government was reduced over time and eventually phased out in 2022.

[7] BYD produced batteries for its own EVs, and AESC only produced batteries for the Renault-Nissan-Mitsubishi alliance. These vertically integrated firms accounted for 14.5% of sales in our sample.

[8] The EV subsidies were not offered at the central level in Canada and Switzerland. For Canada, we construct a population-weighted average based on subsidies offered by British Columbia, Quebec, and Ontario. For Switzerland, we construct a population-weighted average based on tax credits offered by the cantons of Zurich, Lausanne, Basel, Bern, and Geneva.

[9] The subsidy amount was $2500+$415*(capacity-4) but phased out following a pre-set schedule when an EV model hit a cap of 200,000 (Lohawala, 2023). The subsidy policy was extended by the U.S. Inflation Reduction Act in 2023.

Auxiliary Data There are several pieces of auxiliary data. First, we collect socio-economic variables including annual gasoline prices by country from the World Bank and annual income statistics by country from the World Inequality Database (`https://wid.world/`). Second, to facilitate demand estimation, we leverage household surveys on new vehicle buyers for China during 2016-2020 in China and for the U.S. in 2018 (Liang and Xiao, 2024; Leard, Linn, and Springel, 2024). In particular, we construct moment conditions based on the average income of EV buyers for top EV models in these two countries. Third, we obtain export data of Lithium-ion batteries from the UN Comtrade database, annual import prices of key minerals for battery production by country, including lithium carbonates, lithium oxides, manganese oxides, cobalt oxides, and nickel oxides from the UN Comtrade database and, as well as mineral prices from the annual Mineral Commodity Summaries published by the U.S. Geological Survey. Finally, to capture technological progress, we compile information on the number of patents filed and granted by battery suppliers during 2008-2020 from the European Patent Office (EPO)'s PATSTAT database (see Barwick et al. (2024) for detailed data construction procedure).

2.3 Descriptive Evidence

Table 1 presents summary statistics for key variables used in the analysis. During the sample period, the average price of a BEV model was \$45,000, supported by an average subsidy of \$4,700 per unit, while PHEV models had a higher average price of \$72,000 and a lower average subsidy of \$1,900. The driving range of BEVs increased significantly from 105 km in 2013 to 206 km in 2020, with an overall average of 171 km, alongside an increase in battery capacity from 30 kWh to 50 kWh (with an average of 42 kWh). In contrast, PHEVs had a much shorter average driving range of 31 km and a battery capacity of 11.5 kWh, showing only modest improvements over the same period.

The estimate of LBD is fundamentally informed by the relationship between production experience and battery costs. In the absence of detailed micro-level transaction data between battery suppliers and EV firms (which are commercial secrets), we examine the correlation between vehicle prices – where battery costs constitute a significant share – and the production experience of battery suppliers in Figure 1. We first use vehicle price to construct a proxy for battery costs by partialling out vehicle attributes such as horsepower, size, driving range, and the PHEV dummy, along with a rich set of country, brand, and year fixed effects. Panel (a) illustrates changes in these price residuals (our proxy for battery costs) over time, with blue dots representing the average annual price residuals per kWh. These residuals exhibit a substantial decline from 2014 to 2020, closely matching the trend in battery costs reported by Bloomberg NEF (2023), shown as pink diamonds.

Panel (b) of Figure 1 presents a binned scatter plot of price residuals, where each observation corresponds to a country-year-model. The figure reveals a strong and precisely estimated negative relationship between price residuals and supplier experience, indicating that EV models supplied by more experienced battery suppliers tend to have lower prices. Moreover, the figure highlights that production experience increases with cumulative subsidies received by the battery supplier (as reflected by the size of the dots), motivating a key IV strategy for identifying LBD.

From January 2016 to June 2019, China implemented a whitelist policy requiring EV models to use batteries from government-approved "whitelist" producers – all of which were Chinese firms – to qualify for subsidies.[10] Figure A4 provides suggestive evidence of this policy's impacts. During this period, six major battery suppliers dominated the market: two Chinese firms (BYD and CATL), two Japanese firms (AESC and Panasonic), and two South Korean firms (LG and Samsung). Before the policy, Chinese suppliers had less production experience, and vehicles using their batteries were sold at higher prices compared to those with batteries from non-Chinese suppliers (after adjusting for vehicle attributes).

Panel (a) of Table A4 depicts the share of EV models sourcing batteries from Chinese suppliers, distinguishing between those sold in China (solid red line, left y-axis) and outside China (dashed blue line, right y-axis). As intended by the policy, the share of EV models sold in China that sourced batteries from Chinese suppliers rose from below 70% in 2016 to nearly 90% in 2019, then declined after the policy was scrapped. During the whitelist period, the sales of BYD and CATL – China's largest battery suppliers on the whitelist – grew significantly faster than those of the top four non-Chinese suppliers (Panel (b)). As BYD and CATL accumulated production experience, EV models using their batteries experienced a more rapid decline in residualized vehicle prices compared to EV models using batteries from non-Chinese firms, as depicted in Panel (c). The impact of this growth in experience among Chinese suppliers is also evident in Panel (a): for EV models sold outside China, the share that sources batteries from Chinese firms was near zero in 2016, increased to 4% by 2019, and rose sharply to 11% by 2020. This significant increase reflects the rapid cost reductions achieved by Chinese battery producers, consistent with the more rapid battery export price reduction as shown in the UN Comtrade data in Panel (d).

While the descriptive evidence presented above aligns with learning-by-doing (LBD) as a driving force, other confounding factors, such as technological advancements, changes in battery chemistry, and experience in EV assembly, may also play a role. The next section introduces a structural model designed to quantify the extent and scope of LBD while accounting for these potential confounding factors.

[10]This policy raised significant concerns about its compliance with WTO rules, particularly under the Agreement on Subsidies and Countervailing Measures (SCM Agreement). Although no formal WTO case was filed, China removed the policy in 2019 under widespread criticism from foreign firms and governments (USTR, 2019).

3 Model

We develop a structural model that allows us to infer battery costs based on observed EV prices, sales, and the time-varying vertical relationships between EV producers and battery suppliers. The model features EV purchase decisions by heterogeneous consumers, EV producers' pricing strategies, and battery price negotiations between vehicle producers and battery suppliers. We outline the key model elements here and discuss the estimation strategy in Section 4.

We use the following notations throughout: 1) EV producer v, producing a set of vehicles denoted by Ω_v; 2) battery supplier b, supplying batteries for a set of vehicles Ω_b; 3) consumer i, who considers whether to buy vehicle model j in country c in time (year) t; 4) vehicle price p_{jct} before subsidies, consumer subsidy ϕ_{jct}, and battery price τ_{jct}; and 5) EV producers' per-unit markup for each vehicle model $\boldsymbol{mk}^v$, and battery suppliers' per-unit markup $\boldsymbol{mk}^b$. Bolded terms denote vectors (or matrices).

Consumer Demand The EV demand is characterized by a random coefficient discrete choice model following Berry, Levinsohn, and Pakes (1995). In each period t, consumer i in county c chooses among the available EV models, as well as an outside option. Consumer i's utility from buying vehicle j is:

$$U_{ijct} = \alpha_i(p_{jct} - \phi_{jct}) + \mathbf{X}_{jct}\beta_{\mathbf{i}} + \xi_{jct} + \varepsilon_{ijct}. \tag{1}$$

Consumers pay the post-subsidy price, which is retail price p_{jct} net of consumer subsidy ϕ_{jct} offered by the central government. Vector $\mathbf{X}_{jct}$ includes observed vehicle attributes, such as vehicle size, driving range, horsepower, a PHEV dummy, as well as a rich set of fixed effects, including market (country-by-year), automaker (e.g., GM or Hyundai), and body type (i.e., sedan, SUV, and van) fixed effects. We allow preference parameters on price and other vehicle attributes, α_i and $\boldsymbol{\beta}_i$, to vary across consumers. Lastly, ξ_{jct} represents unobserved product characteristics and demand shocks, which render the price variable endogenous, and ε_{ijct} denotes i.i.d. preference shocks with a type-I extreme value distribution.

EV Pricing Equation The retail price of an EV, p_{jct}, can be written as:

$$p_{jct} = \underbrace{mc^b_{jct}}_{\text{Battery cost}} + \underbrace{mc^v_{jct}}_{\text{Non-battery EV cost}} + \underbrace{mk^b_{jct}}_{\text{Battery markup}} + \underbrace{mk^v_{jct}}_{\text{EV markup}}, \tag{2}$$

where mc^b_{jct} is the cost of battery and mc^v_{jct} is the non-battery portion of the EV's production cost. The markup earned by EV producer v is denoted by mk^v_{jct}, while mk^b_{jct} is the margin earned by battery supplier b when supplying batteries for model j. We now describe how the downstream markup mk^v_{jct} is determined through Bertrand-Nash competition and how the upstream markup mk^b_{jct} is determined through Nash-in-Nash bargaining. Once we recover these markups and specify the non-battery portion of the EV cost as a function of vehicle attributes, then we have essentially recovered the cost of producing batteries as the difference between prices and these three other terms (up to some parameters).

Bertrand-Nash Competition among EV firms We assume a Bertrand-Nash game among EV producers (or Original Equipment Manufacturers, OEMs) that choose EV prices to maximize profit from selling different vehicles in a country-year.[11] Producer v's profit is (suppressing country and time indices):

$$\pi^v(p) = \sum_{j\in\Omega_v} (p_j - \tau_j - mc_j^v) q_j(p,\phi),$$

where τ_j is the battery price for vehicle j (paid by firm v to its supplier), mc_j^v is firm v's marginal cost of producing non-battery components, and $p_j - \tau_j - mc_j^v$ is the per-unit markup.

The first order condition (FOC) for vehicle price p_j is given by:

$$q_j + \sum_{k\in\Omega_v} \underbrace{(p_k - \tau_k - mc_k^v)}_{\text{Vehicle markup, } mk_k^v} \frac{\partial q_k}{\partial p_j} = 0. \tag{3}$$

Note that $\frac{\partial q_k}{\partial p_j}$ is known after demand estimation. Inverting the system of FOCs in Equation (3) yields a vector of vehicle markups $\boldsymbol{mk}^v$.

Bargaining between EV Producers and Battery Suppliers Motivated by the two-sided oligopolistic vertical structure between battery suppliers and EV producers, we use the Nash-in-Nash bargaining model (Horn and Wolinsky, 1988) to characterize the negotiation of battery prices between EV producers and battery suppliers, with the exception of BYD and AESC that were vertically integrated.We assume that the battery price bargaining and vehicle price setting happen simultaneously, following Draganska, Klapper, and Villas-Boas (2010); Ho and Lee (2017); Crawford et al. (2018). This is a reasonable approximation if EV prices cannot be adjusted immediately following changes in battery prices (EV prices are often adjusted on an annual basis). The simultaneous bargaining assumption is also computationally and conceptually much simpler than sequential bargaining.[12]

Each EV producer-battery supplier pair $\{v,b\}$ chooses battery price for vehicle $j \in \Omega_v \cap \Omega_b$ (i.e., a vehicle that is produced by v and sources battery from supplier b) to maximize the Nash

[11] Joint ventures (JVs) are common in China. We assume JVs are separate OEMs from local partners that often own their indigenous brands. For example, SAIC-GM, the joint venture between Shanghai Automotive Industry Corporation (SAIC) and GM, is recorded as an OEM in our analysis and sells Chevrolet, Buick, and Cadillac brands. SAIC, which owns indigenous brands such as Roewe and Maxus, is considered a separate profit maximizer.

[12] Nevertheless, we estimate the supply-side parameter assuming sequential bargaining instead, finding very similar results.

product of their net gains from trade, taking as given the battery prices chosen for other vehicles:

$$NP_j(\tau_j, \tau_{-j}) = \underbrace{(\pi^v - d_j^v)}_{\text{v' gains}}{}^{(1-\lambda^b)} \underbrace{(\pi^b - d_j^b)}_{\text{b' gains}}{}^{\lambda^b} \tag{4}$$

where $\lambda^b \in [0,1]$ is the bargaining weight of battery supplier b and $\lambda^b = 0$ implies zero markup for battery suppliers. We use π^v and π^b to denote the profit of EV producer v and battery supplier b, respectively, and d_j^v and d_j^b to denote the *disagreement* payoff (profit if the negotiation fails). The battery supplier's profit is similar to that for the EV producer: $\pi^b(\tau) = \sum_{j \in \Omega_b} (\tau_j - mc_j^b) q_j(p, \phi)$, where mc_j^b denotes supplier b's cost of producing the battery used in vehicle j, and $\tau_j - mc_j^b$ is battery supplier b's per-unit markup.[13]

We assume that if v and b disagree over τ_j, then vehicle j is not produced and consumers shift to other EV models or the outside good.[14] The FOC for battery price τ_j is:

$$(1-\lambda^b) \underbrace{(\pi^b - d_j^b)}_{\text{b's gains from trade}} \frac{\partial \pi^v}{\partial \tau_j} + \lambda^b \underbrace{(\pi^v - d_j^v)}_{\text{v's gains from trade}} \frac{\partial \pi^b}{\partial \tau_j} = 0. \tag{5}$$

From the FOCs, we can express the vector of battery suppliers' markups as a function of vehicle producers' markups:

$$\begin{aligned} \underbrace{mk^b}_{\text{Battery markup}} &= \frac{\lambda^b}{1-\lambda^b} [\boldsymbol{T}^b \otimes \boldsymbol{S}]^{-1} [\boldsymbol{T}^v \otimes \boldsymbol{S}] \underbrace{mk^v}_{\text{Vehicle markup}} \\ &= \frac{\lambda^b}{1-\lambda^b} \underbrace{\overline{mu}^b}_{\text{Battery markup when } \lambda^b = 0.5} \end{aligned} \tag{6}$$

where $\otimes$ denotes element-by-element multiplication, and $\mathbf{T}^v$ and $\mathbf{T}^b$ are ownership matrices for EV producer v and battery supplier b, respectively. Matrix $\boldsymbol{S}$ denotes how market shares of all products change upon disagreement. That is, the $\{j,k\}$ term of $\boldsymbol{S}$ captures changes in product k sales when v and b disagree over the battery price for vehicle j. Ownership matrices are observed from data, and $\boldsymbol{S}$ can be derived from the demand model after estimating consumer preferences. The vector of EV producers' markups, mk^v, is backed out from Equation (3). Consequently, battery suppliers' markup (at equal bargaining weight), denoted as $\overline{mu}^b$, is known after demand estimation. Therefore, Equation (6) suggests that battery markups can be recovered up to the bargaining parameter λ^b after the demand estimation.

Our approach for recovering downstream and upstream markups follows Draganska, Klapper, and Villas-Boas (2010). Intuitively, upstream markups depend on both the bargaining parameter

[13] Note that the simultaneous bargaining assumption ensures that battery prices do not affect downstream demand q_j conditioning on retail prices.

[14] On average,a v and b pair only bargains over 2.3 distinct EV models within a market. Our results are likely similar if we assume instead the entire portfolio that the pair is bargaining over is withdrawn when v and b disagree over j.

and responsiveness of the battery supplier's sales to changes in the battery price. For example, if a small increase in battery price leads to a large reduction in battery sales, then equilibrium upstream markups will tend to be modest. Once the demand system has been estimated and downstream markups recovered, we can infer how battery suppliers' sales respond to changes in battery price, which allows us to pin down the magnitude of upstream markups (up to the bargaining parameter, which we discuss and estimate below).

Pros and Cons Our structural model allows us to estimate the magnitude of LBD without direct information on battery production costs or battery prices so long as we observe downstream EV prices, sales, EV and battery characteristics, and the supply network. A caveat of this approach is that the estimated markups depend on the supply-side assumptions, i.e., a) negotiations between EV producers and battery suppliers follow Nash-in-Nash bargaining, and b) EV producers engage in Bertrand-Nash competition. We explore alternative modeling assumptions in robustness checks and validate estimated battery costs using external data.

4 Estimation

The estimation closely follows Section 3 and proceeds in two steps. The first step estimates the demand model and recovers consumer preference parameters. The second step estimates the supply side and recovers the parameters that govern LBD as well as the bargaining weight. Appendix Section B provides more details.

4.1 Demand Estimation

Price Coefficient The price coefficient α_i in Equation (1) is specified as

$$\alpha_i = \alpha_1 + \frac{\alpha_{c(i)}}{y_i} + \sigma_p v_i^p,$$

where price sensitivity is inversely related to individuals' income y_i. We divide countries into four groups based on income per capita and allow the coefficient on income $\alpha_{c(i)}$ to vary by country groups.[15] If $\alpha_{c(i)}$ is positive, low-income households are more price sensitive than high-income households. The dispersion of price sensitivity across consumers is captured by σ_p, and individual unobserved heterogeneous preference v_i^p is assumed to follow the standard log-normal distribution. We fit the country-year income distribution using a log-normal distribution with parameters mu_{ct}

[15]The first group includes only China, which has the lowest income level. France, Germany, Japan, and Spain are in the second group. The third group has Austria, Netherlands, Sweden, and the UK. The highest income group consists of Canada, Norway, Switzerland, and the U.S.

and σ_{ct} and estimate these parameters using the average household income, the top 10% income share, and the bottom 50% income share for each country-year from the World Inequality Database.

Aggregate Moments To address price endogeneity due to unobserved product attributes ξ_{jct}, we use two sets of instruments. The first set includes the interaction terms of battery capacity with a dummy variable for each of the top six battery suppliers. They capture the fact that batteries with higher capacity are more costly to produce, and these costs vary across suppliers (Li et al., 2021). The second set is the absolute difference between own attributes and average attributes of rival vehicles (within the same car type and market-year) in terms of vehicle size, horsepower, and driving range, following Gandhi and Houde (2019). In total, we use nine excluded instruments $\mathbf{Z}_{jct}$ in addition to the exogenous attributes $\mathbf{X}_{jct}$ to construct the aggregate (macro) moment conditions:

$$E[\xi_{jct}|\mathbf{X}_{jct},\mathbf{Z}_{jct}] = 0.$$

Micro Moments We construct two types of micro-moments to facilitate the identification of preference parameters, particularly the price coefficients. The first type of micro-moments matches the observed average income of households purchasing a specific EV model with the income predicted by the demand model. The household surveys in China and the U.S. provide us with the average household income for 50 popular EV models in China from 2016 to 2020 and 33 popular EV models in the U.S. in 2018, giving us a total of 83 micro-moments for Chinese and U.S. EV buyers. The second type of micro-moments matches the observed share of EV buyers within specific income brackets to the corresponding model-predicted share. We have data for five income groups in Canada (2013), four in Germany (2013), six in Norway (2014), five in Japan (2015), three in Sweden (2015), and four in the Netherlands (2019). Since these income groups are mutually exclusive, we drop one group per country, resulting in a total of 21 micro-moments for the second type. We use two-step GMM and follow Conlon and Gortmaker (2023) to construct the variance-covariance matrix and gradients of the aggregate moments and micro-moments.[16]

4.2 Battery Cost and LBD

Recall that vehicle prices are decomposed into four terms that consist of the marginal costs and markups for both battery suppliers and EV producers, as defined in Equation eqn:priceEqn:

$$p_{jct} = \underbrace{mk^{v}_{jct}}_{\text{EV markup}} + \underbrace{mk^{b}_{jct}}_{\text{Battery markup}} + \underbrace{mc^{v}_{jct}}_{\text{Non-battery EV cost}} + \underbrace{mc^{b}_{jct}}_{\text{Battery cost}}.$$

[16] These micro-moments are obtained from the following studies: Canada from Axsen, Bailey, and Castro (2015); Germany from Plötz et al. (2017); Norway from Bjerkan, Nørbech, and Nordtømme (2016); Sweden from Vassileva and Campillo (2017); Netherlands from Meijssen (2019); and Japan from Okada, Tamaki, and Managi (2019).

The vehicle markup mk^v_{jct} is known after demand estimation, and the battery markup $mk^b_{jct} = \frac{\lambda_b}{1-\lambda_b}\overline{mu}^b_{jct}$ is known up to λ_b following the discussion of Equation (6). We now describe how we separate out the battery cost mc^b_{jct} from the non-battery cost mc^c_{jct} and estimate the cost parameters and λ^b.

The marginal cost for non-battery components is specified as a function of vehicle attributes, such as vehicle size and horsepower, and a rich set of fixed effects. We also include EV producers' past experience to capture reductions in EV costs as a result of LBD in vehicle production.

The marginal cost of producing batteries, the heart of this exercise, is specified as the product of battery capacity in kWh and the cost associated with producing each kWh:[17]

$$mc^b_{jct} = BK_{bjct}\Big(\underbrace{\gamma_0 E_{bt}{}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta_t}_{\text{cost per kWh}}\Big), \tag{7}$$

where BK_{bjct} is battery capacity in kWh. Battery supplier's experience E_{bt} is defined as the past cumulative production and measured in units of all vehicle models sold that source batteries from supplier b:

$$E_{bt} = \sum_{s<t}\sum_{j\in\mathscr{I}\{I_{bcs}=1\}} q_{jcs} \tag{8}$$

where q_{jcs} is the sales of vehicle j in country c and year s, and $\mathscr{I}\{I_{bcs}=1\}$ denotes the set of vehicle models in country c and year s that source batteries from supplier b. The key parameter of interest is the learning coefficient γ^E, which determines the rate at which the cost of manufacturing a kWh of battery decreases when experience in production doubles.[18] The baseline cost without learning, or the initial production cost, is captured by γ^0.

In addition to supplier experience, we also control for battery chemical type CH_{bjct} (e.g., NMC or LFP) and the battery plant's capacity PK_{bt} in GWh that reflects economies of scale.[19] Given the significant changes in production technology over the past decade (advancements in battery size and efficiency), we use year fixed effects η_t to control for industry-wide technological progress over time. As pointed out by (Thompson, 2001), failing to control for factors that influence unit production costs could inflate LBD estimates. We demonstrate in Section 5 below that the LBD estimate reduces by half once we account for technological advancements, changes in chemistry type, economies of scale, and accumulated experience in EV assembly (a shifter in EV producer's marginal cost).

[17] We follow the industry convention that reports battery costs in unit of kWh (Bloomberg NEF, 2023).

[18] The learning rate, or the Spence coefficient, is $1-2^{\gamma_E}$, which can be interpreted as the percentage cost reduction as a result of doubling experience.

[19] As plant size grows, the marginal cost of producing a battery may decrease due to the economies of scale. For multi-plant firms, we use the median capacity across all plants. The LBD estimates are similar whether we use the median, mean, maximum capacity, or the sum of capacity across all plants.

Combining Equations (2), (6), and (7), the LBD estimating equation is defined as follows:

$$p_{jct} - mk^{v}_{jct} = \frac{\lambda^b}{1-\lambda^b}\overline{mu}^{b}_{jct} + BK_{bjct}\left(\underbrace{\gamma_0 {E_{bt}}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta * t}_{\text{Battery cost per kWh}}\right)$$
$$+ \mathbf{x}_{vjct}\boldsymbol{\gamma}_v + \text{fixed effects} + \omega_{jct}, \tag{9}$$

where $\mathbf{x}_{vjct}$ reflects marginal costs of producing a vehicle's non-battery components (e.g., those depending on vehicle size and horsepower, as well as EV producer experience). The set of fixed effects includes country, EV brand (e.g. Tesla), battery supplier (e.g. LG), and year fixed effects. The residual ω_{jct} captures unobserved cost shocks. Different from the standard supply-side analyses (Berry, Levinsohn, and Pakes, 1995), ω_{jct} includes the unobserved cost shocks to *both* EV production *and* battery production (the latter of which is included as part of the battery prices that EV producers pay to battery suppliers).

4.3 Empirical Challenges

There are three challenges in estimating Equation (9). First, the experience variable as defined in Equation (8) is likely to be endogenous. For example, past sales q_{jcs} could be correlated with serially correlated cost shocks ω_{jct} that capture the unobserved production efficiency of battery supplier b. Additionally, the supply network that partially determines past sales could be endogenous in that productive and low-cost battery suppliers might supply more EV models.

To address the endogeneity of experience, we use predicted past experience driven by exogenous variations as an IV:

$$IV_{bt} = \sum_{s<t}\sum_{j}\hat{Pr}_{jbcs}(\mathbf{z}_{jbcs})\hat{q}_{jcs}(\mathbf{X}_{jcs}, \phi_{jcs}), \tag{10}$$

where IV_{bt}, the instrument for past cumulative experience E_{bt}, is the sum of predicted past sales and consists of two sets of predicted outcomes. To address the concern that the observed supplier network is potentially endogenous, we use a discrete choice model of supplier choices to predict the probability that vehicle model j in country c and year s sources batteries from supplier b, $\hat{Pr}_{jbcs}$. The exogenous shifters $\mathbf{z}_{jbcs}$ include home bias (to capture the fact that EV producers are more likely to source from domestic battery suppliers), China's White List policy, EV attributes, battery supplier characteristics that are predetermined in the initial year that we observe them (firm age, average battery size, initial battery chemistry etc.), and the EV producer - battery supplier network in the initial year. These exogenous variables are unlikely to be correlated with unobserved cost shocks ω_{jct} in Equation (9). Appendix B.2 provides more details.

To address the endogeneity in past sales, we use $\hat{q}_{jcs}(\mathbf{X}_{jcs}, \phi_{jcs})$, the predicted sales that are based on the demand model in Equation (1). It depends on vehicle attributes $\mathbf{X}_{jcs}$ and EV subsidies ϕ_{jcs}, the latter of which exhibits rich variations across countries, models, and time. The subsidies serve as powerful instruments because they greatly affect demand for EVs and, hence, the sales of batteries by different suppliers. For example, a battery supplier that sells batteries to EV models eligible for more generous EV subsidies will gain experience more quickly.

The key identification assumption is that China's whitelist policy and variations in EV subsidies across countries are uncorrelated with vehicle and battery costs shocks ω_{jct}. This is likely to hold. For example, the notched subsidy design based on driving range in China lends to an RD-type identification strategy in that the amount of subsidy changes discretely along the range cutoffs, but unobserved vehicle and battery costs are unlikely to change discretely at these cutoffs (Figure A3).

The second challenge in estimating Equation (9) is that the battery firm's markup $\overline{mu}^b_{jct}$ might be endogenous. The battery markup is a function of the EV producer's markups, which could be correlated with cost shocks ω_{jct} that capture the unobserved production efficiency of EV producer v. This is because EV firms' optimal pricing strategies and equilibrium markups depend on their costs. We follow the same strategy as above and construct an IV of predicted markups using only exogenous vehicle attributes and subsidies. To do so, we first regress EV prices on observed attributes, subsidies, and fixed effects to obtain predicted prices for each vehicle model. We then use predicted prices to re-calculate market shares, vehicle markups, and battery markups. By construction, the predicted battery markups are exogenous to cost shocks ω_{jct} and serve as valid IVs.[20] The third challenge is that EV producer's past experience, one of the controls in $\mathbf{x}_{vjct}$ in Equation (9), is also endogenous and correlated with ω_{jct}. We generate predicted EV producer experience in a similar fashion to how we generated predicted battery supplier experience, and use it as an IV for EV experience.

5 Estimation Results

5.1 Demand Results

Table 2 reports parameter estimates for EV demand. There are a total of 4,556 observations. All columns include country, brand, and year fixed effects. The first column shows results from a simple multinomial logit model using OLS (i.e., Berry-logit). The second column instruments for

[20] The bargaining parameter λ^b is identified from changes in vehicle prices that result from exogenous shifts to the bargaining leverage of upstream suppliers. For example, China's whitelist policy enhanced the bargaining position of Chinese battery suppliers relative to EV makers. The degree to which this shift affects vehicle prices is informative of λ^b. If $\lambda^b = 0$ (i.e., EV producers make take-it-or-leave-it offers), batteries are supplied at cost, and changes in upstream bargaining leverage would have no effect on EV prices.

vehicle price using the two sets of IVs discussed earlier: the interactions between battery supplier dummies and battery capacity to capture the cost variation in battery production and BLP IVs based on observed vehicle attributes. As common in the demand literature, the OLS coefficient estimate on vehicle price in column (1) is much smaller in magnitude than the 2SLS estimate in column (2) due to the positive correlation between unobserved product attributes and prices. The OLS coefficient estimate on vehicle volume (i.e., length by width by height) is counter-intuitive. All coefficient estimates from 2SLS are intuitively signed: consumers dislike higher prices but prefer larger sizes and horsepower. Consumers prefer a longer driving range, but the range preference is much weaker for PHEVs.

Column (3) reports results from our preferred specification, the random coefficient model with heterogeneous preferences. As in Column (2), all parameter estimates have the expected sign. High-income households are less price sensitive, and there is significant heterogeneity in how income correlates with price sensitivity across country groups. We allow random coefficients on the constant term, vehicle attributes, and price to capture preference heterogeneity. All the random coefficient estimates are estimated precisely. There are significant variations in price sensitivity even after controlling for income (the random coefficient on price is sizeable).

Panel (a) of Figure 2 presents the histogram of price elasticities for all EV models in our sample.[21] The average price elasticity is -3.51, with a standard deviation of 1.53. These estimates are consistent with findings from the existing literature on EV demand (Li et al., 2017; Li, 2018; Xing, Leard, and Li, 2021; Muehlegger and Rapson, 2022; Springel, 2019). Panel (b) depicts the semi-elasticities against post-subsidy vehicle prices by country group, where the semi-elasticity is the percentage change in sales for a \$1,000 reduction in a vehicle's post-subsidy price. The percentage increase in sales is greater for cheaper vehicles, indicating higher demand elasticity for these models, consistent with the observation that their buyers typically have lower incomes. China has a greater number of EVs with post-subsidy prices below \$40,000 than all other country groups. It also exhibits the highest sales-weighted semi-elasticity (in absolute value) at 10.5%, consistent with Chinese consumers having the lowest average income among the 13 countries studied. The sales-weighted semi-elasticity for the other three country groups ranges from 6.5% to 7.4%.

5.2 Supply Side Results

IVs for Experiences and Markups As explained in Section 4.3, we use exogenous variables, such as changes in EV subsidies and China's whitelist policy, along with the demand model and

[21] The demand elasticity is less than one (in absolute value) for 70 out of 4,556 observations. Given the multi-product nature of auto firms, only nine observations exhibit negative marginal costs, which we keep in the estimation sample.

a supplier choice model, to construct the predicted experience for each battery supplier and year. Similarly, we exploit exogenous variations in prices and consumer subsidies to generate predicted markups for battery suppliers and predicted EV producer experience. Figure A5 presents evidence that these predicted variables are strong IVs, and there is a strong positive correlation between these instruments and their endogenous counterparts after partialing out vehicle attributes and a rich set of country, brand, and year fixed effects.[22]

Coefficient Estimates Table 3 presents the GMM estimates for Equation (9), which characterizes the marginal cost of battery and vehicle production. We categorize the parameters into four groups: (1) those linking battery production costs to a function of learning-by-doing (LBD) and battery attributes, (2) those that relate vehicle production costs (excluding batteries) as a function of vehicle attributes, (3) the bargaining weight, and (4) fixed effects to control for unobserved cost shocks in both battery and vehicle production.[23] The experience of battery suppliers, the experience of EV producers, and the markups of battery suppliers are instrumented in all columns as discussed above.

Column (1) controls only the experience of battery suppliers, vehicle attributes, and fixed effects. The learning parameter γ_E is estimated to be -0.203, suggesting a learning rate of $1 - 2^{-0.203} = 13\%$. The coefficient γ_0 represents the baseline cost, which is the battery production cost when a firm begins production (with experience set to 1). The γ_0 estimate suggests a baseline cost of \$1,095 per kWh in 2013.

Column (2) incorporates industry-wide technological progress in battery production. The estimate on time trend indicates a \$24 reduction in battery cost per kWh each year. At the same time, the learning parameter reduces from -0.203 to -0.135, suggesting that industry-level technology progress could confound LBD estimates. Column (3) further controls for economies of scale by including plant capacity, while Column (4) adds the experience of EV producers to account for potential learning in EV manufacturing. Including these additional controls results in several notable changes in the estimation results.

First, the learning coefficient decreases from 0.203 in Column (1) to 0.113 in Column (4), implying a learning rate (the Spence coefficient) of $1 - 2^{-0.113} = 7.5\%$. That is, the marginal cost of producing batteries is expected to reduce by 7.5% on average with every doubling of production experience. Our preferred estimate in Column (4) is much lower than the 20-28% estimates reported in industry studies using aggregate data (Ziegler and Trancik, 2021), which often do not

[22]The supply-side analysis is nonlinear, so the standard weak IV test statistics do not apply. Nonetheless, the F-statistics from a linear "first-stage" regression controlling for the same set of exogenous regressors in Equation (9) is XX, XX, and XX for the three endogenous variables, respectively.

[23]We cannot separately identify the level of battery cost from that of vehicle cost since some of these fixed effects could affect both cost measures.

adequately control for industry-wide technology progress and other cost shocks. The learning rate in well-known economic studies has typically been found in the range of 20-30%. For example, it is estimated at 20% in the semiconductor industry from 1974-1992 (Irwin and Klenow, 1994) as well as in the construction of Liberty ships during World War II (Thompson, 2001); at approximately 30% in aircraft manufacturing from 1970-1984 (Benkard, 2000); and 14-29% in wind turbine production from 2000 to 2019 (Covert and Sweeney, 2022). Nonetheless, there is considerable variation in learning rate estimates across the studies, driven by multiple factors such as the nature of the industry (capital-intensive versus labor-intensive), knowledge stock depreciation (or organizational forgetting) due to employee turnover, as well as whether other important factors are controlled, such as economies of scale and industry-wide technology progress when estimating the learning curves (Argote and Epple, 1990; Thompson, 2012).

Second, the time trend estimates indicate that the battery costs decrease by $32 per kWh annually, or approximately 4% of the baseline cost ($858 per kWh in Column (4)). This implies substantial technological progress in EV battery production during our data period. Indeed, as we demonstrate below, technological progress accounts for 39.9% of the observed reductions in battery costs. In addition, the γ_0 estimate falls from $1,095 per kWh to $858 per kWh, closer to the reported industry average. The coefficient estimate on plant capacity in Column (4) is intuitively signed and precisely estimated, suggesting economies of scale of about 5.4% (=0.078 in Column (4) $\times \ln(2)$).

Third, the coefficient estimate for EV experience suggests that the unit cost of EV production decreases by $\$1000 * ln(2) * (-0.997) = \$691$ for every doubling of EV manufacturing experience. At this rate, the cumulative experience of EV manufacturers contributed to a reduction of about $3,000 (or 5%) of EV prices.

Lastly, the estimate for battery suppliers' bargaining weight drops from 0.503 in Column (1) to 0.275 in Column (4). Equal bargaining weight between battery suppliers and EV producers is unlikely, given that batteries only account for one-third of the total cost of EV production. In addition, a bargaining weight of 0.5 would imply upstream markups of $180 per kWh, which is implausibly high relative to Bloomberg's battery pack prices of $200 per kWh toward the end of the sample period. In contrast, a bargaining weight of 0.275 in Column (4) suggests upstream markups of approximately $117/kWh, a plausible estimate relative to the battery pack prices. The magnitude is also consistent with the markups reported by CATL.[24]

Column (4) is our preferred specification with all the relevant controls and is used for subsequent counterfactual analyses in Section 6.

[24]CATL's average reported markup (between 2015 and 2020) was $83 per kWh (CATL's Annual Reports).

Magnitude of LBD To better understand the magnitude of LBD and its contribution to the overall reduction in battery prices over the past decade, we simulate sales-weighted predicted battery prices from 2014 to 2020 under different scenarios, as shown in Figure 3. The bottom line represents the battery price index from Bloomberg NEF (2020). The top line shows the predicted prices based solely on the time trend, which captures the industry-wide technological advancements. The coefficient estimate on the time trend suggests an annual reduction of $32 per kWh. Overall, technological progress accounted for 39.9% of the battery price reduction. The second line from the top reflects the combined price reductions due to both LBD and the time trend. The difference between the top two lines indicates that LBD contributed to 35.5% of the reduction in battery price from 2014 to 2020. The third line represents the model-predicted battery prices, which also include the effects of growing economies of scale and changes in battery chemistry.[25]

To illustrate how LBD has contributed to changes in battery prices across the three major production countries, Panel (b) of Figure 3 reports price reductions driven by cumulative production experience for the leading battery suppliers: BYD and CATL in China, Panasonic and AESC in Japan, and LG and Samsung in South Korea. In 2014, the average battery cost was $750 per kWh among top Chinese suppliers ($\gamma_0 E_{bt,\text{China}}{}^{\gamma_E}$), compared to $650 per kWh among the leading South Korean suppliers and $550 per kWh among the top Japanese suppliers. By 2018, Chinese suppliers had caught up with their South Korean counterparts, and by 2020, they had also closed the gap with Japanese suppliers.

5.3 Robustness Checks

Scope of LBD Our analysis thus far has focused on internal LBD, i.e., learning that occurs within a firm. Historically, many policies that target "infant industries" (to which the EV and EV battery sectors belong) have been motivated by the potential for external learning: experience accumulated by local suppliers could generate spillover benefits to other suppliers within the same industry and country (Melitz, 2005). The effects of many current policies, such as the local content requirements for EV subsidies under the IRA, critically hinge on the scope of learning. Therefore, understanding the extent of these learning spillovers has significant policy implications. However, identifying the full scope of such spillovers poses additional empirical challenges, as it requires additional variations and exogenous shocks to assess their impact properly.

We first explore learning spillovers across firms within the same country. We assume that the effective experience of a battery supplier is the sum of its own experience and a fraction (captured

[25] Since we cannot separately identify the level of battery price and the level of vehicle cost, we calibrate the battery price in the base year (2014) to match the Bloomberg price index for that year. Our model prediction aligns well with the overall observed price decline.

by a parameter θ) of the experience of rival firms in the same country. The parameter θ measures the completeness of spillover: if $\theta = 1$, there is complete spillover: learning from rivals' experience is as effective as learning from one's own experience, whereas $\theta = 0$ implies no learning spillover from rival firms. We instrument the effective experience variable using the predicted own experience and predicted rival experience based on exogenous variations as shown in Equation (10).

Appendix Table A3 presents the estimation results for learning spillovers across firms. The estimate for θ is 0.044, indicating that learning from one unit of rival experience is equivalent to only 4.4% of the learning derived from one unit of own experience. The estimate is imprecise due to limited variation in rival experience across firms, especially for small battery suppliers. At $\theta = 0.044$, learning from rivals constitutes a small share of overall learning for the top six leading battery suppliers, but it accounts for 56% of the overall learning for other firms by the end of the sample period.

We also investigate differential learning across chemistry types within the same firm. We measure the experience variable by chemistry type and define effective experience as the sum of a firm's own experience in producing batteries of a given chemistry type and a fraction (θ) of its experience in producing batteries of other chemistry types. The θ parameter is imprecisely estimated. This is because more than 80% of the battery suppliers produce only one chemistry type, leading to limited variation across firms. Finally, we explore global LBD by allowing learning spillover across countries. However, the global LBD is highly correlated with the time trend and cannot be reliably estimated.

Alternative Bargaining Assumptions We assess whether the learning rate estimate is sensitive to the assumptions regarding bargaining conduct. Table 4 presents estimates when varying the battery supplier's bargaining weight λ from 0 to 0.5. We do not consider values greater than 0.5 because a higher bargaining weight for battery suppliers would imply markups exceeding the battery pack price, which is implausible. The LBD estimates remain similar across these different values of λ, suggesting robustness to changes in bargaining assumptions.

As an alternative to the simultaneous bargaining model, we also estimate the supply-side parameters assuming bargaining is sequential instead: EV makers and battery suppliers first negotiate over battery prices, then EV makers set downstream prices (taking as given the negotiated battery prices). If there is disagreement in upstream negotiations, downstream EV suppliers re-adjust their prices for all EV models.[26] Appendix Table A5 presents estimates while varying the battery sup-

[26] Appendix B.3 provides details. Note that by allowing downstream EV prices to adjust in case of disagreement, we relax an assumption researchers often make to make the sequential bargaining model tractable: that disagreement

plier's bargaining weight λ. The LBD estimates are very similar to our baseline estimates and remain robust to different values of λ.

Dynamic Considerations Next, we investigate how learning estimates change when we incorporate dynamic incentives for battery suppliers. Appendix B.4 provides more details.[27] When negotiating with EV makers, forward-looking battery suppliers internalize the benefit of reducing battery prices on future profits (which increases production experience and lowers future production costs) and have stronger incentives to offer lower prices in the early stages of learning compared to myopic suppliers. This is often referred to as dynamic markdown (Irwin and Klenow, 1994; Benkard, 2004). Ignoring dynamic incentives may underestimate the extent of LBD.

Table A4 presents the learning estimates γ_E at different values of λ. At one extreme, when $\lambda = 0$, battery suppliers earn zero markups, and thus no dynamic markdown incentive exists. At the other extreme, with $\lambda = 1$, battery suppliers capture the maximum surplus possible in negotiation, providing the strongest incentives to lower current battery prices to accelerate LBD. The estimates align with this intuition: γ_E is lowest (in absolute value) with $\lambda = 0$ and highest when dynamic incentives are strongest. Nonetheless, the differences are modest and γ_E varies from -0.099 with $\lambda = 0$ to -0.120 with $\lambda = 1$. This is because dynamic incentives dissipate rapidly after a few years for all learning rates we have obtained. We conclude that ignoring dynamics in our setting is unlikely to introduce significant bias into the learning estimates.

Patents and Innovation Our baseline specification includes a time trend in battery costs to account for industry-level technological progress that happens concurrently with learning. To account for the role of firm-level innovation and know-how, we include the logarithm of the cumulative number of patents filed by each battery supplier as a proxy for the firm's knowledge stock (Table A6). We instrument this variable using the cumulative total subsidies received by the battery supplier following Barwick et al. (2024). The coefficient of firm patents is negative and significant, consistent with firm innovations reducing costs. Interestingly, the time trend is no longer negative once patents are controlled for. The learning parameter γ_E remains very similar to the baseline

does not affect downstream prices. This would mean, for example, that if Tesla and Panasonic were to disagree, the downstream vehicle prices offered for all other vehicles would remain the same as the price level with Tesla and Panasonic reaching an agreement. Draganska, Klapper, and Villas-Boas (2010) argues this assumption is inconsistent with the sequential nature of the game because EV producers would know Tesla and Panasonic had disagreed by the time they set vehicle prices.

[27] The empirical literature on dynamic bargaining models is still in its early stage (Lee and Fong, 2013; Deng et al., 2024; Dorn, 2024). Formulating the impact of bargaining outcomes on the value function as well as the disagreement payoffs in a dynamic setting is particularly challenging. To make progress, we assume that forward-looking battery suppliers negotiate with EV producers over the upstream markups instead of battery prices and that they perceive future markups to remain unchanged from today's markups. While restrictive, these assumptions make it feasible to estimate an otherwise intractable problem. See Appendix B.4 for further discussion.

estimate but is noisily estimated due to challenges in finding valid instruments that can separately identify learning effects from innovation.

6 Counterfactual Analyses

We first evaluate the role of LBD and the extent of externality that it generates. Then we quantify the welfare implications of two prominent government policies with and without LBD.

6.1 The Effect of LBD and Externalities

Effect of LBD To investigate the role of LBD and its impact on EV adoption, we simulate aggregate EV sales for the top 13 EV countries during 2013-2020 under four scenarios, as illustrated in Figure 4. These scenarios, represented by the four lines from bottom to top, are as follows: (1) a baseline with no consumer subsidies and no LBD; (2) consumer subsidies without LBD; (3) LBD without consumer subsidies; and (4) both consumer subsidies and LBD.

LBD creates a positive "feedback loop:" subsidies boost EV sales, which enhances battery production experience, leading to lower battery costs and EV prices. These price reductions, in turn, further accelerate EV adoption, amplifying the direct effects of consumer subsidies and other supportive policies. Specifically, compared to the baseline scenario, consumer subsidies alone increased cumulative sales by 24.7% (0.61 million units) during 2013-2020. Absent any subsidies, cost reductions driven by LBD alone resulted in a 121% increase in global EV sales (2.99 million units) during the same period. When both consumer subsidies and LBD were in effect, global EV sales surged by 231% (5.68 million units) relative to the baseline. Remarkably, LBD amplified the cumulative effect of subsidies by a factor of 8.45. This combined "snowball" effect is nearly 60% larger than the sum of their individual contributions, underscoring the strong complementarity between LBD and consumer subsidies.

Externalities Our analysis in Section 5.3 indicates that while the spillovers to other firms in the same country are positive, the estimates are statistically insignificant. If LBD is entirely internal to a firm, can government interventions be justified, apart from environmental benefits and technological spillover to other sectors?[28] To evaluate this empirically, we conduct a counterfactual analysis where we increase battery suppliers' experience (and hence LBD) and examine what happens to downstream firms and consumers, both domestically and globally.

[28] Dasgupta and Stiglitz (1988) argues that LBD often leads to significant market power and high concentration. Import subsidies might be desirable when domestic demand for foreign goods is high and domestic production is too costly. LBD without spillovers is a special case of the model considered in Dasgupta and Stiglitz (1988).

Table A7 presents welfare changes resulting from a one-time increase in the experience of CATL and Panasonic in 2013. This shock reduces upstream firms' (CATL and Panasonic) future production costs, leading to lower input costs and higher profit for downstream firms, and ultimately benefiting end-users (consumers) when some of the cost savings are passed through. We simulate the industry equilibrium from 2013 to 2020 using the model developed in Section 3. To facilitate comparison, we normalize the increase in battery suppliers' profit to 1 (so all numbers are relative to this benchmark). The first three columns report welfare changes for the home country (China for CATL and Japan for Panasonic), the rest of the world, and globally when CATL's experience increases, while the next three columns show these changes when Panasonic's experience increases. Notably, CATL captures only 13.5% of the total surplus generated by its increased LBD, while Panasonic captures 14.7%. In addition, the distribution of welfare gains varies significantly between open and closed economies. China captures the entirety of the global welfare gains with its largely closed supply chain. In contrast, Japan captures only 58% of the global welfare gains resulting from Panasonic's cost reductions, with a significant portion of the surplus accruing to foreign downstream firms and consumers.

These discussions highlight that LBD generates substantial externalities for downstream firms and consumers, with these benefits crossing country borders through international supply chains. Such externalities underpin the large welfare impacts of government interventions, as documented below.[29]

Algorithm for Counterfactual Analyses Next, we conduct counterfactual simulations to examine two types of prominent government policies: (1) consumer subsidies and (2) domestic content requirements, such as China's Whitelist policy. As the latter policy is likely to shift battery sales from foreign to domestic suppliers, we develop a network formation model in Online Appendix B.5. The model features the Whitelist policy and accounts for the higher likelihood of more experienced battery firms supplying a given EV model.[30] For each counterfactual analysis, we perform 100 simulations and report the average outcomes. In each simulation, we 1) construct a supply network based on the network formation model in Appendix B.5, 2) solve for battery prices, vehicle prices, and EV sales, 3) update battery supplier experience and production costs, and (4) repeat steps (1)-(3) for all subsequent years in the sample.

[29] While not the focus of this paper, LBD also creates (intertemporal) complementarities among downstream products that share a common supplier. Positive demand shocks for one product increase the upstream supplier's LBD, leading to lower future prices for rival products with the same supplier and boosting demand for those rival products.

[30] Key controls of this discrete-choice model include: a dummy for China's whitelist policy, battery suppliers' experience, a home bias dummy, dummies for vertically integrated supplier-OEM pairs, the subsidy rate offered by country c at time t for a given EV model, initial attributes of EV suppliers, and the lagged network structure.

6.2 Consumer subsidies

Our first set of counterfactuals examines the impact of consumer subsidies in China, Europe, and the U.S. (including Canada) on EV adoption and social welfare from 2013 to 2020. We do not study Japanese and South Korean subsidies due to the small size of their EV markets. The top row in each panel reports welfare changes by region, measured as the sum of consumer surplus and firm profits minus subsidy expenditures when relevant. The first four columns present the welfare effects for China, Europe, Japan and South Korea, and the U.S., respectively, while the last column, titled "Global," aggregates welfare changes across all regions.[31]

Panel (a) of Table 5 highlights the impact of U.S. subsidies while holding fixed subsidies in other regions (as well as the whitelist policy in China). The U.S. spent \$13.10 billion in subsidies, generated \$16.47 billion in global welfare gains, and captured 49% of the global gains. The interaction of subsidies with LBD significantly lowered battery costs for U.S. (and Canadian) EV producers and reduced vehicle prices for domestic consumers. This led to an increase of 0.75 million EV sales in these countries.

Interestingly, Japan and South Korea benefitted most outside North America, as U.S. EV production heavily relies on batteries supplied by these countries. Similar to their counterparts in the U.S., EV producers and consumers in these countries also benefitted from lower battery costs driven by accelerated learning and cost reductions. Altogether, battery suppliers in Japan and South Korea captured 28% of global welfare gains, while EV producers and consumers in these countries captured another 6%, resulting in these two countries capturing 34% of global welfare gains. Europe and China also experienced gains, though China accounted for only 3% of the global total. This modest share reflects China's limited EV trade, minimal battery exports (in contrast to Japan and South Korea) and imports during the sample period. The only group of players that were hurt by U.S.' subsidies are Chinese battery suppliers because their rivals in Japan and Korea became more competitive through enhanced experience and stole their market shares, especially in the Chinese EV battery market.

Subsidies generate welfare gains through two primary channels. Both the EV sector and EV-battery sector are highly concentrated. Subsidies mitigate deadweight losses from market power distortions (as shown in Barwick, Kwon, and Li (2024)). The second channel works through accelerating LBD, which reduces upstream production costs and increases welfare.

Panel (b) shows that European subsidies had broadly similar effects to those of U.S. subsidies, generating substantial welfare gains for consumers and EV producers. Japan and South Korea ben-

[31] Profits for battery suppliers and EV producers are allocated to their headquarters country. Results are qualitatively similar if we allocate EV producers' profits to the EV production country.

efitted the most, as EVs sold in Europe also primarily sourced batteries from these two countries. However, there are notable differences: European governments invested \$16.44 billion in subsidies but achieved only \$11.60 billion in global welfare gains, of which the EU captured just 26%. This lower capture rate reflects Europe's higher import share of EVs. Additionally, the global return on EU subsidies (measured as net welfare gains per dollar spent) was lower than that of the U.S. subsidies, partly due to the common use of uniform subsidies in Europe, which proved less effective in generating consumer surplus compared to the battery-capacity-based subsidies employed in the U.S. (Barwick, Kwon, and Li, 2024).

Panel (c) examines the impact of Chinese subsidies totaling \$22.27 billion. These subsidies generated \$32.27 billion in global welfare gains, with 92.6% captured domestically. Although the subsidies produced some spillovers to other regions, these were small relative to those from U.S. and European subsidies due to China's limited EV imports and its domestic sourcing of EV batteries. EV sales in China increased by over 2.7 million units during 2013–2020, driven by generous subsidies and the more elastic demand among Chinese consumers.

Table 5 highlights several important findings. First, consumer subsidies generate welfare gains that are magnified by LBD and spillovers to other countries through the linkage in battery supply networks. Table A9 confirms that both the welfare gains and the cross-country spillovers are several factors smaller in the absence of LBD. Second, the extent of cross-country spillovers crucially hinges on the overlap of the battery supply networks. Consumer subsidies in China generated much smaller spillovers in other regions because EVs sold in China mainly rely on domestic battery producers. The strong spillovers between the US and the EU arise because EVs sold in these two regions use the same battery suppliers from Japan and South Korea. In contrast, the spillovers from US or European subsidies to China are nearly non-existent because of the limited overlap in battery suppliers between EV producers in the US and Europe and those in China. Finally, results in Table 5 echo findings in Section 6.1 and illustrate that privately chosen experience level (and the degree of LBD) is unlikely to be socially optimal. Government subsidies have the potential to address the under-provision of LBD.

6.3 Domestic content requirements

Whitelist To explore the impact of domestic content requirements, we begin by analyzing China's whitelist policy, introduced midway through our sample period. We compare outcomes with and without the whitelist to assess: (a) the extent to which the policy propelled top Chinese battery suppliers to industry leadership, and b) its welfare implications for domestic and foreign firms and consumers, which depend on cost differentials between whitelist battery suppliers and non-whitelist ones.

Figure A6 shows that the Whitelist policy significantly benefited Chinese battery suppliers, with sales increasing by 24% between 2016 - 2020. The policy successfully accelerated experience accumulation among Chinese battery suppliers, particularly CATL and BYD, enhancing their global competitiveness. This drove their market share growth even after the policy ended (Figure A4). However, these gains came at the expense of non-Chinese battery suppliers, whose sales declined by 14% relative to a no-whitelist scenario.

Panel (a) of Table 6 presents the impact of the Whitelist policy while holding the subsidies fixed. The policy increased the profit of Chinese battery suppliers by over $3.17 billion but hurt domestic consumers. While the overall welfare impact in China is positive, the policy had negative spillovers abroad. Japanese and South Korean battery suppliers faced reduced demand and profit losses, which slowed down their LBD. This slowdown negatively affected downstream EV producers in Europe and the U.S. that rely on these suppliers, leading to slower EV adoption in those regions. Collectively, the EU, Japan and South Korea, and the U.S. and Canada experienced a $5.88 billion welfare loss.

The effect on domestic EV producers was nuanced. In its early years, some domestic EV producers were forced to switch from initially lower-cost foreign suppliers to higher-cost domestic ones, leading to profit declines in 2016 and 2017 to the no-whitelist scenario. However, the policy facilitated sales concentration among two dominant domestic suppliers, enabling faster LBD accumulation. As shown in Figure (b) of 3, China's top suppliers closed the cost gap with South Korean suppliers by 2018 and matched Japanese competitors by 2020. These significant cost reductions ultimately benefited domestic EV producers, whose profits increased in 2018, 2019, and 2020 relative to the no-whitelist scenario. Over time, the policy's impact shifted from negative to positive.

Panel (b) of Table 6 presents the combined effect of the Whitelist policy and consumer subsidies in China. While the Whitelist slightly increased China's overall welfare gains from consumer subsidies, it reduced and even reversed the positive cross-country spillovers of these subsidies, particularly for Japan, South Korea, the U.S., and Canada.

These results indicate that Chinese battery suppliers were the primary beneficiaries of the whitelist policy. While domestic EV producers eventually gained, the policy had adverse effects on all other stakeholders. This highlights the tradeoffs created by protective policies that distort market forces. Consistent with our simulation results, the policy was discontinued in late 2019 following opposition from EV producers and non-Chinese battery producers.

Timing China's Whitelist was introduced at a crucial (and opportune) moment: the learning curve for battery production was steep, and China became the largest EV and EV battery market in 2015. We examine the effect of implementing the Whitelist four years later, from 2021 to 2024, when most battery cost reductions had already taken place. We assumed the global market structure and subsidy rates stayed as they were in 2020.[32] Table 8 summarizes the results.[33] As expected, the negative impact on other countries becomes much smaller. By 2021, the gap in production experience between leaders and followers is much wider than that in 2021. The economic benefits from LBD are also smaller, as battery costs had fallen below $200 per kWh compared to $600-$800 in 2014. While Chinese battery suppliers still gained, their profit increases are an order of magnitude smaller, given the large cost advantage held by Japan and Korea.[34] Chinese consumers and EV firms experienced greater losses. As a result, the counterfactual whitelist policy is also detrimental to China.

IRA The IRA of the Biden administration put into place local content requirements for batteries as part of the eligibility rules for consumer subsidies. While a policy simulation of the local content requirements under IRA is out of the sample of our study, our analysis suggests that the policy will likely generate welfare impacts across consumers, battery suppliers, and EV producers in the US that are qualitatively similar to those observed under the counterfactual Whitelist policy (2021-2024) in China. The switch to batteries produced in North America from cheaper batteries made elsewhere will likely lead to losses in consumer surplus, reduced profit among EV producers as well as slower EV adoption in the U.S. and elsewhere.

Without LBD To illustrate how LBD interacts with policies, we simulate the impacts of Chinese consumer subsidies and the Whitelist policy without LBD. Table 7 shows that welfare gains and positive cross-country spillovers from subsidies drop to about 20% of those with LBD, while negative spillovers from the Whitelist policy are significantly reduced. These results underscore the importance of accounting for LBD in evaluating the cost-effectiveness and broad impacts of EV policies.

[32] See Appendix B.5 for details.

[33] Panel (a) of Table 8 reports welfare impacts of the observed Whitelist from 2016 to 2019. These results differ from Panel (a) of Table 6, which covers 2013-2020, to align with Panel (b) of Table 6.

[34] Another contributing factor is that global subsidy rates in 2020 were different from those in 2016. Results are qualitatively similar if we used 2016 subsidy rates instead.

7 Conclusion

This paper, to our knowledge, represents the first attempt to causally quantify learning by doing (LBD) in the global EV battery market and to examine the implications of LBD for EV purchase subsidies and local content requirements on batteries. The learning rate is estimated to be 7.5% after controlling for industry-wide technological progress, economies of scale, and learning-by-doing in EV production. LBD in battery production accounts for 35.5% of the overall battery cost reduction during 2014–2020 and has substantially accelerated EV adoption. The feedback loop from LBD greatly amplified the effects of EV subsidies and local content requirements on EV adoption and social welfare by severalfold.

In terms of policy impacts, EV subsidies in one country generate spillover benefits for other countries, with the extent of these spillovers critically depending on the degree of overlap among battery suppliers. By shifting demand, China's whitelist policy accelerated learning among Chinese suppliers at the expense of others. The timing of policy implementation is crucial: if China had delayed the policy by five years, its effectiveness in helping Chinese suppliers gain a competitive advantage would have diminished significantly, and its welfare impact on China would have shifted from positive to negative.

We conclude by highlighting two directions for future research. First, our analysis abstracts from market entry and production location decisions (Head et al. (2024) makes an important headway in that direction by developing a multi-stage production model, though without incorporating LBD). These factors are critical for understanding the impacts of local content requirements recently implemented in the U.S. and Europe, especially given Asia's dominance in battery production. Second, we do not explicitly model the effect on traditional auto firms producing gas vehicles, which remains an important question for future research.

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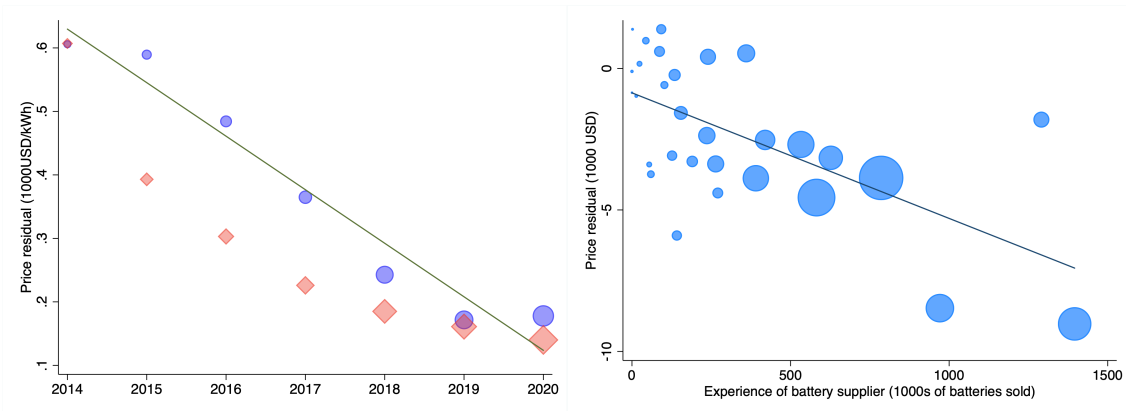
Figures & Tables

Figure 1: Vehicle Price vs. Battery Supplier Experience

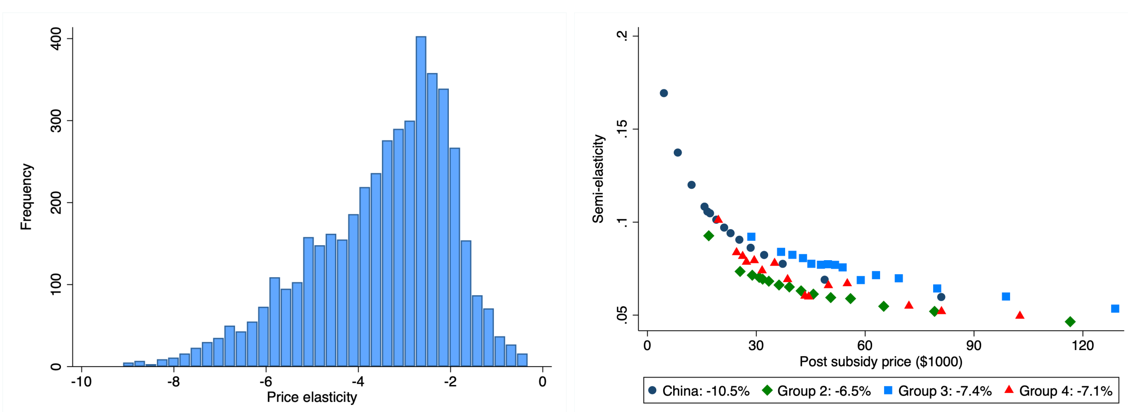
(a) Residualized Prices Over Time **(b)** Residualized Prices vs. Supplier Experience



Notes: The residualized vehicle prices in these graphs are EV prices partialing out vehicle attributes (horsepower, size, driving range, and the PHEV dummy), country, brand, and year fixed effects. In Panel (a), the purple dots depict the average residualized price (in $1000 per kWh) by year while the red diamonds represent the average battery pack prices from Bloomberg NEF (2023) (BNEF), with the marker size proportional to the total EV sales in a given year. The residualized price is scaled so that it coincides with the BNEF battery pack price in 2014. The binned scatter plot in Panel (b) shows the residualized prices (in $1000) against the cumulative experience of battery suppliers. The size of the dot is proportional to the cumulative subsidy received by battery suppliers.

Figure 2: Demand Elasticities

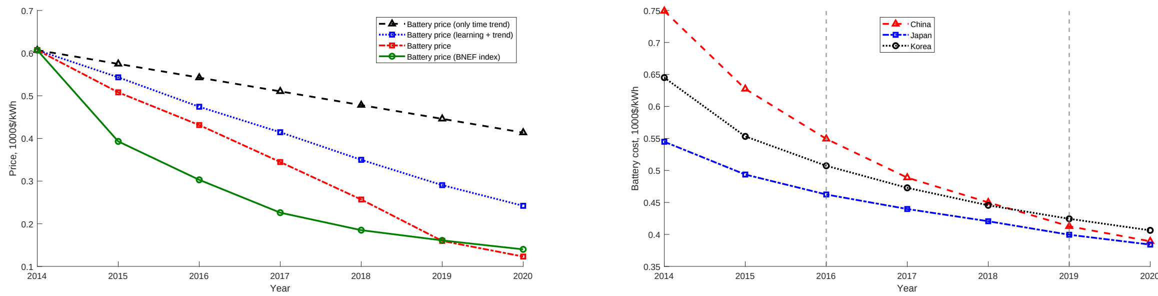
(a) Price Elasticity **(b)** Semi-elasticity When Price Drops by $1000)



Notes: Panel (a) shows the histogram of price elasticities. The average is 3.51. The demand elasticity is less than one (in absolute value) for 70 out of 4,556 observations. Given the multi-product nature of auto firms, only nine of the 70 observations exhibit negative marginal costs. Panel (b) depicts the binned scatter plot for semi-elasticities (the percentage change in sales for a $1,000 reduction in own prices) by country group. The sales-weighted average semi-elasticity is 10.5% for China and varies from 6.5% to 7.4% for other country groups. The increase in the percentage of sales is more pronounced for cheaper vehicles, implying more sensitive demand.

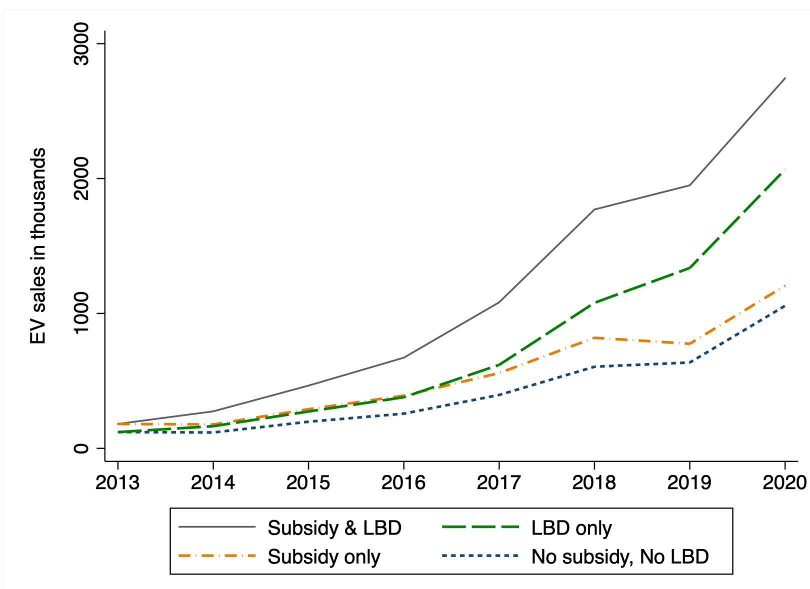
Figure 3: LBD and Battery Price Reduction

(a) Global **(b)** By Country



Notes: Panel (a) decomposes the reduction in sales-weighted average battery prices from 2014 to 2020 into two components: one driven by LBD and one by time trend. The bottom green line shows the battery price index from the Bloomberg New Energy Finance series, while the red line from the second to the bottom depicts our model predictions. Panel (b) shows the reduction in sales-weighted average battery prices that correspond to the learning component $\gamma_0 E_{bt}{}^{\gamma_E}$. The red triangles represent battery costs for BYD & CATL in China, the black circles stand for LG & Samsung in South Korea, and the blue squares stand for Panasonic & AESC in Japan. Chinese battery suppliers had higher costs initially but experienced a faster reduction over time and closed the gap with their rivals by 2020.

Figure 4: Effect of Subsidies and LBD on Global EV Sales



Notes: This figure illustrates total EV sales across the top 13 EV countries under various scenarios. The solid black line at the top represents observed EV sales with both LBD and consumer subsidies in effect. The second dashed green line shows EV sales with LBD but no subsidies, while the third dash-dot orange line represents EV sales with subsidies but no LBD. The dotted blue line at the bottom shows EV sales with neither LBD nor subsidies. LBD greatly amplifies the sales-expansion effect of subsidies.

Table 1: Summary Statistics

	BEVs			PHEVs		
	# of Obs.	Mean	Std. Dev.	# of Obs.	Mean	Std. Dev.
Panel A: Vehicle Information						
Sales	2,325	2886.7	9861.9	2,231	1343.8	3803.6
MSRP ($1,000)	2,325	45.12	28.26	2,231	71.93	33.68
Subsidy ($1,000)	2,325	4.72	4.57	2,231	1.94	2.09
Volume (m^3)	2,325	12.49	3.63	2,231	13.80	1.95
Horsepower	2,325	156.84	116.33	2,231	212.25	82.60
Driving Range (km)	2,325	171.19	79.95	2,231	31.46	24.61
Panel B: Battery Information						
Battery Capacity (kWh)	2,325	41.95	22.11	2,231	11.53	3.59
Chemistry: NMC	2,325	0.629	0.483	2,231	0.949	0.219
Chemistry: LFP	2,325	0.045	0.208	2,231	0.006	0.076
Chemistry: NCA	2,325	0.100	0.300	2,231	0.002	0.042
Panel C: Battery Supplier Information						
Production Experience (# EV supplied)	204	86,672	199,272			
Median Plant Capacity (GWh)	204	1.03	3.05			
Cumulative Patents	204	542.6	1,437.0			
Panel D: Market-level Information						
Lithium Price Index (100 in 2011)	104	190.09	75.24			

Notes: The sample covers 13 countries with the largest EV sales in the world from 2023 to 2020: Austria, Canada, China, France, Germany, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the UK, and the U.S. All prices are in nominal $. The three major battery chemistry types are: NMC, Nickel Manganese Cobalt; LFP, Lithium iron phosphate; and NCA, Nickel Cobalt Aluminum Oxide. The production capacity is the median capacity across all plants operated by a battery supplier (a supplier has three plants on average). The lithium price is an index normalized to 100 in 2011 and is collected from COMTRADE for China and Europe, USGS for the U.S., and from Benchmark Mineral Intelligence for other countries.

Table 2: Demand Estimation Results

	(1) OLS logit		(2) IV logit		(3) Full model	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Linear Parameters						
Consumer Price (α_1)	-0.016	0.002	-0.057	0.010	-0.017	0.009
PHEV	4.763	0.898	4.787	0.911	4.402	0.958
log(volume)	-0.744	0.245	0.749	0.417	1.346	0.413
log(HP)	0.285	0.154	1.217	0.277	1.191	0.274
log(range)	1.229	0.163	0.918	0.184	1.025	0.192
log(range) x PHEV	-0.780	0.209	-0.868	0.214	-0.638	0.219
Non-linear Price Coefficients (α_{2c}/y_i)						
α_2 for China	-	-	-	-	0.318	0.013
α_2 for JP/SP/FR/DE	-	-	-	-	0.220	0.020
α_2 for UK/NL/AT/SE	-	-	-	-	1.221	0.111
α_2 for CA/NO/US/CH	-	-	-	-	0.616	0.026
Random Coefficients (σ)						
Constant	-	-	-	-	0.330	0.038
log(volume)	-	-	-	-	0.077	0.013
log(HP)	-	-	-	-	0.032	0.004
Consumer Price	-	-	-	-	0.123	0.009
Fixed Effects						
Country	✓	✓	✓	✓	✓	✓
EV Brand	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓

Notes: The demand estimation is based on annual sales by vehicle model by country in the top 13 EV countries from 2013 to 2020. The number of observations is 4,556. Columns (1) and (2) report results for the OLS and 2SLS Berry-logit regressions, respectively. Price instruments include battery supplier dummies interacted with battery capacity, as well as three BLP IVs. Column (3) is the random coefficient multinomial logit model and is estimated using simulated GMM with micro-moments. The price coefficient α_i is specified as $\alpha_1 + \frac{\alpha_{c(i)}}{y_i} + \sigma_p v_i^p$, where y_i is consumer income and v_i^p is unobserved preference shocks (i.i.d. log-normal draws). All regressions include country, brand, and year fixed effects. The standard errors are clustered at the country by brand level.

Table 3: Supply-side Estimation Results

	(1)	(2)	(3)	(4)
Battery Cost Parameters				
Learning Parameter γ_E	-0.203	-0.135	-0.137	-0.113
	(0.048)	(0.044)	(0.045)	(0.052)
γ_0(1000$/kWh)	1.095	1.071	1.082	0.858
	(0.218)	(0.169)	(0.17)	(0.164)
BK * Time Trend		-0.024	-0.024	-0.032
		(0.007)	(0.007)	(0.006)
BK * log(Plant Capacity)			0.024	-0.078
			(0.043)	(0.035)
BK * Battery Chemistry Dummies	✓	✓	✓	✓
BK * Lithium Prices	✓	✓	✓	✓
Vehicle Cost Parameters				
EV Experience				-0.997
				(0.421)
PHEV	11.741	10.998	11.223	2.172
	(2.017)	(2.098)	(2.164)	(1.104)
Horsepower	0.273	0.274	0.275	0.244
	(0.011)	(0.011)	(0.011)	(0.007)
Volume	-2.796	-2.524	-2.597	0.807
	(0.647)	(0.657)	(0.678)	(0.232)
Bargaining Parameter				
Bargaining Weight λ^b	0.503	0.484	0.488	0.275
	(0.074)	(0.08)	(0.08)	(0.132)
Fixed Effects				
Country	✓	✓	✓	✓
EV Brand	✓	✓	✓	✓
Battery Supplier	✓	✓	✓	✓
Year	✓	✓	✓	✓

Notes: This table reports parameter estimates for Equation (9). The dependent variable (EV price minus EV markups) is in $1,000. The number of observations is 4,556. All specifications use 2-step GMM estimation with battery supplier experience, battery markup (the variable corresponding to bargaining weight), and EV producer experience instrumented. The marginal cost of battery pack is specified as: $BK_{bjct}\left(\gamma_0 E_{bt}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta t\right)$. BK is battery capacity, γ_E is the learning parameter, and γ_0 capture the baseline cost with $E_{bt} = 1$. The regression has four sets of controls. The first set includes variables relevant to batteries' marginal cost: battery capacity interacted with battery chemistry (NMC, NCA, LFP) and lithium prices (with the coefficient different for Chinese and non-Chinese EV models), battery capacity interacted with the time trend (to capture industry-wise technological progress or cost shocks) and with production capacity (to capture economies of scale). The second set includes vehicle attributes such as vehicle fuel type (BEV or PHEV), vehicle size, horsepower, and EV producer experience (i.e., cumulative EV production by each EV producer in logarithm) to capture LBD in EV manufacturing. The third set of controls is battery suppliers' markups (with equal bargain weights). The last set of controls includes country, EV brand, battery supplier, and year fixed effects.

Table 4: Supply-side Estimation Results: Robustness to Bargaining Parameter

Bargaining Parameter	Estimated (1)	$\lambda^b = 0$ (2)	$\lambda^b = 0.25$ (3)	$\lambda^b = 0.5$ (4)
Battery Cost Parameters				
Learning Parameter γ_E	-0.113	-0.100	-0.128	-0.132
	(0.052)	(0.05)	(0.059)	(0.055)
γ_0(1000$/kWh)	0.858	0.877	0.781	0.829
	(0.164)	(0.166)	(0.145)	(0.159)
BK * Time Trend	-0.032	-0.035	-0.032	-0.029
	(0.006)	(0.007)	(0.007)	(0.006)
BK * log(Plant Capacity)	-0.078	-0.082	-0.078	-0.070
	(0.035)	(0.037)	(0.036)	(0.034)
BK * Battery Chemistry Dummies	✓	✓	✓	✓
BK * Lithium Prices	✓	✓	✓	✓
Vehicle Cost Parameters				
EV Experience	-0.997	-1.011	-0.998	-0.964
	(0.421)	(0.431)	(0.422)	(0.407)
PHEV	2.172	2.819	2.250	1.134
	(1.104)	(1.133)	(1.109)	(1.064)
Horsepower	0.244	0.252	0.245	0.232
	(0.007)	(0.007)	(0.007)	(0.007)
Volume	0.807	0.893	0.817	0.665
	(0.232)	(0.24)	(0.234)	(0.222)
Bargaining Parameter				
Bargaining Weight λ^b	0.275	0.00	0.25	0.50
	(0.132)			
Fixed Effects				
Country	✓	✓	✓	✓
EV Brand	✓	✓	✓	✓
Battery Supplier	✓	✓	✓	✓
Year	✓	✓	✓	✓

Notes: This table reports parameter estimates for Equation (9). The dependent variable (EV price minus EV markups) is in $1,000. Column(1) is identical to Column (1) in Table 3. Columns (2)-(4) fix the bargaining parameter λ and estimate the remaining parameters by GMM with battery supplier experience and EV producer experience instrumented. See Table 3 for variable definitions.

Table 5: Impact of Consumer Subsidies

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of US Subsidies					
Δ Welfare ($ bn.)	0.49	2.24	5.65	8.09	16.47
Δ Consumer surplus (+)	0.14	0.96	0.04	13.35	14.48
Δ Battery profit (+)	-0.21	-	4.59	-	4.38
Δ EV profit (+)	0.51	1.67	1.03	7.85	11.06
Δ Gov't expenditure (-)	-0.05	0.39	0.01	13.10	13.45
Δ EV sales	6,646	50,224	2,266	754,788	813,925
Panel (b): Impacts of European Subsidies					
Δ Welfare ($ bn.)	0.75	3.03	5.49	2.32	11.60
Δ Consumer surplus (+)	0.15	14.63	0.04	0.89	15.71
Δ Battery profit (+)	-0.11	-	3.97	-	3.87
Δ EV profit (+)	0.68	4.82	1.49	1.80	8.79
Δ Gov't expenditure (-)	-0.04	16.44	0.01	0.36	16.77
Δ EV sales	8,650	751,021	2,766	50,749	813,185
Panel (c): Impacts of Chinese Subsidies					
Δ Welfare ($ bn.)	29.89	1.05	0.11	1.22	32.27
Δ Consumer surplus (+)	27.04	0.67	0.01	0.33	28.05
Δ Battery profit (+)	7.52	-	-0.11	-	7.41
Δ EV profit (+)	17.60	0.62	0.21	1.02	19.45
Δ Gov't expenditure (-)	22.27	0.24	0.00	0.13	22.65
Δ EV sales	2,696,916	30,267	732	18,780	2,746,696

Notes: This table shows the impacts (aggregated during 2013-2020) of consumer subsidies on social welfare and EV adoption separately for China, Europe, Japan & South Korea, and US & Canada. Panel (a) estimated impacts of US subsidies capture the difference between two scenarios with and without US subsidies but holding consumer subsidies in China and Europe fixed. Panels (b) and (c) are obtained similarly.

Table 6: Impacts of China's Whitelist Policy

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of China's Whitelist itself in the presence of subsidies					
Δ Welfare ($ bn.)	3.65	-0.59	-3.88	-1.41	-2.23
Δ Consumer surplus (+)	-0.80	-0.48	-0.01	-0.58	-1.87
Δ Battery profit (+)	3.17	-	-3.73	-	-0.56
Δ EV profit (+)	0.19	-0.32	-0.13	-1.07	-1.33
Δ Gov't expenditure (-)	-1.08	-0.21	0.00	-0.24	-1.53
Δ EV sales	-61,375	-26,162	-742	-33,196	-121,475
Panel (b): Impacts of China's policy combination: Whitelist and Subsidies					
Δ Welfare ($ bn.)	33.54	0.46	-3.77	-0.19	30.04
Δ Consumer surplus (+)	26.24	0.19	0.00	-0.25	26.18
Δ Battery profit (+)	10.69	-	-3.85	-	6.85
Δ EV profit (+)	17.79	0.30	0.08	-0.05	18.13
Δ Gov't expenditure (+)	21.19	0.04	0.00	-0.11	21.11
Δ EV sales	2,635,542	4,105	-10	-14,416	2,625,221

Notes: This table shows the impacts (aggregated during 2013-2020) of China's policies on social welfare and EV adoption separately for China, Europe, Japan & South Korea, and US & Canada. Panel (a) presents the impacts of China's whitelist policy, the difference between the two scenarios with and without the whitelist policy but holding consumer subsidies in place. Panels (b) shows the impacts of the police combination (whitelist and consumer subsidies), the difference between the two scenarios with and without the policy combination.

Table 7: LBD and Policy Interactions

($ bn.)	World	China	Rest of World
With LBD			
Δ Welfare, Chinese subsidies	32.27	29.89	2.38
Δ Welfare, Whitelist	-2.23	3.65	-5.88
Without LBD			
Δ Welfare, Chinese subsidies	6.71	6.00	0.71
Δ Welfare, Whitelist	-0.19	0.67	-0.86

Notes: This table shows the welfare impacts (aggregated during 2013-2020) of China's consumer subsidies and the whitelist policy with and without LBD.

Table 8: Impacts of China's Whitelist Policy during 2013 - 2025

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of China's Whitelist during 2016 - 2019					
Δ Welfare ($ bn.)	5.08	-1.74	-7.07	-3.19	-6.92
Δ Consumer surplus (+)	-1.66	-1.85	-0.04	-1.64	-5.18
Δ Battery profit (+)	5.37	-	-6.45	-	-1.08
Δ EV profit (+)	0.17	-0.80	-0.58	-2.25	-3.47
Δ Gov't expenditure (-)	-1.20	-0.92	-0.01	-0.70	-2.82
Δ EV sales	-115,613	-109,131	-2,445	-96,335	-323,525
Panel (b): Impacts of China's Whitelist during 2021 - 2024					
Δ Welfare ($ bn.)	-1.65	-0.47	-0.98	-0.42	-3.51
Δ Consumer surplus (+)	-3.39	-0.18	0.00	-0.10	-3.68
Δ Battery profit (+)	0.29	-	-0.80	-	-0.51
Δ EV profit (+)	-1.40	-0.37	-0.17	-0.36	-2.31
Δ Gov't expenditure (-)	-2.85	-0.09	0.00	-0.04	-2.98
Δ EV sales	-303,293	-10,817	-245	-6,178	-320,533

Notes: This table shows the impacts (aggregated during 2013-2025) of China's policies on social welfare and EV adoption separately for China, Europe, Japan & South Korea, and US & Canada. Panel (a) presents the impacts of China's whitelist policy during 2016 - 2019, the difference between the two scenarios with and without the whitelist policy but holding consumer subsidies in place. Panels (b) shows the impacts when the whitelist policy was implemented 5 years later (during 2021 - 2024).

Online Appendix

Drive Down the Cost: Learning by Doing and Government Policies in the Global EV Battery Industry

Panle Jia Barwick Hyuk-soo Kwon Shanjun Li Nahim Bin Zahur

A Data Construction Appendix

Data on battery suppliers' plants are compiled from the 2022 lithium-ion battery gigafactory database by Automotive Logistics (AL) and analysis reports from Marklines[1]. The AL dataset provides detailed plant characteristics by year and region, including manufacturing start year, capacity in 2022, predicted capacity from 2023-2030, and city-level location. As of 2022, there are 204 battery cell plants in Asia Pacific with a total capacity of 703 GWh, 73 cell plants in Europe with a total capacity of 160 GWh, and 48 cell plants in North America with a total capacity of 95 GWh. The Marklines reports offer production capacity data from 2018-2021 for the top ten Chinese cell suppliers (CATL, LG Energy, Panasonic, Findreams/BYD, EVE, CALB, Gotion High-tech, Farasis Energy, SVOLT, and Sunwoda). We manually merged these two data sources. For plants with missing capacity information, we supplemented the data by searching online news reports. The following table illustrates the data collection process: The completed battery capacity

Table A1: Examples of Battery Plant Capacity Collection

Plant Name	Cell Supplier	News Report	Start Year	Capacity 2022 (GWh)	Address
CATL Yibin manufacturing site (1st and 2nd phase)	CATL	CATL has completed the first expansion stage of its battery cell plant in the city of Yibin in southwest China's Sichuan Province, for which it has already commissioned the equipment. The company puts the annual capacity of the completed section at 15 GWh. After completing the second construction phase in two years as planned, the annual production capacity is expected to total 30 GWh. CATL indicates that a total of six phases of the project are planned...	2021	30	Yibin, Sichuan
Panasonic-Tesla	Panasonic	Today a portion of Tesla's vision became reality, with Panasonic and Tesla beginning production of their "2170" cylindrical lithium-ion batteries at their "Gigafactory" in Reno, Nevada. These cells will be used in Tesla's Powerwall 2 and Powerpack 2 battery products, as well as its Model 3 EVs. Tesla notes that production for qualification began in December at the Gigafactory, which when complete will be the largest factory on earth. The mammoth building is being completed in phases so that production can being inside finished sections and expand later, and by 2018 the company expects the facility to be making 35 gigawatt-hours per year of battery cells...	2016	35	Reno, Nevada

dataset contains 263 plants of 99 cell suppliers ranging from 1992 to 2023. The top 10 cell suppliers by total capacity are CATL, BYD, SVOLT, LG Energy, CALB, EVE Energy, Panasonic, AESC, Gotion High-tech, Farasis, which consist of 83.04% of global battery capacity.

B More Details on Estimation and Counterfactual Analyses

B.1 Income Distribution Calibration

The World Inequality Database (WID) provides annual data on three key metrics for most countries: (1) average income, (2) the income share of the bottom 50% (p0-50), and (3) the income

[1] See: Automotive Logistic and Markline Analysis Report.

share of the top 10% (p90-100). Using these statistics, we calibrate the location and dispersion parameters of the Lognormal distribution, Lognormal(μ_m, σ_m) for each market m (a country-year pair). First, we express μ_m as a function of σ_m by matching the mean of the lognormal distribution, $\exp(\mu_m + \sigma_m^2/2)$, to the average income reported by WID for the market. We then determine σ_m (and consequently $\mu_m(\sigma_m)$) by minimizing the following objective function:

$$(\text{predicted p0-50} - \text{observed p0-50})^2 + (\text{predicted p90-100} - \text{observed p90-100})^2.$$

B.2 IV Construction for Battery Experience

We construct the IV for battery experience using Eqn (10): $IV_{bt} = \sum_{s<t} \sum_j \hat{Pr}_{jbcs}(\mathbf{z}_{jbcs}) \hat{q}_{jcs}(\mathbf{X}_{jcs}, \phi_{jcs})$, which has two components: 1) the probability that EV model j sold in country c at time s chooses battery supplier b, and 2) predicted sales of model j. We use the demand model in Section 3 to generate predicted sales $\hat{q}_{jcs}$, as explained in the main text. Here we discuss how we predict the probability that model j chooses supplier b: $\hat{Pr}_{jbcs}$.

EV models rarely switch battery suppliers during our sample. Hence, we assume that an EV maker selects a battery supplier (from a choice set that includes all battery suppliers active in that country) during the year when an EV model is first released in a given country. The unit of analysis is an EV model and battery supplier pair by country and model-release-year. We allow EV makers to choose different battery suppliers for the same EV model sold in different countries.[2] This is because batteries are expensive to transport and it may be cost-efficient to source from nearby production facilities. In addition, EV makers may choose domestic battery suppliers to satisfy domestic content requirements.

We use a logit model, where the outcome variable is one if an EV model chooses a supplier and zero otherwise. We only use variables that are likely uncorrelated with cost shocks ω_{jct} as controls. They are a dummy variable for China's White List policy (that equals one for EVs in China and if the supplier is Chinese from 2016-2019, and 0 otherwise), a home bias dummy (that equals one if the supplier-OEM pair has the same country-of-origin), dummies for supplier-OEM pairs that are vertically integrated (BYD - BYD and AESC - RNM), the initial supply network (a dummy that equals one if the supplier-OEM pair had a supply relationship at the beginning of the sample period), a dummy for whether the initial supply relationship was in the same country as the one where the EV is produced and age of each supplier. We also control for a supplier's characteristics in the initial year: average battery capacity, the most common chemistry of batteries produced, and the average number of models for which the firm was a battery supplier. Finally, we include interaction terms between initial supply-network links, supplier characteristics, and EV characteristics (volume, horsepower, battery capacity, range, and battery chemistry).

B.3 Sequential Bargaining Estimation

In the sequential bargaining game, EV makers and battery suppliers first negotiate battery prices, after which EV makers set EV prices based on the observed battery prices. The battery prices are determined to maximize Equation (4) and the bargaining FOCs are the same as before. However, two changes arise in Equation (5) due to the new timing assumptions:

[2] For example, Hyundai's Kia K5 model in 2018 used CATL batteries for the model sold in China but batteries from LG for the model sold in other countries.

- The deviation profits d_j^v and d_j^b depend on the new equilibrium prices without the disagreed EV model j, instead of the current prices.

- The derivatives of downstream profits π^v with respect to battery prices differ from the previous case.

Gains from trade The gain from trade for EV maker v is expressed as

$$\pi^v - d_j^v = \sum_k T^v(k,j)\left[mk_k^v(p,\tau)\; q_k(p) - mk_k^v(\widetilde{p},\tau)\; \widetilde{q}_k(\widetilde{p})\right]$$

where p and τ denote the EV and battery prices, while $\widetilde{q}$ and $\widetilde{p}$ represent the equilibrium EV sales and prices excluding product j from the market. In matrix form, this can be rewritten as $(T^v \otimes M^v)\cdot l$. Here, M^v captures the changes in vehicle k profits when there is disagreement over the battery price for vehicle j, $\otimes$ denotes element-by-element multiplication, and l is a vector consisting entirely of ones. Similarly, the gain from trade for battery supplier b is given by

$$\pi^b - d_j^b = \sum_k T^b(k,j)\left[mk_k^b(\tau)\; q_k(p) - mk_k^b(\tau)\; \widetilde{q}_k(\widetilde{p})\right]$$

which can be rewritten as $(T^b \otimes S)\cdot mk^b$. In this case, S represents the changes in sales upon disagreement, as defined in Section 3.

Profit derivatives The derivative of the EV maker's profit with respect to the battery price τ_j is expressed as

$$\frac{\partial \pi^v}{\partial \tau_j} = \sum_k T^v(k,j)\frac{d\pi_k^v}{d\tau_j}$$

and in matrix form, it can be rewritten as $(T^v \otimes \Delta_\tau^{\pi^v})\cdot l$, where $\Delta_\tau^{\pi^v}$ collects the derivatives of downstream profits with respect to upstream prices. In addition, the derivative of the battery supplier's profit with respect to a battery price is given by

$$\frac{\partial \pi^b}{\partial \tau_j} = \sum_k T^b(k,j)\frac{d\pi_k^b}{d\tau_j} = \sum_k T^b(k,j)\left(\mathbb{1}\{k=j\}\cdot q_k + mk_k^b \frac{\partial q_k}{\partial \tau_j}\right)$$

and in matrix form, it becomes $q + (T^b \otimes \Delta_\tau^q)\cdot mk^b$, where Δ_τ^q collects the derivatives of downstream sales with respect to battery prices.

Upstream markup Then, the bargaining FOC becomes

$$(1-\lambda^b)\left[(T^b \otimes S)\cdot mk^b\right] \otimes \left[(T^v \otimes \Delta_\tau^{\pi^v})\cdot l\right] + \lambda^b\left[(T^v \otimes M^v)\cdot l\right] \otimes \left[q + (T^b \otimes \Delta_\tau^q)\cdot mk^b\right] = 0$$

From this, we can derive upstream markups as a function of downstream markups as follows:

$$mk^b = -\left[\frac{(1-\lambda^b)}{\lambda^b}\cdot X_t \cdot (T^b \otimes S) + (T^b \otimes \Delta_\tau^q)\right]^{-1}\cdot q$$

where X_t is a diagonal matrix:

$$X_t := diag\left(\left[(T^v \otimes \Delta_\tau^{\pi^v})\cdot l\right] \oslash \left[(T^v \otimes M^v)\cdot l\right]\right)$$

The notation $\oslash$ denotes element-wise division. Once the upstream markups are expressed as a function of the downstream markups, the estimation process follows the steps as outlined in Section 4.2.

B.4 Dynamic Bargaining Estimation

We estimate a dynamic bargaining model as a robustness check. We assume that battery suppliers are forward-looking while EV makers are myopic (and maximize current period profits). Battery suppliers and EV firms bargain over battery prices while downstream EV markups are chosen simultaneously to maximize EV firms' profits $\pi^v(p) = \sum_{j\in\Omega_v}(p_j - \tau_j - mc_j^v)q_j(p,\phi)$. The assumption that markups are chosen simultaneously ensures that changes in negotiated battery prices directly affect downstream EV prices (i.e., $\frac{\partial p_j}{\partial \tau_j} \neq 0$). These price adjustments influence EV sales and, in turn, battery sales, which subsequently impact battery suppliers' production experience and future production costs.[3]

Battery supplier b and EV producer v bargain over battery price τ_j to maximize the following Nash product:

$$NP_{vb,t}(\tau_{jt},\tau_{-jt}) = \underbrace{(\pi_t^v - d_{vb,t}^v)}_{\text{v' gains}}{}^{(1-\lambda^b)}\underbrace{(V_t^b - D_{vb,t}^b)}_{\text{b' gains}}{}^{\lambda^b} \tag{A1}$$

In the Nash product, the downstream profits π_t^v and deviation payoffs $d_{vb,t}^v$ are the same as those in Equation (4). On the other hand, battery suppliers' gains from trade is a dynamic value function that incorporates future profit gains. Battery supplier's payoff upon agreement V_t^b is defined as:

$$V_t^b = \sum_{k\in\Omega_t^b} mk_{kt}^b \cdot q_{kt}(mk_{kt}^v + mk_{kt}^b + mc_{kt}) + \sum_{s=1}^{\infty}\beta^s \sum_{k\in\Omega_{t+s}^b} mk_{kt+s}^b \cdot q_{kt+s}(mk_{kt+s}^v + mk_{kt+s}^b + mc_{kt+s}) \tag{A2}$$

where mk^v represents the downstream markup, mk^b denotes the upstream markup, and mc is the total marginal cost of production, consisting of marginal costs of producing batteries and non-battery vehicle components ($mc^b + mc^v$). The equilibrium quantity q is determined by the final EV price, which is equal to $mk^v + mk^b + mc$.[4] The second term in Equation (A2) is the discounted sum of future profits and reflects the battery supplier's dynamic considerations. We set the time discount rate β to 0.95. Battery supplier's deviation payoff is defined as:

$$D_{vb,t}^b = \sum_{k\in\Omega_t^b\setminus j} mk_{kt}^b \cdot \widetilde{q}_{kt}(mk_{kt}^v + mk_{kt}^b + mc_{kt}) + \sum_{s=1}^{\infty}\beta^s \sum_{k\in\Omega_{t+s}^b} mk_{kt+s}^b \cdot q_{kt+s}(mk_{kt+s}^v + mk_{kt+s}^b + \widetilde{mc}_{kt+s})$$

where $\widetilde{q}_{kt}$ represents sales when product j is withdrawn from the market.[5] In the second term, $\widetilde{mc}_{t+s}$ refers to future marginal costs when the quantity in period t is $\widetilde{q}_t$ instead of q_t.

We add three simplification assumptions:

A1) Both the battery supplier and EV producer perceive the current market structure, consumer preference, and market size to continue indefinitely:

$$\Omega_{t+s}^b = \Omega_t^b \text{ for all } s = 1,2,...$$

[3] The bargaining model in the main text assumes that EV prices are determined simultaneously with the negotiated battery prices. Under this assumption, battery suppliers have no direct influence on downstream prices or sales $\frac{\partial p_j}{\partial \tau_j} = 0$. Consequently, they cannot lower the negotiated battery price today to increase experience tomorrow.

[4] The battery price for EV model k is equal to its production cost plus the battery supplier's markup $\tau_k = mc_k^b + mk_k^b$.

[5] Prices of other EVs remain unchanged by construction.

A2) Battery Suppliers do not consider the impact of the current battery price on future markups:

$$\frac{\partial mk^v_{kt+s}}{\partial \tau_{jt}} = \frac{\partial mk^b_{kt+s}}{\partial \tau_{jt}} = 0 \text{ for all } j,k, \text{ and } s$$

In other words, they only consider changes in future profits as a result of changes in future marginal costs via learning.

A3) Battery Suppliers and EV producers perceive the future markups to remain the same as the current level:

$$mk^v_{jt+s} = mk^v_{jt} \text{ and } mk^b_{jt+s} = mk^b_{jt} \text{ for all } j \text{ and } s$$

With these assumptions, the bargaining FOC with respect to battery prices is as follows:

$$(1-\lambda^b)(V^b_t - D^b_{vb,t})\frac{\partial \pi^v_t}{\partial \tau_{jt}} + \lambda^b(\pi^v_t - d^v_{vb,t})\frac{\partial V^b_t}{\partial \tau_{jt}} = 0$$

The derivative of battery suppliers' payoff under agreement w.r.t. battery price becomes:

$$\begin{aligned}\frac{\partial V^b_t}{\partial \tau_{jt}} = q_{jt} + \sum_{k\in\Omega^b_t} mk^b_{kt}\cdot\frac{\partial q_{kt}}{\partial p_{jt}} \quad &\Big\}\text{ Impact on current profit}\\ + \sum_{s=1}^{\infty}\beta^s \sum_{k\in\Omega^b_t} mk^b_{kt}\cdot\sum_m \frac{\partial q_{kt+s}}{\partial p_{mt+s}}\frac{dmc_{mt+s}}{d\tau_{jt}} \quad &\Big\}\text{ Impact on future profits via LBD}\end{aligned}$$

In matrix notation, the bargaining FOC can be rewritten as:

$$(1-\lambda^b)\left[(T^b_t\otimes S^+_t)\cdot mk^b_t\right]\otimes[(T^v_t\otimes\Delta_t)\cdot mk^v_t] + \lambda^b[(T^v_t\otimes S_t)\cdot mk^v_t]\otimes\left[q_t + (T^b_t\otimes\Delta^+_t)\cdot mk^b_t\right] = 0$$

where $\otimes$ is the element-wise multiplication. Note that T and S are the same as those defined in Equation 6. In contrast, S^+ is a deviation matrix that incorporates dynamic terms. Specifically, the (j,k)-element of S^+ is given by:

$$(q_{kt} - \widetilde{q}_{kt}) + \sum_{s=1}^{\infty}\beta^s\cdot(q_{jt+s} - \widetilde{q}_{jt+s}) \tag{A3}$$

In comparison, S only includes the first term in Equation A3. The matrix Δ represents the derivative of EV demand in period t with respect to EV prices. The Δ^+_t incorporates the derivatives of future EV demand due to changes in future marginal costs through LBD. Specifically, the (j,k)-element of Δ^+_t is:

$$\frac{\partial q_{kt}}{\partial p_{jt}} + \sum_{s=1}^{\infty}\beta^s\sum_m \frac{\partial q_{kt+s}}{\partial p_{mt+s}}\frac{dmc_{mt+s}}{d\tau_{jt}} \tag{A4}$$

Note that Δ_t only includes the first term in Equation A4.

Finally, we derive the upstream markup as a function of the downstream markup from the bargaining FOC, similar to the approach in Section 3:

$$mk^b_t = -\left[\frac{(1-\lambda^b)}{\lambda^b}\cdot X_t\cdot(T^b_t\otimes S^+_t) + (T^b_t\otimes\Delta^+_t)\right]^{-1}\cdot q_t$$

where X_t is a diagonal matrix:

$$X_t := diag\left([(T_t^v \otimes \Delta_t) \cdot mk_t^v] \oslash [(T_t^v \otimes S_t) \cdot mk_t^v] \right)$$

The notation $\oslash$ denotes element-wise division. Once the upstream markups are expressed as a function of the downstream markups, the estimation process follows the steps as outlined in Section 4.2.

B.5 Additional Details of Counterfactual Analyses

Supply Network Formation Model We conduct counterfactual simulations to examine two types of policies: (1) consumer subsidies and (2) domestic content requirements. As the domestic content requirement policy is likely to affect the supply network and shift battery sales from foreign to domestic suppliers, we need to develop a network formation model that predicts supply links with and without the domestic content requirement.

The unit of analysis for the network formation model is an EV model-battery supplier-country-year combination, with a total of 23,495 observations. The model includes a rich set of controls for the lagged network structure, a dummy for China's whitelist policy, the subsidy rate offered by country c in time t for a given EV model, the experience of the battery supplier, a home bias dummy, dummies for supplier-OEM pairs that are vertically integrated, and initial attributes of EV suppliers. Table A8 reports estimation results for this network formation model. The generosity of subsidies provided is a key variable of interest that generates exogenous variation in the predicted network formation. It equals the subsidy per EV sold, provided the supply relationship meets the eligibility requirement for EV consumer subsidies (i.e., the domestic content requirement). During China's whitelist policy in 2016-2019, Chinese EV models that sourced batteries from suppliers not on the list (e.g., non-Chinese battery suppliers) were ineligible for subsidies. The coefficient estimate is large in magnitude and statistically significant. The other variables have the expected signs. For example, battery suppliers with more accumulated experience are more likely to be selected, and EV makers are more likely to select battery suppliers with whom they have past relationships.

Algorithm for Counterfactual Analyses For each counterfactual analysis, we conduct 100 simulations and report the average outcomes. The simulation process involves the following steps: in the initial year of 2013, given EV and battery production costs, battery prices are determined by the upstream bargaining FOCs in Equation (5), and EV prices are set based on the downstream price competition FOCs in Equation (3). Equilibrium EV sales are calculated based on these prices. We update the cumulative production experience of battery producers using these equilibrium EV sales, and increased cumulative production experience results in lower battery production costs in 2014 (LBD). If new EV models enter the market in 2014, we draw a battery supplier based on the link formation model and the predicted probabilities of supplier selection. Using the updated production costs and battery supply chain, equilibrium prices and sales are recalculated. This process is repeated annually through 2020. Because the link formation process involves randomness, we simulate the equilibrium path from 2013 to 2020 a total of 100 times. The welfare tables and figures are based on the average outcome across these 100 simulations.

When simulating the effect of the Whitelist policy, EV models are allowed to choose a battery supplier in 2016, the policy's beginning year. Hence, in simulations where the Whitelist policy is in place, EV models have two opportunities to choose a battery supplier: once upon entering the market and again in 2016 (for those that entered before 2016). One of the counterfactual analyses (Table 8) examines the welfare implications of postponing the whitelist to 2021-2025 after the final sample year. To simulate firm profit and consumer surplus from 2021 to 2025, we assume that the market structure and global subsidies during this period remain the same as the final sample year 2020. Specifically, EV firms, EV models, and battery suppliers are assumed to be the same as in 2020. Note that China's subsidy rates declined steadily from 2013 to 2020, while subsidies in other regions fluctuated. As battery suppliers accumulate production experience, the learning-induced reduction in production costs persists throughout the forward simulation. All EV models choose a battery supplier in the first year of the forward simulation (2021) when the Whitelist becomes effective. The subsequent steps of the simulation follow the procedures described above.

B.6 EV's Environmental Benefits

Here we describe the environmental benefits of replacing a gasoline vehicle with an EV. Replacing a gasoline vehicle with an electric vehicle (EV) delivers significant environmental benefits through reductions in carbon emissions and air pollution. These benefits are monetized as carbon benefits (via the social cost of carbon) and health benefits (via reduced pollutant exposure). We explain how these two items are calculated below.

Carbon Benefit The carbon benefit reflects the avoided economic damages from reduced CO_2 emissions. A typical gasoline vehicle emits 4.6 tons of CO_2 annually, assuming an average annual vehicle miles traveled (VMT) of 11,500 miles in the U.S. (FHWA, 2022). The average annual VMT for China, Europe, and South Korea / Japan is 10,000 miles (CMT, 2022), 9,500 miles/year (Eurostat, 2020), and 10,200 miles/year (KTI, 2023), respectively. Emission reductions when a gas vehicle is replaced with an EV vary by the carbon intensity of electricity grids (IEA, 2023). The emission reduction factor is estimated to be 50% for China (due to its coal-heavy grid), 70% for the U.S. (due to its relatively clean grid with renewables and natural gas), 60% for Europe (moderately clean grid with significant renewables), and 52.5% for South Korea and Japan (mixed reliance on fossil fuels and nuclear). Finally, the latest estimate of the social cost of carbon is \$185 per ton of CO_2, based on comprehensive global evidence (et al, 2022). The lifetime CO_2 savings for each region is calculated as: 4.6 tons of CO_2 per year $\times \frac{\text{Region VMT}}{\text{US VMT}} \times$ Emission Reduction Factor $\times$ Vehicle lifetime of 12 years.

Health Benefit The health benefit is derived from reductions in air pollutants such as $PM_{2.5}$, NO_x, and VOCs, which are linked to respiratory and cardiovascular diseases, premature deaths, and other health issues. The health costs of different pollutants are: \$100,000 to \$200,000 per ton of $PM_{2.5}$ (HEI, 2022), \$10,000 to \$40,000 per ton of NO_x (EPA, 2021), and \$5,000 to \$15,000 per ton of VOCs (Holland et al., 2016). The total lifetime health benefit is calculated similarly to carbon savings.

Environmental Benefits The lifetime environmental benefits of replacing a gasoline vehicle with an EV are summarized in Table A2. In summary, the lifetime environmental benefit of replacing a gasoline vehicle with an EV ranges from \$16,465 (South Korea & Japan) to \$19,506 (China). These estimates are based on CO_2 savings valued using the social cost of carbon and health benefits from reduced air pollutants. Regional variations reflect differences in annual vehicle miles traveled, grid carbon intensity, and air quality conditions.

Table A2: Lifetime Environmental Benefits of Replacing a Gasoline Vehicle with an EV by Region

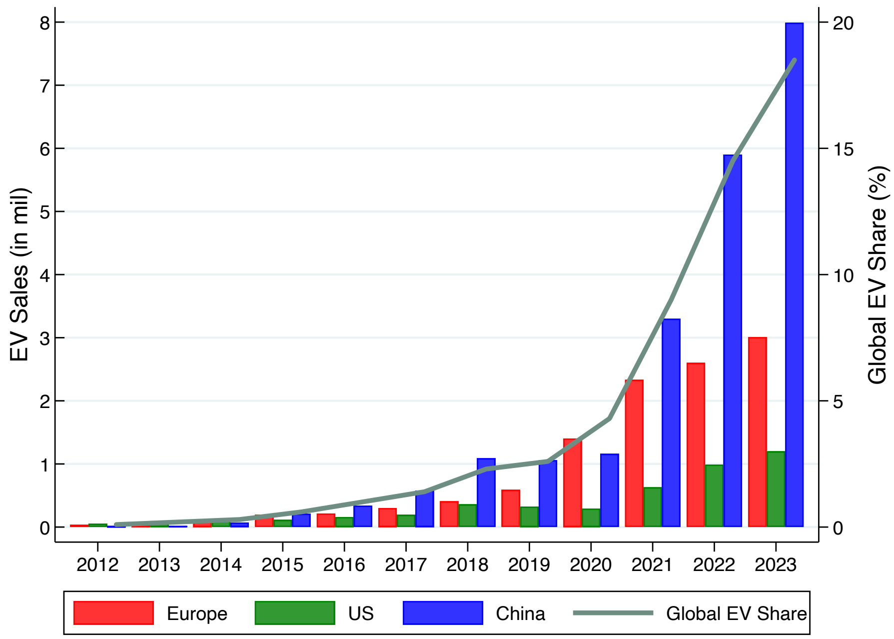
Region	CO_2 Savings (ton/year)	Carbon Benefit ($)	Health Benefit ($)	Total Benefit ($)
China	2.3	5,106	14,400	19,506
United States	3.22	7,141	12,000	19,141
Europe	2.76	6,124	10,800	16,924
South Korea & Japan	2.42	5,365	11,100	16,465

Notes: The calculation of environmental benefits assumes 12 years of vehicle lifetime.

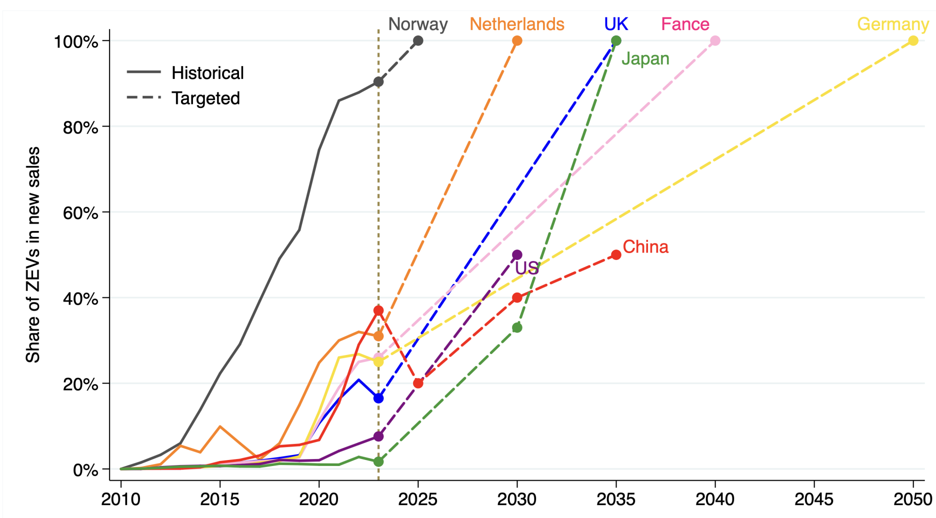
C Appendix Figures

Figure A1: Global EV Diffusion

(a) EV Sales by Region



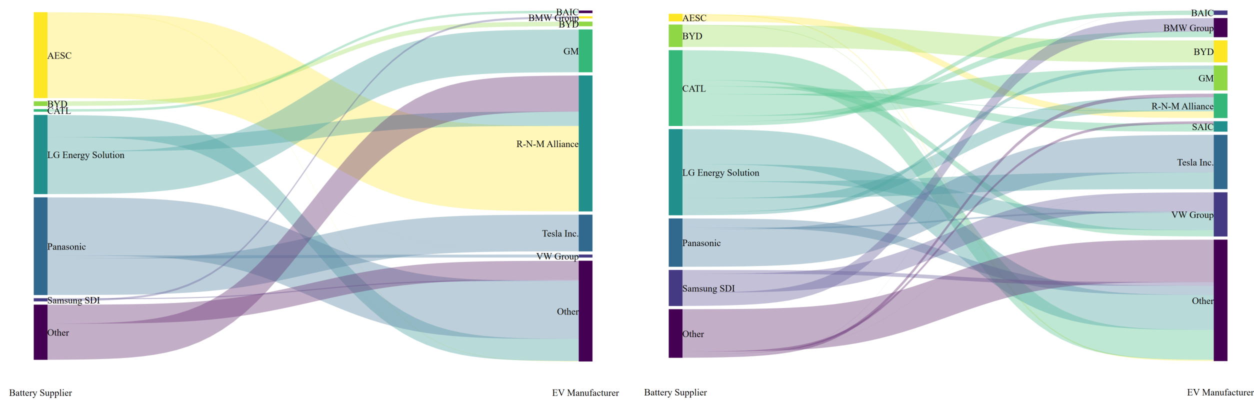
(b) ZEV Targets and Market Shares



Notes: in Panel (a), the bars (left y-axis) report the annual sales of new EVs (BEVs and PHEVs) by region from 2012 to 2023. China, Europe, and the U.S. accounted for over 95% of global EV sales during the data period. The grey line (right y-axis) depicts the global share of EVs in new vehicle sales. Panel (b) depicts the zero-emission vehicle (ZEV) targets and market shares over time by country. ZEVs include EVs and fuel cell vehicles but are predominantly EVs. Source: International Energy Agency and the International Council on Clean Transportation.

Figure A2: Battery supplier network

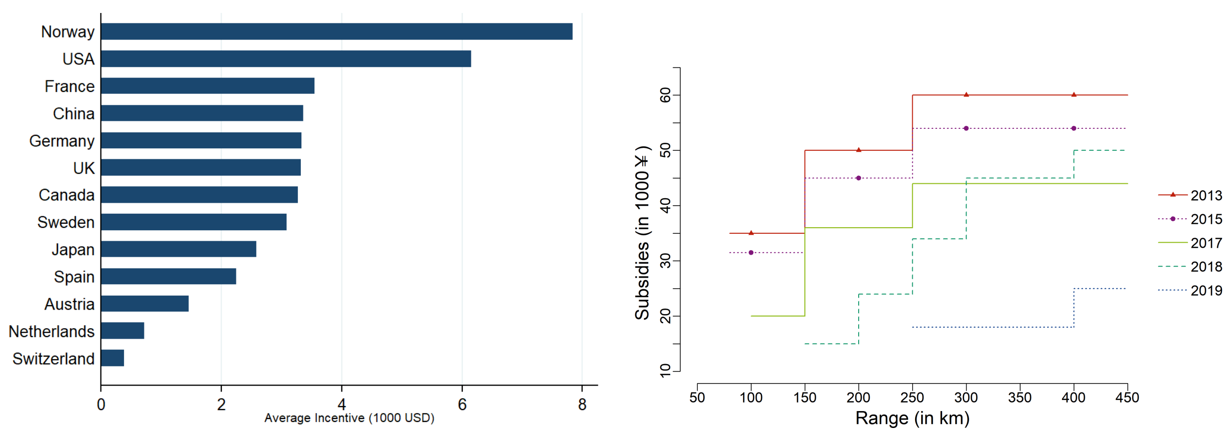
(a) 2013 network **(b)** 2020 network



Notes: The figure depicts the vertical relationship between battery suppliers (on the left) and EV producers (on the right). The top 6 battery suppliers and top 8 EV producers are shown separately, illustrating a two-sided duopoly market structure. The thickness of the lines represents the battery sales volume in units.

Figure A3: EV Subsidies

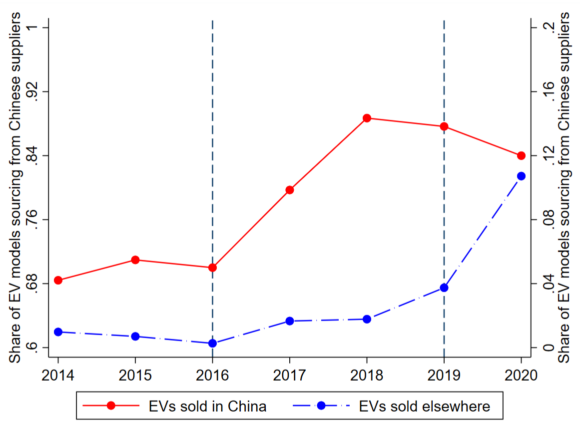
(a) Average subsidies by country **(b)** Subsidy design in China



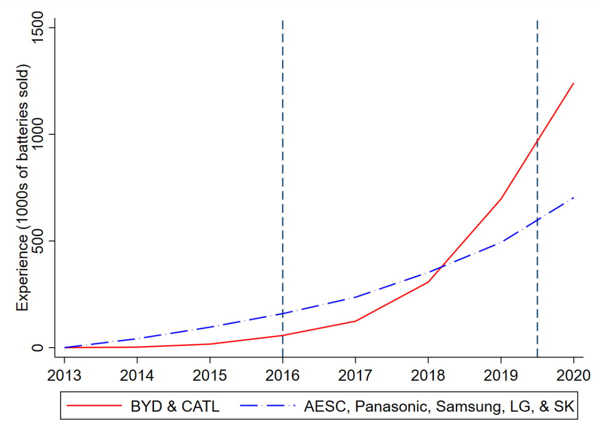
Notes: Panel (a) shows the average federal subsidy per eligible EV by country during 2013-2020 while Panel (b) shows the subsidy schedule for BEVs in China where the amount of subsidy is based on driving range (Barwick, Kwon, and Li, 2024).

Figure A4: China's whitelist policy

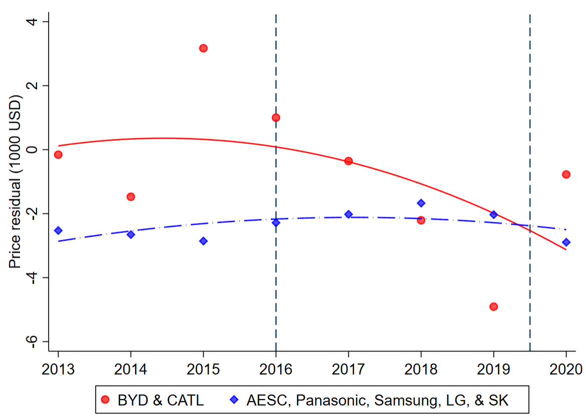
(a) Domestic sourcing of batteries



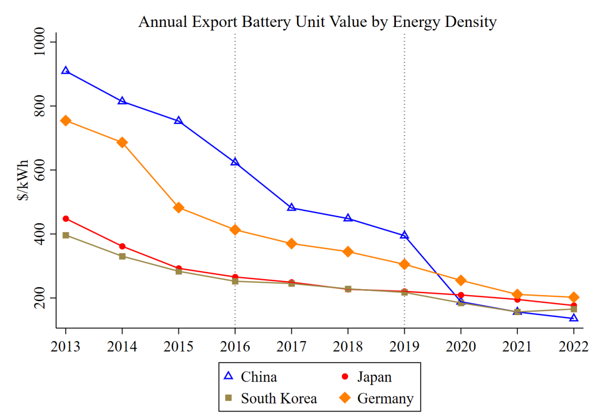
(b) Battery sales



(c) Residualized Vehicle price



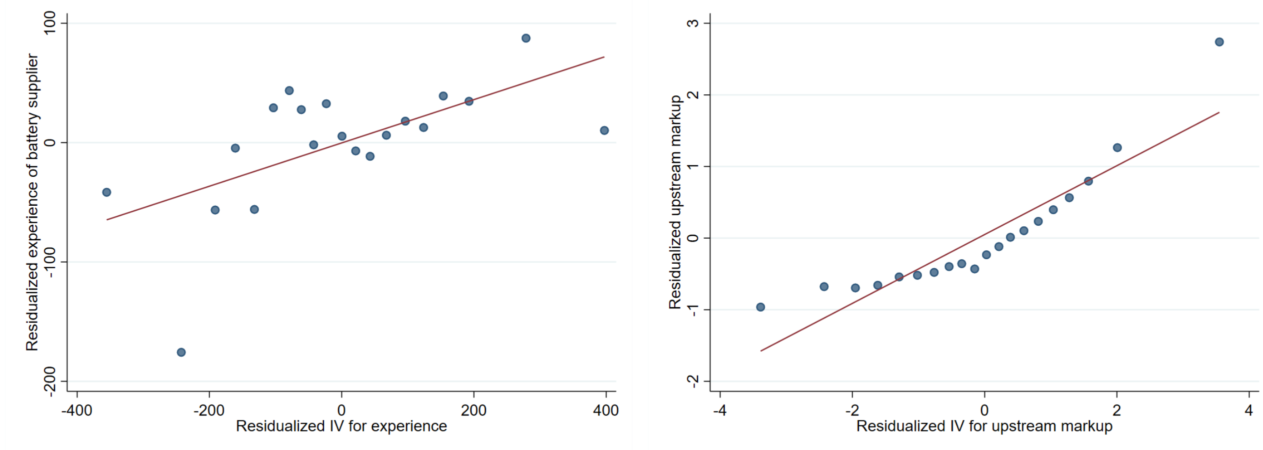
(d) Battery Export Price



Notes: Panel (a) shows the share of EV models sourcing from Chinese battery suppliers separately for EV models sold in China, and those sold elsewhere. Panel (b) shows the growth of (average) experience of battery suppliers overtime separately for the top-two Chinese suppliers, and the top-four non-Chinese suppliers. Panel (c) depicts the average EV price by year for the two groups. The two dotted vertical lines defines China's whitelist policy. Panel (d) shows the free-on-board battery price ($/kWh) by country-of-origin from UN Comtrade. The price unit in Comtrade was $/liter and we transform it to $/kWh based on average energy density for each year during the period.

Figure A5: Instruments for Experience and Battery Markups

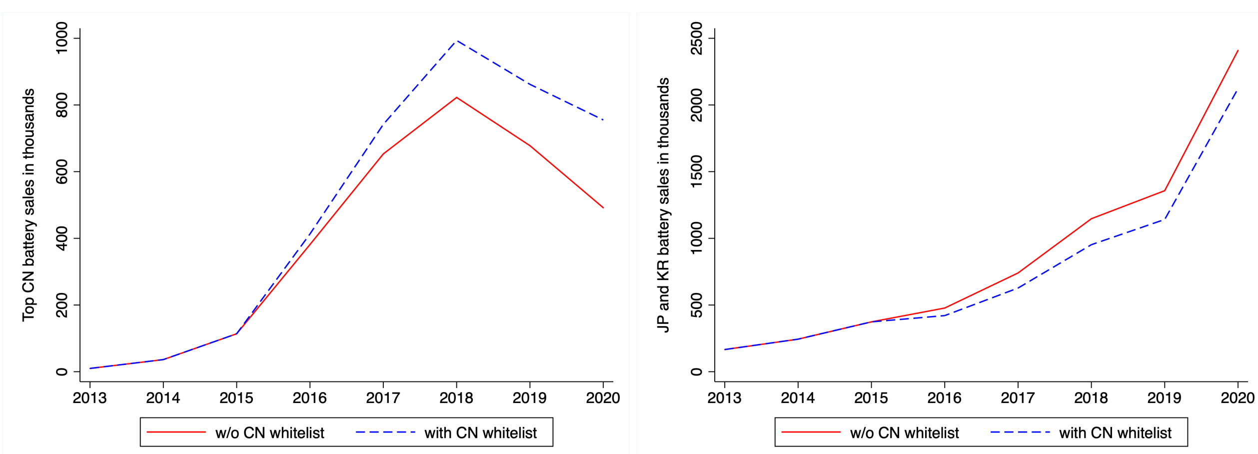
(a) Experience **(b)** Battery markup



Notes: Binned scatter plots to illustrate the strength of the IVs for the experience and markups of battery suppliers. Residuals are obtained from partialing out vehicle attributes, as well as country fixed effects, brand fixed effects, and year fixed effects.

Figure A6: Impact of China's Whitelist policy on battery production

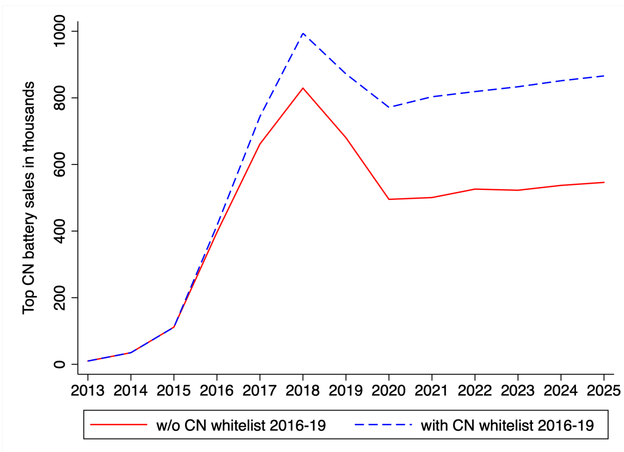
(a) Chinese Battery **(b)** JP & KR Battery



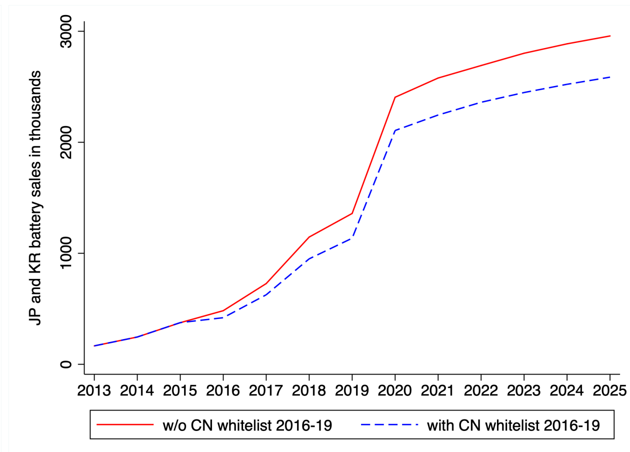
Notes: Panel (a) shows EV battery production by Chinese suppliers with and without China's Whitelist policy. Panel (b) depicts battery production by non-Chinese suppliers under the two scenarios.

Figure A7: Impact of late and early China's Whitelist policy on battery production

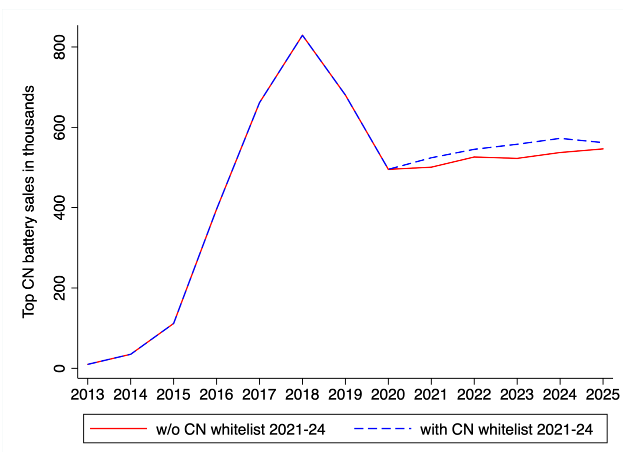
(a) Early Whitelist, Chinese Battery



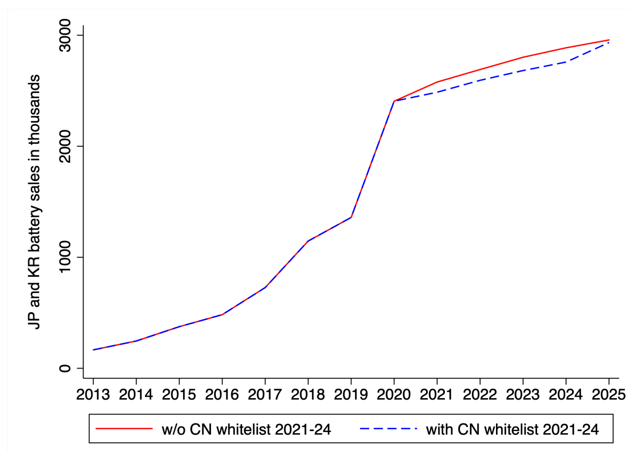
(b) Eearly Whitelist, JP & KR Battery



(c) Late Whitelist, Chinese Battery



(d) Late Whitelist, JP & KR Battery



Notes: Panel (a) illustrates EV battery production by Chinese suppliers under scenarios with and without China's Whitelist policy. Panel (b) presents battery production by non-Chinese suppliers under the same scenarios. Panels (c) and (d) depict the impact on forward-simulated battery production if the Whitelist policy were implemented between 2021 and 2024.

D Appendix Tables

Table A3: LBD: Spillovers Across Firms

	(1) No spillovers	(2) Spillovers
Battery Cost Parameters		
Learning para. γ_E	-0.113	-0.173
	(0.052)	(0.093)
γ_0(1000$/kWh)	0.858	1.029
	(0.164)	(0.371)
*BK**Time Trend	-0.032	-0.022
	(0.006)	(0.006)
*BK**log(Plant Capacity)	-0.078	-0.062
	(0.035)	(0.018)
Within-country spillover, θ		0.044
		(0.131)
*BK**battery chemistry dummies	✓	✓
*BK**lithium prices	✓	✓
Vehicle Cost Parameters		
EV Experience	-0.997	-1.032
	(0.421)	(0.412)
PHEV	2.172	2.064
	(1.104)	(1.102)
Horsepower	0.244	0.243
	(0.007)	(0.007)
Volume	0.807	0.877
	(0.232)	(0.23)
Bargaining Parameter		
Bargaining weight, λ^b	0.275	0.274
	(0.132)	(0.133)
Fixed Effects		
Country	✓	✓
EV brand	✓	✓
Battery supplier	✓	✓
Year	✓	✓

Notes: This table reports the parameter estimates for Equation (9). Column(1) is identical to Column (1) from Table 3. In Column (2), we include the experience of rival firms in the same country scaled by a parameter θ that we estimate; we instrument for rival experience using predicted rival experience constructed based on Equation (10). All specifications use GMM estimation with battery supplier experience, battery markup (the variable corresponding to bargaining weight), and EV producer experience being instrumented. The marginal cost of battery pack is specified as: $BK_{bjct}\left(\gamma_0 E_{bt}{}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta * t\right)$. See Table 3 for variable definitions.

Table A4: LBD Estimation Results With Forward-Looking Battery Suppliers

Bargaining Parameter	$\lambda^b = 0$	$\lambda^b = 0.25$	$\lambda^b = 0.5$	$\lambda^b = 0.75$	$\lambda^b = 1$
	(1)	(2)	(3)	(4)	(5)
Battery Cost Parameters					
Learning para. γ_E	-0.099	-0.105	-0.110	-0.115	-0.120
	(0.051)	(0.053)	(0.055)	(0.058)	(0.06)
γ_0(1000$/kWh)	0.873	0.856	0.839	0.820	0.801
	(0.168)	(0.168)	(0.168)	(0.168)	(0.168)
*BK**Time Trend	-0.035	-0.033	-0.032	-0.031	-0.030
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
*BK**log(Plant Capacity)	-0.081	-0.079	-0.077	-0.075	-0.073
	(0.037)	(0.036)	(0.035)	(0.034)	(0.034)
*BK**battery chemistry dummies	✓	✓	✓	✓	✓
*BK**lithium prices	✓	✓	✓	✓	✓
Vehicle Cost Parameters					
EV Experience	-0.973	-0.981	-0.992	-1.005	-1.021
	(0.43)	(0.424)	(0.419)	(0.413)	(0.408)
PHEV	2.778	2.314	1.864	1.425	0.999
	(1.132)	(1.113)	(1.094)	(1.076)	(1.059)
Horsepower	0.251	0.247	0.242	0.237	0.232
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Volume	0.912	0.845	0.777	0.708	0.636
	(0.24)	(0.235)	(0.231)	(0.226)	(0.222)
Fixed Effects					
Country	✓	✓	✓	✓	✓
EV brand	✓	✓	✓	✓	✓
Battery supplier	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓

Notes: This table reports supply-side parameter estimates when battery firms are forward-looking (with a discount factor of 0.95) (Appendix B.4). We calibrate different values of the bargaining parameter λ and estimate the remaining parameters by GMM with battery supplier experience and EV producer experience being instrumented. The marginal cost of battery pack is specified as: $BK_{bjct}\left(\gamma_0 E_{bt}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta t\right)$. BK is battery capacity; γ_E is the learning parameter; and γ_0 capture the baseline cost. The regression has three sets of controls. The first set includes the variables specified in the battery marginal cost: battery capacity interacting with battery chemistry (NMC, NCA, LFP), battery capacity interacting with time trend to capture industry-wise technological progress or cost shocks, battery capacity interacted with lithium prices (with the coefficient allowed to be different for Chinese and non-Chinese EV models), and battery capacity interacted with production capacity of the firm to capture economies of scale. The second set includes vehicle attributes such as vehicle fuel type (BEV or PHEV), vehicle size, horsepower, and EV producer experience (i.e., cumulative EV production by each EV producer in logarithm) to capture LBD in automobile manufacturing. The third set of controls include country fixed effects, EV brand fixed effects, battery supplier fixed effects, and year fixed effects.

Table A5: LBD Estimation Results With Sequential Bargaining

Bargaining Parameter	$\lambda^b = 0$	$\lambda^b = 0.25$	$\lambda^b = 0.5$	$\lambda^b = 0.75$	$\lambda^b = 1$
	(1)	(2)	(3)	(4)	(5)
Battery Cost Parameters					
Learning para. γ_E	-0.101	-0.106	-0.111	-0.117	-0.123
	(0.05)	(0.051)	(0.052)	(0.052)	(0.053)
γ_0(1000$/kWh)	0.873	0.863	0.851	0.839	0.826
	(0.163)	(0.167)	(0.165)	(0.162)	(0.159)
BK*Time Trend	-0.035	-0.034	-0.032	-0.031	-0.030
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
BK*log(Plant Capacity)	-0.081	-0.079	-0.076	-0.073	-0.070
	(0.037)	(0.036)	(0.035)	(0.034)	(0.033)
BK*battery chemistry dummies	✓	✓	✓	✓	✓
BK*lithium prices	✓	✓	✓	✓	✓
Vehicle Cost Parameters					
EV Experience	-0.979	-0.985	-0.989	-0.991	-0.992
	(0.431)	(0.425)	(0.419)	(0.413)	(0.407)
PHEV	2.781	2.350	1.917	1.491	1.075
	(1.133)	(1.114)	(1.093)	(1.072)	(1.05)
Horsepower	0.252	0.247	0.241	0.236	0.230
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Volume	0.906	0.834	0.757	0.676	0.592
	(0.24)	(0.236)	(0.231)	(0.226)	(0.221)
Fixed Effects					
Country	✓	✓	✓	✓	✓
EV brand	✓	✓	✓	✓	✓
Battery supplier	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓

Notes: This table reports supply-side parameter estimates under sequential bargaining (Appendix B.3). We calibrate different values of the bargaining parameter λ and estimate the remaining parameters by GMM with battery supplier experience and EV producer experience being instrumented. The marginal cost of battery pack is specified as: $BK_{bjct}\left(\gamma_0 E_{bt}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta t\right)$. BK is battery capacity; γ_E is the learning parameter; and γ_0 capture the baseline cost. The regression has three sets of controls. The first set includes the variables specified in the battery marginal cost: battery capacity interacting with battery chemistry (NMC, NCA, LFP), battery capacity interacting with time trend to capture industry-wise technological progress or cost shocks, battery capacity interacted with lithium prices (with the coefficient allowed to be different for Chinese and non-Chinese EV models), and battery capacity interacted with production capacity of the firm to capture economies of scale. The second set includes vehicle attributes such as vehicle fuel type (BEV or PHEV), vehicle size, horsepower, and EV producer experience (i.e., cumulative EV production by each EV producer in logarithm) to capture LBD in automobile manufacturing. The third set of controls include country fixed effects, EV brand fixed effects, battery supplier fixed effects, and year fixed effects.

Table A6: LBD Estimates After Controlling for Firm-Level Patent Stock

	(1)	(2)
Battery Cost Parameters		
Learning para. γ_E	-0.113	-0.122
	(0.052)	(0.094)
γ_0(1000$/kWh)	0.858	0.587
	(0.164)	(0.155)
*BK**Time Trend	-0.032	0.022
	(0.006)	(0.008)
*BK**log(Plant Capacity)	-0.078	-0.111
	(0.035)	(0.04)
*BK**log(Cumulative Patents)		-0.095
		(0.01)
*BK**battery chemistry dummies	✓	✓
*BK**lithium prices	✓	✓
Vehicle Cost Parameters		
EV Experience	-0.997	-1.280
	(0.421)	(0.401)
PHEV	2.172	-1.331
	(1.104)	(1.055)
Horsepower	0.244	0.225
	(0.007)	(0.007)
Volume	0.807	0.848
	(0.232)	(0.216)
Bargaining Parameter		
Bargaining weight, λ^b	0.275	0.487
	(0.132)	(0.049)
Fixed Effects		
Country	✓	✓
EV brand	✓	✓
Battery supplier	✓	✓
Year	✓	✓

Notes: This table reports the parameter estimates for Equation (9). Column(1) is identical to Column (1) from Table 3. All specifications use GMM estimation with battery supplier experience, battery markup (the variable corresponding to bargaining weight), and EV producer experience being instrumented. In Column (2), we allow the per-kWh battery cost to depend on the logarithm of cumulative patents applied for by the battery firm; we instrument for this using the cumulative sum of subsidies received by the battery firm, as well as the interaction between cumulative subsidies and battery capacity.

Table A7: Impact of Increase in CATL or Panasonic Experience in 2013

	CATL experience			Panasonic experience		
	Chian	RoW	Global	Japan	RoW	Global
Δ Battery profit	1.00	0.00	1.00	1.00	-0.02	0.98
Δ EV profit	2.60	-0.01	2.59	2.56	-0.08	2.48
Δ Consumer surplus	6.06	0.00	6.06	2.13	2.95	5.08
Δ Expenditure	2.25	0.00	2.25	1.77	-0.04	1.73
Δ Welfare	7.41	-0.01	7.39	3.93	2.88	6.81

Notes:This table shows welfare changes resulting from an increase in the experience of CATL or Panasonic starting in 2013 (and continuing thereafter as experience accumulates). The impact on battery profits in the respective countries (China for CATL and Japan for Panasonic) is normalized to one. All other values represent relative changes compared to the battery profit in the corresponding country.

Table A8: Network Formation Model for Counter-factual Simulations

	Dep. var.: Link formed
Eligible Subsidy	0.471^{***}
	(0.111)
log(Supplier Experience)	0.666^{***}
	(0.159)
Supplier-OEM lagged link	2.884^{***}
	(0.199)
Supplier-OEM lagged link, same country	0.501^{***}
	(0.127)
Dummies for vertically integrated firms	Yes
Initial link or home bias	Yes
Fixed effects for top 6 suppliers	Yes
Supplier characteristics	Yes
Log-likelihood	-1265.59
Observations	23495

Note: The unit of analysis is a model-country-year-battery supplier combination. The dependent variable is one if the EV producer (i.e., OEM) for that EV model sources battery from a given battery supplier, and zero otherwise. The results are from a conditional logit regression. Standard errors are clustered at the country - OEM level.
For the counter-factual simulations, we assume the choice set for each OEM includes every top 15 battery supplier that had already entered the global market. We also allow EV makers to choose a new battery supplier for each EV model in the year 2016 (even for existing models), since some of our counter-factual simulations involve unexpected policy shocks in the year 2016.
Eligible subsidy equals the subsidy per EV sold, provided the supply relationship meets the eligibility requirement for EV consumer subsidies: during China's whitelist period 2016-2019, EVs in China are ineligible for subsidies if their battery supplier is not on the White List. We control for the lagged network structure by including a dummy variable that equals one if the supplier-OEM pair had a supply relationship in the previous period, and another dummy variable for whether they had a previous supply relationship in the same country.
Other controls include a control for home bias, which is a dummy variable being one if the supplier-OEM pair has the same country of origin. We include dummies for all supplier-OEM pairs that are vertically integrated: namely, BYD - BYD and AESC - RNM alliance. We also include the age of each supplier, as well as the following *initial* characteristics of the supplier: the average battery capacity, the most common chemistry of batteries initially supplied, and the average number of models for which the firm was a battery supplier. Finally, fixed effects for each of the top 6 battery suppliers are included.

Table A9: Impact of Consumer Subsidies without Learning

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of US Subsidies					
Δ Welfare	0.19	0.90	1.78	1.47	4.33
Δ Consumer surplus	0.00	0.00	0.00	3.87	3.87
Δ Battery profit	0.03	-	1.21	-	1.24
Δ EV profit	0.16	0.90	0.57	1.58	3.22
Δ Gov't Expenditure	0.00	0.00	0.00	3.99	3.99
Panel (b): Impacts of European Subsidies					
Δ Welfare	0.30	2.06	1.48	0.21	4.05
Δ Consumer surplus	0.00	5.25	0.00	0.00	5.25
Δ Battery profit	0.06	0.01	1.13	0.00	1.19
Δ EV profit	0.25	2.22	0.36	0.21	3.04
Δ Gov't expenditure	0.00	5.43	0.00	0.00	5.43
Panel (c): Impacts of Chinese Subsidies					
Δ Welfare	6.00	0.21	0.27	0.22	6.71
Δ Consumer surplus	6.06	0.00	0.00	0.00	6.06
Δ Battery profit	1.66	0.00	0.19	0.00	1.85
Δ EV profit	4.33	0.21	0.08	0.22	4.85
Δ Gov't expenditure	6.04	0.00	0.00	0.00	6.04

Notes: This table shows the impacts (aggregated during 2013-2020) of consumer subsidies on social welfare separately for China, Europe, Japan & South Korea, and US & Canada in the absence of LBD. Panel (a) estimated impacts of US subsidies capture the difference between two scenarios with and without US subsidies but holding consumer subsidies in China and Europe fixed. Panels (b) and (c) are obtained similarly.