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 more than 90% over 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 EV 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 and strategic pricing behaviors of EV producers and battery suppliers. The model allows us to recover battery costs for each EV model and quantify the extent of LBD in battery production. The learning rate is estimated to be 7.5% during our sample period after controlling for industry technological progress, economies of scale, input costs, and EV assembly experience. LBD magnifies the effectiveness of consumer EV subsidies and drives cross-country spillovers from these subsidies. Upstream battery suppliers capture only a minor share of LBD's economic benefits, and consumer EV subsidies correct for the under-provision of learning and improve social welfare. China's local content requirement helps domestic suppliers gain a competitive advantage at the cost of consumers and foreign suppliers but would have harmed domestic welfare if delayed by five years.

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

JEL Classification: F13, L52, L62, Q48

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1 Introduction

The electrification of passenger transportation through the widespread adoption of electric vehicles (EVs) and the simultaneous transition to a cleaner electricity grid is a crucial strategy to mitigate climate change. To achieve these goals, 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, 2023). 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 share 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. LBD associated with the enhanced production experience reduces 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 (domes-

[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.

tic) producers. Similarly, to qualify for consumer subsidies, the U.S. IRA mandates EV models 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 to 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 and generate repercussions extending well beyond country borders. Consequently, a global analysis is essential to accurately evaluate policy implications.

This paper takes advantage of a comprehensive database on the global EV and battery industries that have three key components. The first dataset 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 dataset contains financial incentives for EV purchases in each country over time. In addition, we have also collected socioeconomic variables and household surveys on vehicle ownership across countries.

Estimating the extent of LBD entails addressing two key 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 develop a framework of price-setting behaviors of battery suppliers and EV producers to infer upstream and downstream markups. This allows us to recover battery costs based on observed vehicle prices and estimated demand elasticity. We investigate and estimate a variety of supply-side models, including Nash-Bargaining (simultaneous vs. sequential) and linear pricing, with and without incorporating battery suppliers' forward-looking behavior. We also validate our battery cost estimates using industry reports and trade data.

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 cost shocks are more likely to sell a large quantity and accumulate more experience. We construct an IV for battery supplier experience by leveraging demand shifters. Specifically, we exploit 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 accumulate experience faster 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*. Our IV also exploits the shock of China's whitelist policy, which generated exogenous variation in production experience across battery suppliers. In addition, we control for a range of other confounding factors, including industry-wide technological progress.

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, input costs, and economies of scale. This implies that doubling battery production experience would reduce unit production costs by 7.5%. Although this learning rate is on the lower end of estimates reported for EV batteries and other technologies (e.g., Argote and Epple, 1990; Irwin and Klenow, 1994; Ziegler and Trancik, 2021; Covert and Sweeney, 2022), LBD alone accounted for a sizable 35.5% of the overall decline in battery costs from 2013 to 2020. Industry-wide technological progress was responsible for an additional 39.9% of the cost reduction, with the remainder explained by LBD in EV assembly, changes in battery chemistry, input cost fluctuations, and economies of scale. These results are robust across all supply-side models we estimated and remain robust after controlling for firm innovation.

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 29.9% 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 170% relative to the baseline with neither subsidies nor LBD. This combined effect is 60% greater than the sum of the effects from subsidies and LBD individually, highlighting their complementarity. 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 nature of 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, net of subsidy expenditure. The U.S. (and Canada) captured 49% of these welfare gains, as the interaction between subsidies and LBD significantly reduced input costs (batteries) for domestic EV producers and lowered vehicle prices for domestic consumers. U.S. subsidies also benefited battery suppliers in Japan and South Korea, which captured 28% of the global welfare gains. Europe also benefited significantly from U.S. subsidies; in contrast, China captured only 3% of the global gains. This modest share reflects China's limited trade in EVs and EV batteries with foreign countries during our sample period.

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 are 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, upstream LBD creates significant externalities through the supply chain, with upstream firms capturing only a small fraction of the associated economic benefits due to the oligopolistic nature of the supply chain. Our simulations indicate that CATL, the leading battery supplier in China, captures 22.0% of the total surplus generated by its increased LBD, while Panasonic, the largest battery supplier in Japan, captures 21.7%. 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 losses. 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 the whitelist policy facilitated 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 losses would have outweighed the gains to battery suppliers. The negative impact on other countries would have been 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 local content requirements considered in other countries.

Our study is related to several strands of literature. First, it adds to the growing economics literature on 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. Our methodology could be applied to estimate LBD in the production of intermediate inputs in other contexts.

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; Wang and Xing, 2024). Our work is also related to Goldberg et al. (2024), which examines the role of industrial policies in the presence of LBD in the global semiconductor industry. We add to this literature by quantifying the size and scope of LBD in the upstream sector and evaluating its interactions with prominent industrial policies in the downstream sector. 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.

Lastly, this paper is related to studies that analyze vertical relationships between upstream (input) suppliers and downstream producers (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. We explore and estimate a variety of vertical models and verify the robustness of our LBD estimate across different modeling assumptions. We also extend the existing vertical literature by considering firm forward-looking behavior in a dynamic bargaining model.

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).[2]

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.[3] 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 features suggest that production know-how by managers and engineers gained through experience

[2]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%.

[3]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/#.

could help improve production efficiency and reduce scrap rates, both leading to lower costs.[4]

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 dataset, sourced from EV Volumes and IHS Markit, contains annual EV sales and vehicle prices 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.[5] 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 high 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 dataset 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 past production) for each battery supplier in each year based on the vertical supply relationships 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).

[4] 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).

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

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 bilateral 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.[6] 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). There are a variety of financial incentives, 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.[7] 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 subsidy amount 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.[8] 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 EV models eligible for more generous subsidies would sell more units and gain experience faster.

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.

Auxiliary Data There are several pieces of auxiliary data. First, we collect socioeconomic variables and annual gasoline prices by country from the World Bank and annual income statistics

[6]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.

[7]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.

[8]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.

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). 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, as well as mineral prices from the annual Mineral Commodity Summaries published by the U.S. Geological Survey. Finally, to capture firm-level innovation, we compile information on the number of patents filed 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. PHEV models had a higher average price of \$72,000 and a lower average subsidy of \$1,900. The average 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 average 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 an average battery capacity of 11.5 kWh, showing only modest improvements over the same period.

The estimation 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 – of which battery costs constitute a significant share – and the production experience of battery suppliers in Figure 1. We first use vehicle prices to construct a proxy for battery costs by partialling out vehicle attributes such as horsepower, size, and the PHEV dummy, along with a rich set of country, brand, and year fixed effects. Panel (a) illustrates changes in these price residuals divided by battery capacity over time. The blue dots represent the sales-weighted average annual price residuals per kWh, a proxy for unit battery costs. These residuals per kWh exhibit a substantial decline from 2014 to 2020 (after controlling for year fixed effects in vehicle prices), closely matching the trend in battery costs reported by Bloomberg NEF (2023), shown as red diamonds.[9]

Panel (b) of Figure 1 presents a binned scatter plot of price residuals, where each observation

[9] The Bloomberg costs are based on 303 survey data points on battery prices for passenger cars, buses, commercial vehicles, and stationary storage. While the overall trend from Bloomberg NEF (2023) is informative, our analysis focuses on lithium-ion batteries for passenger EVs.

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 to identify 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. Panel (a) of Figure 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 data period of 2013-2020, 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). Panel (b) shows that, 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. 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 of models that sourced 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 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 behind cost reductions, other confounding factors, such as technological advancements, changes in battery chemistry and input costs, 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 and price-setting behaviors of EV producers and battery suppliers. We use the following notation 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, considering whether to buy vehicle model j in country c at time (year) t; 4) vehicle retail price p_{jct} before subsidies, unit sales q_{jct}, consumer subsidy ϕ_{jct}, and battery price τ_{jct}. Bold terms denote vectors (or matrices).

To set the stage for the structural model, we write the retail price of an EV as:

$$p_{jct} = \underbrace{mc^b_{jct}}_{\text{Battery cost}} + \underbrace{mc^v_{jct}}_{\text{Non-battery EV cost}} + \underbrace{mk^b_{jct}}_{\text{Battery markup}} + \underbrace{mk^v_{jct}}_{\text{EV markup}}, \tag{1}$$

where mc^b_{jct} is the cost of battery and mc^v_{jct} denotes the non-battery portion of the EV's production cost. Battery supplier b's markup is denoted by mk^b_{jct} and EV producer v's markup is mk^v_{jct}. The goal of the empirical model is to first quantify the upstream and downstream markups by characterizing the price-setting behaviors of battery suppliers and EV producers. This then allows us to recover the cost of producing batteries and EVs and estimate LBD based on cost estimates. We outline the key model elements below and discuss the estimation strategy in Section 4.

3.1 EV Demand and Downstream Markups

Consumer Demand EV demand is characterized by a random coefficients 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:

$$U_{ijct} = \alpha_i(p_{jct} - \phi_{jct}) + \mathbf{X}_{jct}\beta_{\mathbf{i}} + \xi_{jct} + \varepsilon_{ijct}. \tag{2}$$

Consumers pay the post-subsidy price, which is the retail price p_{jct} net of the consumer subsidy ϕ_{jct} offered by the central government. The vector $\mathbf{X}_{jct}$ includes observed vehicle attributes, such as vehicle size, driving range, horsepower, and 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. ξ_{jct} represents unobserved product characteristics and demand shocks, which renders the price variable endogenous. ε_{ijct} denotes i.i.d. preference shocks with the Type-I Extreme Value distribution.

Downstream Markups The downstream markup mk^v_{jct} is determined through Bertrand-Nash competition and is recovered after estimating demand following the standard practice in the literature. Specifically, EV producer v (or Original Equipment Manufacturer, OEM) chooses EV prices to maximize variable profits from selling different vehicles in a country-year (suppressing country and time indices):[11]

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

where τ_j is the battery price for vehicle j (paid by firm v to its supplier), mc^v_j is firm v's marginal cost of producing non-battery components, and $p_j - \tau_j - mc^v_j$ is the per-unit markup. The vector $\mathbf{p}$ denotes prices for all EVs in the market. The first order condition (FOC) with respect to vehicle price p_j is given by:

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

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 markups for all EV producers $\boldsymbol{mk}^v = \{mk^v_j\}_{j=1,\dots,|\Omega_v|; v=1,\dots,V}$ (where $|\Omega_v|$ is the number of products by firm v and V is the total number of EV producers).

3.2 Upstream Markups

We explore a variety of supply-side models to recover upstream markups, including two variations of the Nash-in-Nash bargaining model (Horn and Wolinsky, 1988), the linear pricing model, and a dynamic model that extends the static framework to incorporate forward-looking behaviors.[12] Our preferred approach is the bargaining model because it is well-suited to the market structure of the EV supply chain with a small number of downstream firms and upstream suppliers. This approach is more flexible than the linear pricing model and uses data variation to infer which party has greater bargaining power. We discuss these models in turn.

Nash-in-Nash Bargaining Our first approach uses a bargaining model, where EV producers and battery suppliers engage in bilateral negotiations to determine battery prices (with the exception of BYD and AESC, which were vertically integrated with downstream EV producers). 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 from supplier b) to maximize the Nash product of their net gains

[11] Joint ventures (JVs) are common in China. We assume JVs are separate OEMs from local partners that produce their own 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] We restrict attention to models of short-term contracts with linear prices, consistent with publicly released information on a few battery supply agreements (see Appendix A.4).

from trade, taking as given the battery prices chosen for other vehicles:

$$NP_j(\tau_j, \tau_{-j}) = \underbrace{(\pi^v \quad - \quad d^v)}_{\text{v' gains from trade}}{}^{(1-\lambda^b)} \underbrace{(\pi^b \quad - \quad d^b)}_{\text{b' gains from trade}}{}^{\lambda^b},$$

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

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:

$$(1-\lambda^b)(\pi^b - d^b)\frac{\partial \pi^v}{\partial \tau_j} + \lambda^b(\pi^v - d^v)\frac{\partial \pi^b}{\partial \tau_j} = 0. \tag{4}$$

Simultaneous Contracting and Pricing In a vertical setting like ours with upstream suppliers and downstream firms, there are two commonly used timing assumptions for modeling negotiations: simultaneous contracting and pricing, and sequential contracting and pricing. In the former case (Draganska, Klapper, and Villas-Boas, 2010; Ho and Lee, 2017; Crawford et al., 2018; Sheu and Taragin, 2021), battery price negotiation and vehicle price setting happen simultaneously. Consequently, EV prices remain unchanged in the event of a bargaining breakdown. This is likely a reasonable approximation in our setting, as EV prices are typically adjusted annually rather than immediately following changes in battery prices. This timing assumption is also computationally and conceptually much simpler than the sequential assumption and has been adopted by many recent studies.

With this timing assumption, EV producer v's disagreement payoff is:

$$d^{v,\text{Simult}}(\mathbf{p}) = \sum_{k \in \Omega_v, k \neq j} (p_k - \tau_k - mc_k^v)\tilde{q}_k(\mathbf{p}, \phi),$$

where $\tilde{q}_k(\mathbf{p}, \phi)$ is the sales of vehicle k in the scenario where vehicle j is not produced due to a disagreement. The formulation of battery supplier b's disagreement payoff is analogous. By combining the FOCs defined in Equations (3) and (4) following Draganska, Klapper, and Villas-Boas (2010), we can express the vector of battery suppliers' markups as a function of vehicle

[13] We examine the boundary cases below, where $\lambda^b = 0$ implies EV producers make take-it-or-leave-it (TIOLI) offers to battery suppliers. When $\lambda^b = 1$, battery suppliers make TIOLI offers to EV producers, which (with sequential contracting and pricing, see below) is equivalent to linear pricing.

[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.

producers' markups (see Appendix B.1 for the derivation):

$$\begin{aligned}\underbrace{\boldsymbol{mk}^b}_{\text{Battery markup}} &= \frac{\lambda^b}{1-\lambda^b}[\boldsymbol{T}^b \otimes \boldsymbol{S}]^{-1}[\boldsymbol{T}^v \otimes \boldsymbol{S}] \underbrace{\boldsymbol{mk}^v}_{\text{Vehicle markup}} \\ &\equiv \frac{\lambda^b}{1-\lambda^b} \underbrace{\overline{\boldsymbol{mk}}^b}_{\text{Battery markup when } \lambda^b = 0.5}, \end{aligned} \tag{5}$$

where $\otimes$ denotes element-by-element multiplication, and $\mathbf{T}^v$ and $\mathbf{T}^b$ are ownership matrices for EV producers and battery suppliers, respectively. Matrix $\boldsymbol{S}$ denotes how market shares of all products change upon disagreement: the $\{j,k\}$ term of $\boldsymbol{S}$ captures changes in sales of product k 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, $\boldsymbol{mk}^v$, is backed out from Equation (3). Intuitively, upstream markups depend on both the bargaining parameter and responsiveness of the battery supplier's sales to changes in the battery price. For example, if a small increase in the battery price leads to a large reduction in battery sales, then equilibrium upstream markups will tend to be modest. Equation (5) suggests that battery markups can be recovered up to the bargaining parameter λ^b after the demand estimation.

Sequential Contracting and Pricing The second bargaining model we consider assumes sequential contracting and pricing (Crawford and Yurukoglu, 2012), where negotiations over battery prices occur first, followed by price competition among EV producers. This model allows vehicle producers to change EV prices after a bargaining breakdown, which differs from the simultaneous bargaining model. For example, if Tesla and Panasonic fail to reach an agreement, prices of other vehicles would likely increase given the reduced competition in the market.

EV producer v's disagreement payoff is:

$$d^{v,\text{Sequential}}(\mathbf{p}) = \sum_{k \in \Omega_v, k \neq j} (\tilde{p}_k - \tau_k - mc_k^v)\tilde{q}_k(\tilde{\mathbf{p}}, \phi),$$

where $\tilde{p}_k$ and $\tilde{\mathbf{p}}$ are the new equilibrium prices under negotiation disagreement (when vehicle j would not be produced). The disagreement payoff for battery supplier b is analogously defined. The components of the FOC Equation (4) are more complex in this model for two reasons. First, calculating the disagreement payoff is more challenging and requires solving for new equilibrium prices for all downstream products for *each* bargaining pair that may disagree. Second, the derivatives of both firms' profits with respect to battery prices are more complex because both parties internalize the impact of changing battery prices on EV prices and sales. We present the upstream markups in vector form in Equation (A2), with the derivation provided in Appendix Section B.2.

Linear Pricing Another common approach to recovering upstream markups is to assume linear pricing, also called double-marginalization or a "take-or-leave-it offer" game. Battery suppliers post battery prices, and EV producers purchase batteries at these posted prices and set EV prices that include a markup over production costs. In our setting, linear pricing is a special case of sequential contracting and pricing where battery suppliers have full bargaining power $\lambda^b = 1$. The upstream markup is:

$$\boldsymbol{mk}^b = -(\mathbf{T^b} \otimes \mathbf{\Delta}^q_\tau)^{-1}\boldsymbol{q}, \tag{6}$$

where $\mathbf{T}^b$ is the ownership matrix, $\otimes$ denotes element-by-element multiplication, $\mathbf{\Delta}^q_\tau$ is a matrix that collects the derivatives of vehicle sales q with respect to battery prices τ, and $\boldsymbol{q}$ is a vector of all vehicles' sales (see Appendix B.3).

Dynamic Bargaining The presence of LBD can induce forward-looking behavior, where a battery supplier reduces prices in the current period to accelerate experience accumulation and lower cost more rapidly in future periods (Irwin and Klenow, 1994; Benkard, 2004); such incentives may be especially strong during the early stages of learning. The models discussed above assume static price-setting (and use time and battery supplier fixed effects to proxy the dynamic incentives). We now extend the static framework to incorporate dynamic considerations (see Appendix B.4).

The empirical literature on dynamic bargaining models is in its early stages (Lee and Fong, 2013; Deng et al., 2024; Dorn, 2024), partly due to the complexities of formulating disagreement payoffs and the impact of bargaining outcomes on future profits. To make progress, we make two assumptions: a) battery suppliers and EV producers negotiate over battery prices while EV producers set downstream markups; and b) they expect future markups (and future supply network) to remain at current levels.[15] Our approach captures the essence of LBD dynamic considerations in which upstream suppliers use low prices to stimulate downstream demand, while abstracting from modeling complications that would make the problem intractable (including downstream firms' incentives to manipulate prices). With dynamics, the gains from trade in the Nash product incorporate future payoffs:

$$NP_j(\tau_j, \tau_{-j}) = \underbrace{(\pi^v \quad - \quad d^v)}_{\text{v' gains from trade}}{}^{(1-\lambda^b)} \underbrace{(V^b \quad - \quad D^b)}_{\text{b' gains from trade}}{}^{\lambda^b},$$

where battery suppliers are forward-looking due to the LBD incentives, V^b represents the sum of today's profit and discounted future profits under agreement, and D^b captures the sum of today's profit and discounted future profits in the event that today's negotiation breaks down (we assume disagreement lasts for one period, following which the parties return to the negotiating table). With forward-looking battery suppliers, the upstream markups are defined by Equation (A8) in Appendix B.4.

[15] The assumption that EV producers choose markups implies full pass-through: reductions in battery prices are 100% reflected in EV prices, achieving the largest demand expansion associated with battery price cuts. This assumption maximizes battery suppliers' dynamic incentives.

4 Estimation

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.

4.1 Demand Estimation

Price Coefficient The price coefficient α_i in Equation (2) is specified as

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

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.[16] 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 ν_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 μ_{ct} 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

[16]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.

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.[17]

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 (1) (bringing back the country and time subscripts for clarity):

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

The vehicle markup mk^v_{jct} is known after demand estimation, and the battery markup $mk^b_{jct} = \frac{\lambda^b}{1-\lambda^b}\overline{mk}^b_{jct}$ is known up to bargaining weight λ^b following the discussions in Section 3.2. 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 assembly.

The marginal cost of producing batteries – the heart of this exercise – is specified as the product of battery capacity in kWh (denoted as BK_{bjct}) and the cost associated with producing each kWh:[18]

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

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:

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

[17] 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).

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

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 unit cost (i.e., per kWh) of battery manufacturing decreases when production experience doubles.[19] 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), the battery plant's capacity PK_{bt} in GWh that reflects economies of scale,[20] and input costs. Given the significant changes in production technology over the past decade (advancements in battery size and efficiency), we use a time trend $\eta * t$ to control for industry-wide technological progress over time. As pointed out by Thompson (2001), failure to control for factors that influence unit production costs could inflate LBD estimates. We demonstrate in Section 5 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).

Combining Equations (1), (5) (or (A2), (6), and (A8) for alternative supply-side models), and (7), the LBD estimating equation is defined as follows:

$$p_{jct} - mk^v_{jct} = \frac{\lambda^b}{1-\lambda^b}\overline{mk}^b_{jct} + BK_{bjct}\left(\underbrace{\gamma_0 E_{bt}{}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta * t}_{\text{Battery cost per kWh}}\right)$$
$$+ \mathbf{x}_{vjct}\boldsymbol{\gamma}_v + \text{fixed effects} + \omega_{jct}, \tag{8}$$

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, capturing unobserved cost shocks in different dimensions. For example, country fixed effects control for unobserved cost differentials at the country level, such as supply chain advantages in China vs. other countries. The battery supplier and year fixed effects capture supplier reputation and other industry-level dynamics. The residual ω_{jct} captures the remainder of unobserved cost shocks. Different from the standard supply-side analyses (Berry, Levinsohn, and Pakes, 1995), ω_{jct} includes 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.

[19]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.

[20]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.

4.3 Empirical Challenges

There are three challenges in estimating Equation (8). First, battery firms' cumulative experience 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 experience driven by exogenous variation in the spirit of Gowrisankaran, Ho, and Town (2006) and Covert and Sweeney (2022):

$$IV_{bt} = \sum_{s<t}\sum_{c}\sum_{j}\hat{Pr}_{jbcs}(z_{jbcs})\hat{q}_{jcs}(\mathbf{X}_{cs}, \phi_{cs}), \tag{9}$$

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 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 (8). Appendix A.3 provides more details.

To address the endogeneity of past sales, we use $\hat{q}_{jcs}(\mathbf{X}_{cs}, \phi_{\mathbf{cs}})$, the predicted sales based on the demand model in Equation (2). It depends on vehicle attributes $\mathbf{X}_{cs} = \{\mathbf{X}_{jcs}\}_{j=1}^{J_{cs}}$ and EV subsidies $\phi_{\mathbf{cs}} = \{\phi_{jcs}\}_{j=1}^{J_{cs}}$ (where J_{cs} is the number of EV models sold in country c at time s), the latter of which exhibits rich variation 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 subsidies will gain experience more quickly.

The key identification assumption is that China's whitelist policy and variation in EV subsidies across countries are uncorrelated with vehicle and battery costs shocks ω_{jct}. This is likely to hold in our setting. For example, the notched subsidy design based on the driving range in China lends to an RD-type variation in that the amount of subsidy changes discretely at 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 (8) is that the battery firm's markup $\overline{mk}^{b}_{jct}$ could be correlated with cost shocks ω_{jct} that capture the unobserved production efficiency of battery supplier b. This is because 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 variation in subsidies, whitelist policy, and vehicle attributes. 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 a valid IV. The bargaining parameter λ^b is identified from changes in vehicle prices due to exogenous shifts to battery suppliers' markups as a result of changes in their bargaining leverage. For example, China's whitelist policy enhanced the bargaining position of Chinese battery suppliers relative to EV makers. The degree to which this change 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.

The third challenge is that EV producer's past experience, a control in $\mathbf{x}_{vjct}$ in Equation (8), is also endogenous and correlated with ω_{jct}. We generate predicted EV producer experience in a similar fashion to how we generate 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 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 IVs based on observed vehicle attributes. As common in the demand literature, the OLS estimate on vehicle prices 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 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 coefficients 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 of which are estimated precisely. There is significant variation 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; Springel, 2019; Xing, Leard, and Li, 2021; Muehlegger and Rapson, 2022). 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. This is 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 Experience 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 a supplier choice model, to construct predicted experience for each battery supplier and year. Similarly, we exploit exogenous variations in prices and government policies to generate predicted markups for battery suppliers, and predicted EV producer experience. Figure A5 presents evidence that these predicted variables are strong IVs: there is a strong positive correlation between these instruments and their endogenous counterparts after partialling out vehicle attributes and a rich set of country, brand, and year fixed effects.

Cost Estimates with Simultaneous Contracting and Pricing We first present cost estimates and magnitude of LBD for our preferred supply-side model (bargaining with simultaneous contracting and pricing), followed by results from alternative supply-side models.

Table 3 presents the GMM estimates for Equation (8). We categorize the parameters into four groups: (1) those linking battery production costs to a function of 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

[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.

and vehicle production.[22] The experience and markups of battery suppliers and the experience of EV producers are instrumented in all columns as discussed above.

Column (1) controls for 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-wide technology progress could confound LBD estimates. Column (3) further controls for economies of scale by including plant capacity and Column (4) adds the experience of EV producers to account for potential learning in EV assembly. Column (4) is our preferred specification with all the relevant controls and is used for subsequent counterfactual analyses in Section 6. Including these additional controls in Column (4) 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, when production experience doubles, the marginal cost of producing batteries is expected to decrease by 7.5% on average. 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 adequately control for industry-wide technological progress and other cost shocks. The learning rate in well-known economic studies varies between 8-30%. 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), between 14-29% in wind turbine production from 2000-2019 (Covert and Sweeney, 2022), and around 5-8% in the global semiconductor sector from 2004-2015 (Goldberg et al., 2024). 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 when estimating the learning curves, such as industry-wide technology progress and economies of scale (Argote and Epple, 1990; Thompson, 2012).

Second, the time trend estimates indicate that battery costs decrease by $32 per kWh annually, or approximately 4% of the baseline cost ($858 per kWh in Column (4)). This implies substantial

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

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 that doubling capacity lowers costs by about \$54/kWh (=0.078 in Column (4) $\times \ln(2) \times 1000$).

Third, the coefficient estimate for EV experience suggests that, every time EV manufacturing experience doubles, the unit cost of EV production decreases by $\$1000 \times \ln(2) \times (-0.997) = \$691$. At this rate, the cumulative experience of EV manufacturers contributed to a reduction of about \$3,000 (or 5%) in 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 a third of the total cost of EV production; it 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.[23]

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 green line with circles represents the battery price index from Bloomberg NEF (2023). The black line with triangles shows the predicted prices based solely on the time trend (an annual reduction of \$32 per kWh), which captures the industry-wide technological advancements. Overall, technological progress accounted for 39.9% of the battery price reduction. The blue line with diamonds (the second line from the top) reflects the combined price reductions due to both LBD and the time trend. The difference between these two lines indicates that LBD contributed to 35.5% of the reduction in battery price from 2014 to 2020. The red line with diamonds (the third line from the top) represents the model-predicted battery prices, which also include the effects of growing economies of scale and changes in battery chemistry and input costs.[24]

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

[24] Since we cannot separately identify the level of battery price and vehicle cost, we calibrate the battery price in the base year (2014) to match the Bloomberg price index for that year. Our model's prediction aligns well with the overall observed price decline reported by Bloomberg. The discrepancies are partly driven by coverage difference: we focus on passenger EVs, whereas Bloomberg's index is based on survey data that also covers commercial vehicles and storage batteries alongside passenger EVs.

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. These cost estimates align closely with the free-on-board battery price by country-of-origin reported in UN Comtrade, as shown in Panel (d) of Appendix Figure A4. By 2020, Chinese battery exports were the least expensive among all major exporting countries.

5.3 Alternative Specifications

Cost Estimates from Alternative Bargaining Models We begin by examining whether the learning rate estimate is sensitive to the bargaining parameter. Table 4 reports cost estimates when the battery supplier's bargaining weight λ varies from 0 to 0.5, using the same supply-side model as in Table 3. Values greater than 0.5 are excluded because they would imply negative marginal costs for battery production. The LBD estimates remain similar across different λ values. Intuitively, while bargaining weights affect the level of predicted battery prices (higher λ leads to greater markups for suppliers and higher battery prices), LBD is determined by the relationship between changes in battery prices and cumulative experience. Although the battery price level is affected by bargaining parameters (and supply-side assumptions in general), its slope with respect to production experience remains robust and stable across different specifications.

As an alternative to the simultaneous contracting and pricing model, we also estimate cost parameters under the assumption of sequential contracting and pricing: EV makers and battery suppliers first negotiate 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. Appendix Table A3 presents cost estimates while varying the bargaining weight λ^b. The linear pricing model (double-marginalization) is a special case of sequential contracting and pricing with $\lambda^b = 1$ and is presented in the last column. The LBD estimates are similar to our baseline estimates and remain robust to different values of λ.[25]

Cost Estimates from Dynamic Bargaining Table A4 presents the learning estimates γ_E when battery suppliers are forward-looking at different values of λ. At one extreme, when $\lambda = 0$ (Column (1)), battery suppliers earn zero markups and thus no dynamic markdown incentive exists. At the

[25] The specifications in Columns (4) and (5) of Tables A3 and A4 lead to negative marginal costs. We present these results mainly to illustrate the robustness of LBD estimates to changes in bargaining weights.

other extreme, when $\lambda = 1$ (Column (5)), battery suppliers capture the maximum surplus possible in negotiations, providing the strongest incentives to lower current battery prices to accelerate LBD. The estimates across columns 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 when $\lambda = 0$ to -0.120 when $\lambda = 1$, compared to -0.113 in our baseline specification in Column (4) of Table 3.

These results suggest that while LBD in battery production could theoretically generate forward-looking behavior, ignoring dynamics does not introduce a significant bias into the learning rate estimates in our setting. There are at least several reasons. First, all of our empirical specifications include time fixed effects, which capture dynamic incentives at the industry level. Second, due to the oligopolistic market structure in *both* upstream and downstream sectors (and the fact that upstream firms' bargaining weight is much less than one), upstream battery suppliers only capture a small fraction of the economic benefits created by LBD as shown in Section 6.1, thus dampening the dynamic incentive of battery suppliers. Third, for the range of learning rates we have obtained, dynamic incentives dissipate rapidly after a few years.[26]

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 for 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 and requires additional variation 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 of the experience of rival firms in the same country. The parameter θ measures the completeness of spillover. If $\theta = 1$, the spillover is complete and learning from rivals' experience is as effective as learning from one's own experience, whereas $\theta = 0$ implies that there is no learning spillover from

[26]Consider a hypothetical scenario where supplier b reduces battery prices by 30% in year t. This translates to a 10% reduction in prices of EV models (battery is 30% of the EV price) that source from firm b and a 35% increase in their sales in year t at our estimated demand elasticity. Assuming supplier b has no prior production experience (so the effect of LBD is strongest), the 35% increase in sales translates to a 35% increase in cumulative experience. At a learning rate of 7.5%, battery costs in year $t+1$ would drop by 2.3%. Supposing all cost savings are passed through to battery prices and fully reflected in EV prices, this would lead to a 1% reduction in EV prices and a 3.5% sales increase in year $t+1$. However, this smaller sales increase results in a marginal gain in experience in year $t+2$ and a negligible cost reduction in future years.

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 (9).

Appendix Table A5 presents the estimation results for learning spillovers across firms. The θ estimate is 0.044, indicating that learning from one unit of rival experience is equivalent to only 4.4% of the learning derived from 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 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 the production of batteries of a given chemistry type and a fraction (θ) of its experience in the production of batteries of other chemistry types. The θ parameter is imprecisely estimated, as more than 80% of the battery suppliers produce only one chemistry type, leading to limited variation across firms. Similarly, we explore learning spillover across countries. However, the global LBD is highly correlated with the time trend and cannot be reliably estimated.

Patents and Innovation While our baseline specification includes a time trend in battery costs to account for industry-wide technological progress, one might worry that firm-level innovation could confound LBD. To address this, we include the cumulative number of patents filed by each battery supplier since 2008 sourced from the PATSTAT Global database. Because patenting activity could be correlated with cost shocks, we instrument for it using the battery firm's exposure to industrial policies that target the EV sector across countries. EV industrial policies are compiled from the Global Trade Alert database and classified using Natural Language Processing following Juhász et al. (2023). The policy exposure is a sales-weighted sum of policy counts where the weights are the predicted sales of EV models that source batteries from a give battery supplier. The predicted sales are from our EV demand model that relies on exogenous demand shifters (which are also used to construct the IV for battery supplier experience). The details about data construction on both patents and industrial policies is provided in Barwick et al. (2024), which also documents a positive relationship between the EV industrial policies and patenting, motivating our IV strategy.

The results in Table A6 show a negative coefficient estimate on the patent variable, consistent with firm innovation reducing costs. The coefficient estimate on the time trend becomes smaller, reflecting the fact that industry-wide technological progress is partly driven by innovation at individual firms. Nevertheless, the LBD estimate remains nearly identical to the baseline estimate, suggesting that LBD on the production floor and innovation through patenting activities are distinct sources of cost reduction.

6 Counterfactual Analyses

We now evaluate the role of LBD in promoting EV demand and the externalities it generates. We then quantify the welfare effects of prominent EV policies with and without LBD incorporated. Given the stability of the LBD estimate across supply-side assumptions, all counterfactual simulations are conducted based on our preferred specification in Column (4) of Table 3.

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 from 2013-2020 under four scenarios, as illustrated in Figure 4. These scenarios, represented by the four lines from bottom to top, are: (1) a baseline with neither consumer subsidies nor 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 29.9% (1.01 million units) during 2013-2020. Absent any subsidies, cost reductions driven by LBD alone resulted in a 78.3% increase in global EV sales (2.65 million units) during the same period. When both consumer subsidies and LBD were in effect, global EV sales surged by 170% (5.75 million units) relative to the baseline. 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?[27] To evaluate this empirically, we conduct counterfactuals in which we individually increase battery suppliers' experience (and hence LBD) and examine what happens to downstream firms and consumers, both domestically and globally.

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 profits for downstream firms, ultimately

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

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 outlined in Section 3. For ease of comparison, we normalize the increase in the battery supplier's own profit to one (so that all numbers are relative to this benchmark). The first three columns report welfare changes for the home country (China for CATL), the rest of the world, and globally when CATL's experience increases. The next three columns present welfare changes associated with Panasonic's increased experience. Notably, CATL captures only 22.0% of the global surplus generated by its increased LBD, while Panasonic captures 21.7%. In addition, the distribution of welfare gains varies significantly with the degree of localization of the supply chain. China captures the entirety of the global welfare gains with its largely localized EV supply chain. In contrast, Japan captures only 22% of the global welfare gains resulting from Panasonic's cost reductions, with a significant portion of the surplus accruing to downstream firms and consumers in other countries. These results highlight that upstream LBD generates substantial externalities for downstream firms and consumers, with the benefits crossing country borders through global supply chains. Such externalities underpin the large welfare impacts of government interventions, as documented below.[28]

6.2 Algorithm for Counterfactual Policy 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 Appendix C. The model features the whitelist policy and accounts for the higher likelihood of more experienced battery firms supplying a given EV model.[29] 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 C, (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.

6.3 Consumer Subsidies

We examine 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

[28] 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.

[29] 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.

subsidies due to the small size of their EV markets. The results are presented in Table 5. 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.[30]

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 benefited 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 benefited 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 also experienced significant gains; in contrast, 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 limited battery 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 share, especially in the Chinese EV battery market.[31]

Panel (b) shows that the effects of European subsidies are broadly similar to those of U.S. subsidies, generating substantial welfare gains for consumers and EV producers. Japan and South Korea benefited the most because EVs sold in Europe 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. This was partly due to the common use of uniform subsidies in Europe

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

[31] Table A9 reports the welfare impacts including the environmental impacts of EV adoption as described in Appendix C.3. The environmental benefits are of the same magnitude as non-environmental benefits from the subsidies.

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.

Summary 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.[32] Table A10 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 the US or European subsidies to China are nearly nonexistent because of the limited overlap in battery suppliers between EV producers in the US and Europe and those in China. Third, results in Table 5 echo findings in Section 6.1 and illustrate that the 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.

6.4 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: (1) the extent to which the policy propelled top Chinese battery suppliers to global industry leadership, and (2) the welfare implications for domestic and foreign firms and consumers, which depend on cost differentials between approved suppliers and the others.

Panel (a) of Figure A6 shows that the Whitelist policy significantly benefited Chinese battery suppliers, with their sales increasing by 24% between 2016 and 2020. The policy successfully accelerated experience accumulation for Chinese battery suppliers, particularly CATL and BYD,

[32] Subsidies generate welfare gains through at least two channels. First, LBD reduces production costs and generates economic benefits that are not fully captured by upstream suppliers, as discussed in Section 6.1. Subsidies correct for the underprovision of LBD. Second, subsidies mitigate deadweight losses from market power distortions as shown in Barwick, Kwon, and Li 2024.

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 were 14% lower relative to a no-whitelist scenario as shown in Panel (b).

Panel (a) of Table 6 presents the impact of the whitelist policy while holding the subsidies fixed. The policy increased the profits of Chinese battery suppliers by over \$3.17 billion but hurt domestic consumers by \$0.80 billion. While the overall welfare impact in China was 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 in LBD 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 Chinese domestic EV producers was nuanced. In the early years of the whitelist policy, some Chinese 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 relative to the no-whitelist scenario. However, the policy facilitated sales concentration among two dominant domestic suppliers, enabling faster LBD accumulation. As shown in Panel (b) of Figure 3, China's top suppliers closed the cost gap with South Korean suppliers by 2018 and matched their Japanese counterparts by 2020. These significant cost reductions ultimately benefited Chinese 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 Chinese EV producers eventually gained (with a modest profit increase over the entire period), 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 of Protective Policies 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 five years later (i.e., shifting the policy from 2016-2019 to 2021-2024) when most battery cost reductions had already taken place. We assumed the global market structure and subsidy rates in future years stayed as they were in 2020, as discussed in Appendix C. Panels (c) and (d) in Figure A6 shows the impacts on sales and Table 7 summarizes the welfare results. As expected, the negative impact on other countries becomes much smaller. By 2021, the gap in production experience between (foreign) leaders and (Chinese) followers would have been much wider than that in 2016. 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 would still have gained, their profit increases would be an order of magnitude smaller, given the large cost advantages held by suppliers from Japan and South Korea.[33] Chinese consumers and EV firms experienced greater losses. As a result, the counterfactual whitelist policy is also detrimental to China.

The IRA of the Biden administration put into place local content requirements for EV batteries as part of the eligibility criteria for consumer subsidies. A policy simulation of the local content requirements under IRA is beyond the scope of our study, as it requires modeling changes in battery and EV production locations amid the currently limited battery production capacity in North America. Nevertheless, our analysis indicates that in the short run, the policy will likely generate welfare impacts across consumers, battery suppliers, and EV producers that are qualitatively similar to those under China's delayed whitelist policy (2021-2024).

Accounting for LBD in Policy Analysis To illustrate the importance of accounting for LBD in policy analysis, we simulate the impacts of Chinese consumer subsidies and the whitelist policy without LBD. Table 8 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 also significantly reduced. These results underscore the importance of accounting for LBD in the evaluation of the cost-effectiveness and broad impacts of EV policies.

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, input costs, and LBD in EV assembly. LBD in battery production accounts for 35.5% of the overall battery cost reduction during 2014–2020. The feedback loop from LBD amplified the effects of EV subsidies and local content requirements on EV adoption and social welfare by severalfold. Upstream battery

[33] 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.

suppliers capture a small fraction of the benefits generated by LBD to downstream producers and consumers, highlighting the potential role of government interventions.

In terms of policy implications, EV subsidies in one country generate spillover benefits for other countries, with the extent of these spillovers critically depending on the nature of the supply network and the degree of supplier overlap. 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 global 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 of automakers and battery suppliers, which 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. Head et al. (2024) makes important headway in that direction by developing a multi-stage production model, albeit without incorporating LBD. Second, we do not explicitly account for the impacts on the gasoline vehicle segment. How the EV policies affect this segment through substitution and product line choices remains an open question.

References

Allcott, Hunt, Reigner Kane, Maximilian S Maydanchik, Joseph S Shapiro, and Felix Tintelnot. 2024. "The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act." Working Paper 33032, National Bureau of Economic Research.

Argote, Linda and Dennis Epple. 1990. "Learning Curves in Manufacturing." *Science* 247 (4945):920–924.

Axsen, Jonn, Joseph Bailey, and Marisol Andrea Castro. 2015. "Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers." *Energy Economics* 50:190–201.

Banares-Sanchez, Ignacio, Robin Burgess, David Laszlo, Pol Simpson, John Van Reenen, and Yifan Wang. 2024. "Chinese Innovation, Green Industrial Policy and the Rise of Solar Energy." Working Paper.

Barwick, Panle Jia, Hyuk-Soo Kwon, and Shanjun Li. 2024. "Attribute-based Subsidies and Market Power: an Application to Electric Vehicles." Working Paper 32264, National Bureau of Economic Research.

Barwick, Panle Jia, Hyuk-Soo Kwon, Shanjun Li, Yucheng Wang, and Nahim Bin Zahur. 2024. "Industrial Policies and Innovation: Evidence from the Global Automobile Industry." Working Paper 33138, National Bureau of Economic Research.

Barwick, Panle Jia, Hyuk-soo Kwon, Binglin Wang, and Nahim Bin Zahur. 2023. "Pass-through of Electric Vehicle Subsidies: A Global Analysis." *AEA Papers and Proceedings* 113:323–28.

Benkard, C. Lanier, Przemyslaw Jeziorski, and Gabriel Y. Weintraub. 2015. "Oblivious equilibrium for concentrated industries." *Rand Journal of Economics* 46(4).

Benkard, Lanier. 2000. "Learning and Forgetting: The Dynamics of Aircraft Production." *American Economic Review* 90 (4):1034–1054.

———. 2004. "A Dynamic Analysis of the Market for Wide-bodied Commercial Aircraft." *Review of*

Economic Studies 71:581–611.

Berry, Steven T., James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4):841–890.

Bjerkan, Kristin Ystmark, Tom E Nørbech, and Marianne Elvsaas Nordtømme. 2016. "Incentives for promoting battery electric vehicle (BEV) adoption in Norway." *Transportation Research Part D: Transport and Environment* 43:169–180.

Bloomberg NEF. 2023. "BloombergNEF Annual Battery Price Survey." Https://about.bnef.com/blog/lithium-ion-battery-pack-prices-hit-record-low-of-139-kwh/.

Bollinger, Bryan, Kenneth Gillingham, Todd Gerarden, Drew Vollmer, and Daniel Xu. 2024. "Strategic Avoidance and Welfare Impacts of Solar Panel Tariffs." Working Paper.

Chipty, Tasneem and Christopher M. Snyder. 1999. "The Role of Firm Size in Bilateral Bargaining: A Study of the Cable Television Industry." *The Review of Economics and Statistics* 81 (2):326–340.

CMT. 2022. "Vehicle Miles Traveled in Urban and Rural China." Tech. rep., Chinese Ministry of Transport.

Conlon, Christopher and Jeff Gortmaker. 2023. "Incorporating Micro Data into Differentiated Products Demand Estimation with PyBLP." Tech. rep., National Bureau of Economic Research.

Covert, Thomas R. and Richard L. Sweeney. 2022. "Winds of Change: Estimating Learning by Doing without Cost or Input Data." Working paper.

Crawford, Gregory S, Robin S Lee, Michael D Whinston, and Ali Yurukoglu. 2018. "The welfare effects of vertical integration in multichannel television markets." *Econometrica* 86 (3):891–954.

Crawford, Gregory S. and Ali Yurukoglu. 2012. "The Welfare Effects of Bundling in Multichannel Television Markets." *American Economic Review* 102 (2):643–85.

Dasgupta, Partha and Joseph Stiglitz. 1988. "Learning-by-Doing, Market Structure and Industrial and Trade Policies." *Oxford Economic Papers, New Series* 40(2):246–268.

Deng, Shanglyu, Dun Jia, Mario Leccese, and Andrew Sweeting. 2024. "Bargaining and Dynamic Competition." *Working Paper* .

Dorn, Jacob. 2024. "Dynamic Bargaining between Hospitals and Insurers." *Working Paper* .

Draganska, Michaela, Daniel Klapper, and Sofia B. Villas-Boas. 2010. "A Larger Slice or a Larger Pie? An Empirical Investigation of Bargaining Power in the Distribution Channel." *Marketing Science* 29 (1):57–74.

EPA. 2021. "Motor Vehicle Emissions Simulator (MOVES)." Tech. rep., U.S. Environmental Protection Agency (EPA).

Eurostat. 2020. "Passenger Mobility Statistics in the European Union." Tech. rep., Eurostat.

Fan, Ying and Chenyu Yang. 2020. "Competition, Product Proliferation, and Welfare: A Study of the US Smartphone Market." *American Economic Journal: Microeconomics* 12 (2):99–134.

FHWA. 2022. "Annual Vehicle Miles Traveled in the United States." Tech. rep., Federal Highway Administration (FHWA).

Gandhi, Amit and Jean-François Houde. 2019. "Measuring substitution patterns in differentiated products industries." Tech. rep., National Bureau of Economic Research.

Gerarden, Todd D. 2023. "Demanding Innovation: The Impact of Consumer Subsidies on Solar Panel Production Costs." *Management Science* 69 (12):7799–7820.

Goldberg, Pinelopi K, Réka Juhász, Nathan J Lane, Giulia Lo Forte, and Jeff Thurk. 2024. "Industrial Policy in the Global Semiconductor Sector." Working Paper 32651, National Bureau of Economic Research.

Gowrisankaran, Gautam, Vivian Ho, and Robert J Town. 2006. "Causality, learning and forgetting in surgery." Working Paper.

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town. 2015. "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry." *American Economic Review* 105 (1):172–203.

Gowrisankaran, Gautam and Marc Rysman. 2012. "Dynamics of Consumer Demand for New Durable Goods." *Journal of Political Economy* 120 (6):1173–1219.

Grennan, Matthew. 2013. "Price Discrimination and Bargaining: Empirical Evidence from Medical Devices." *American Economic Review* 103 (1):145–77.

Head, Keith. 1994. "Infant industry protection in the steel rail industry." *Journal of International Economics* 37 (3):141–165.

Head, Keith, Thierry Mayer, Marc Melitz, and Chenying Yang. 2024. "Industrial policies for multi-stage production: The battle for battery-powered vehicles." Working Paper.

HEI. 2022. "State of Global Air Report." Tech. rep., Health Effects Institute.

Ho, Kate and Robin S. Lee. 2017. "Insurer Competition in Health Care Markets." *Econometrica* 85 (2):379–417.

Holland, Stephen, Erin Mansur, Nicholas Muller, and Andrew Yates. 2016. "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors." *American Economic Review* 106 (12):3700–3729.

Horn, Henrick and Asher Wolinsky. 1988. "Bilateral Monopolies and Incentives for Merger." *The RAND Journal of Economics* 19 (3):408–419.

International Energy Agency. 2021. "Global EV Outlook 2021." Tech. rep., IEA, Paris. Https://www.iea.org/reports/global-ev-outlook-2021.

———. 2023. "Global EV Outlook 2023." Https://www.iea.org/reports/global-ev-outlook-2023.

Irwin, Douglas A. and Peter J. Klenow. 1994. "Learning-by-Doing Spillovers in the Semiconductor Industry." *Journal of Political Economy* 102 (6):1200–1227.

Juhász, Réka, Nathan Lane, Emily Oehlsen, and Verónica C Pérez. 2023. "The who, what, when, and how of industrial policy: A text-based approach." *What, When, and How of Industrial Policy: A Text-Based Approach* .

KTI. 2023. "Annual Vehicle Miles Traveled in South Korea and Japan." Tech. rep., Korea Transportation Institute.

Küpper, Daniel, Kristian Kuhlmann, Sebastian Wolf, Cornelius Pieper, Gang Xu, and Justin Ahmad. 2018. "The Future of Battery Production for Electric Vehicles." *Boston Consulting Group Working Paper* .

Leard, Benjamin, Joshua Linn, and Katalin Springel. 2024. "Vehicle Attribute Tradeoffs and the Distributional Effects of US Fuel Economy and Greenhouse Gas Emissions Standards." Working Paper.

Lee, Robin S. and Kyna Fong. 2013. "Markov-Perfect Network Formation: An Applied Framework for Bilateral Oligopoly and Bargaining in Buyer-Seller Networks." *Working Paper* .

Li, Jing. 2023. "Compatibility and Investment in the U.S. Electric Vehicle Market." Working paper.

Li, Shanjun. 2018. "Better lucky than rich? Welfare analysis of automobile license allocations in Beijing and Shanghai." *Review of Economic Studies* 85 (4):2389–2428.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. "The Market for Electric Vehicles: Indirect Network Effects and Policy Impacts." *Journal of the Association of Environmental and Resource Economists* 4 (1):89–133.

Li, Shanjun, Xianglei Zhu, Yiding Ma, Fan Zhang, and Hui Zhou. 2021. "The Role of Government in the Market for Electric Vehicles: Evidence from China." *Journal of Policy Analysis and Management* .

Liang, Jing and Junji Xiao. 2024. "The Incidence and Distributional Effects of Electric Vehicle Subsidies in China." Working Paper.

Lohawala, Nofisa. 2023. "Roadblock or Accelerator? The Effect of Electric Vehicle Subsidy Elimination." RFF Working Paper.

Meijssen, Aart. 2019. "Dutch electric vehicle drivers' preferences regarding vehicle-to-grid contracts." *TU Delft, Delft* .

Melitz, Marc. 2005. "When and How Should Infant Industries Be Protected?" *Journal of International Economics* 66:177–196.

Muehlegger, Erich and David S. Rapson. 2022. "Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California." *Journal of Public Economics* 216:104752.

Ohashi, Hiroshi. 2005. "Learning by doing, export subsidies, and industry growth: Japanese steel in the 1950s and 1960s." *Journal of International Economics* 66 (2):297–323.

Okada, Takanori, Tetsuya Tamaki, and Shunsuke Managi. 2019. "Effect of environmental awareness on purchase intention and satisfaction pertaining to electric vehicles in Japan." *Transportation Research Part D: Transport and Environment* 67:503–513.

Plötz, Patrick, Till Gnann, Martin Kagerbauer, and Michael Heilig. 2017. "Can models predict electric vehicle users?" .

Remmy, Kevin. 2022. "Adjustable product attributes, indirect network effects, and subsidy design: The case of electric vehicles." Working Paper.

Rennert,Kevin and Others. 2022. "Comprehensive evidence implies a higher social cost of CO_2." *Nature* September:687–692.

Sheu, Gloria and Charles Taragin. 2021. "Simulating mergers in a vertical supply chain with bargaining." *Rand Journal of Economics* 52(3):596–632.

Springel, Katalin. 2019. "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives." *American Economic Journal: Economic Policy* 13 (4):393–432.

Thompson, Peter. 2001. "How Much Did the Liberty Shipbuilders Learn? New Evidence for an Old Case Study." *Journal of Political Economy* 109 (1):103–137.

———. 2012. "The Relationship between Unit Cost and Cumulative Quantity and the Evidence for Organizational Learning-by-Doing." *Journal of Economic Perspectives* 26 (3):203–24.

Thornton, Rebecca Achee and Peter Thompson. 2001. "Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding." *American Economic Review* 91 (5):1350–1368.

USTR. 2019. "United States Trade Representative 2018 Report to Congress On China's WTO Compliance."

Vassileva, Iana and Javier Campillo. 2017. "Adoption barriers for electric vehicles: Experiences from early adopters in Sweden." *Energy* 120:632–641.

Villas-Boas, Sofia Berto. 2007. "Vertical relationships between manufacturers and retailers: Inference with limited data." *The Review of Economic Studies* 74 (2):625–652.

Wang, Jingyuan and Jianwei Xing. 2024. "Subsidizing Industry Growth in a Market with Lemons:Evidence from the Chinese Electric Vehicle Market." Working Paper.

Wright, Theodore P. 1936. "Factors affecting the cost of airplanes." *Journal of the Aeronautical Sciences* 3 (4):122–128.

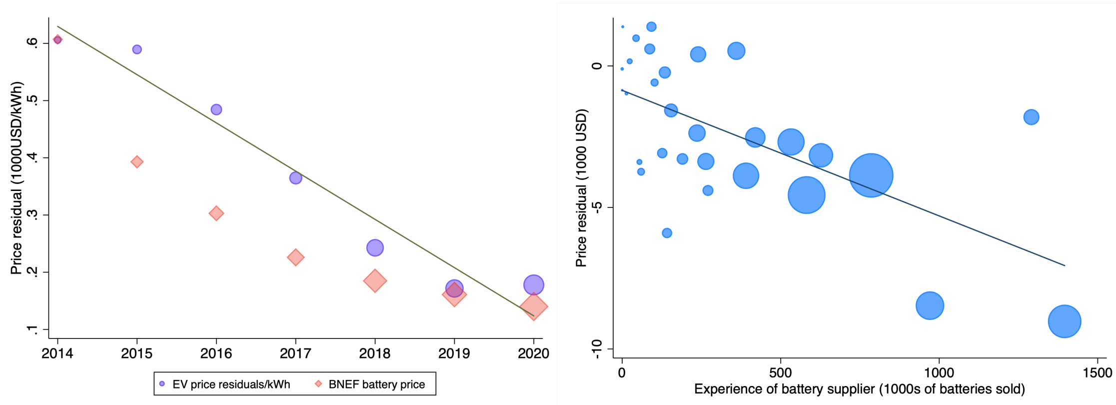
Xing, Jianwei, Benjamin Leard, and Shanjun Li. 2021. "What Does an Electric Vehicle Replace?" *Journal of Environmental Economics and Management* 107:102432.

Ziegler, Micah S. and Jessica E. Trancik. 2021. "Re-examining rates of lithium-ion battery technology improvement and cost decline." *Energy & Environmental Science* 14:1635–1651.

Figures & Tables

Figure 1: Vehicle Price vs. Battery Supplier Experience

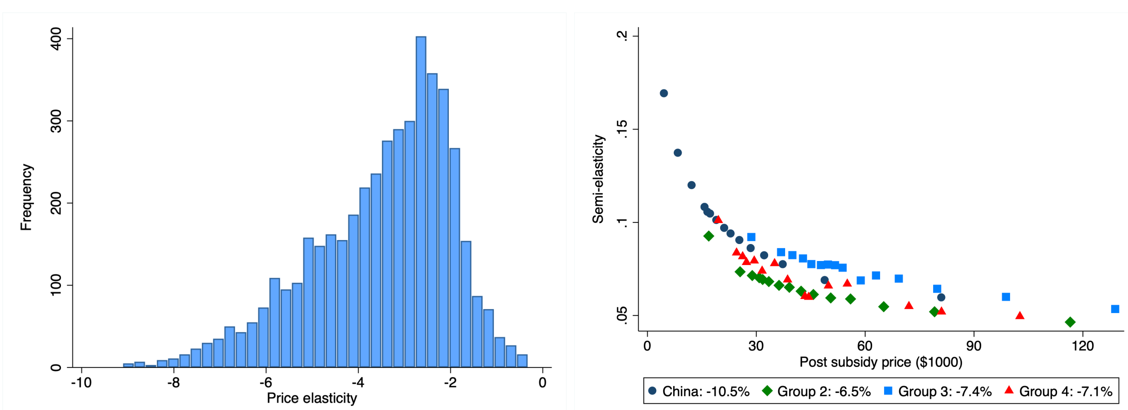
(a) Residualized Prices Over Time **(b)** Residualized Prices vs. Supplier Experience



Notes: The residualized vehicle prices in these graphs are EV prices partialling out vehicle attributes (horsepower, size, and the PHEV dummy), and country, brand, and year fixed effects. In Panel (a), the price residuals are divided by battery capacity as a proxy for battery costs per kWh, and the purple dots depict the sales-weighted average annual price residuals per kWh (in \$1000). The red diamonds are the average battery pack price from Bloomberg NEF (2023) (BNEF). The marker size is 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 dots is proportional to the cumulative subsidy received by battery suppliers.

Figure 2: Demand Elasticities

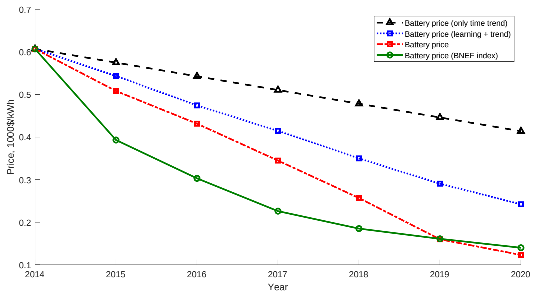
(a) Price Elasticity **(b)** Semi-elasticity When Price Drops by \$1000)



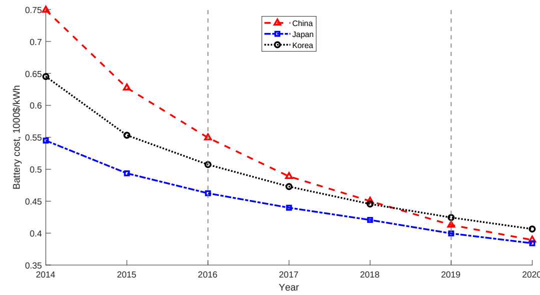
Notes: Panel (a) shows the histogram of price elasticities. The average is 3.51. The demand elasticity is less than one (in absolute value) for 70 out of 4,556 observations. Given the multi-product nature of auto firms, only nine of the 70 observations exhibit negative marginal costs. Panel (b) depicts 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 elastic demand.

Figure 3: LBD and Battery Price Reduction

(a) Global

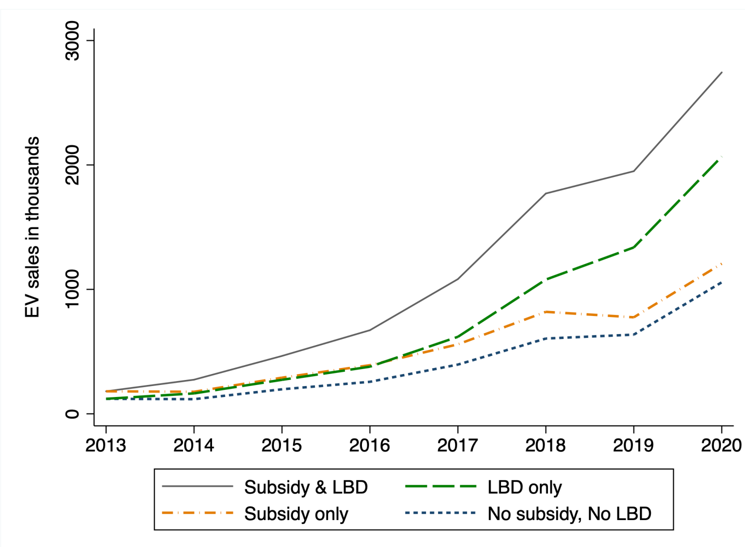


(b) By Country



Notes: in Panel (a), the black line with triangles shows prices based on the time trend (technological progress), and the blue line with diamonds (the second line from the top) reflects the combined price reductions due to both LBD and the time trend. The red line with diamonds (the third line from the top) is model-predicted battery prices, and the green line with circles shows the Bloomberg New Energy Finance (BNEF) battery price index. The differences are partly driven by coverage: we focus on passenger EVs, whereas BNEF index is based on survey data that also covers commercial vehicles and storage batteries. Panel (b) shows the reduction in sales-weighted average battery prices that correspond to the learning component $\gamma_0 {E_{bt}}^{\gamma_E}$. The line with red triangles represents battery costs for BYD & CATL in China, the line with black circles stands for LG & Samsung in South Korea, and the line with blue squares stands 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 2013 to 2020: Austria, Canada, China, France, Germany, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the UK, and the U.S. All prices are in nominal U.S. dollars ($). 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_c/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-logit regressions, respectively. Price instruments include battery supplier dummies interacted with battery capacity, as well as three IVs based on vehicle attributes. Column (3) is the random coefficient multinomial logit model and is estimated using simulated GMM with IVs and 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 the unobserved preference shock (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 (8). 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 that instruments battery supplier experience, battery markup (the variable corresponding to bargaining weight), and EV producer experience. The marginal cost of battery pack is specified as: $BK_{bjct}\left(\gamma_0 E_{bt}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta t\right)$, where BK is battery capacity, γ_E is the learning parameter, and γ_0 captures 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) 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., the logarithm of cumulative EV production by each EV producer) 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 (8). 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): Impact 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 Variable Profit (+)	-0.21	-	4.59	-	4.38
Δ EV Variable 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): Impact 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 Variable Profit (+)	-0.11	-	3.97	-	3.87
Δ EV Variable 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): Impact 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 Variable Profit (+)	7.52	-	-0.11	-	7.41
Δ EV Variable 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 impact (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) estimates the impact of US subsidies by comparing scenarios with and without US subsidies but holding consumer subsidies in China and Europe fixed. Panels (b) and (c) are obtained similarly.

Table 6: Impact of China's Whitelist Policy

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impact of China's Whitelist Policy 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 Variable Profit (+)	3.17	-	-3.73	-	-0.56
Δ EV Variable 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): Impact of China's Whitelist Policy 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 Variable Profit (+)	10.69	-	-3.85	-	6.85
Δ EV Variable 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 impact (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 impact of China's 2016-2019 whitelist policy by comparing scenarios with and without the whitelist policy but holding consumer subsidies in place. Panel (b) shows the impact of the policy combination (whitelist and consumer subsidies together) by comparing scenarios with and without the policy combination.

Table 7: Impact of China's Counterfactual (Delayed) Whitelist Policy

	China	Europe	JP & KR	US & CA	Global
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 Variable Profit (+)	0.29	-	-0.80	-	-0.51
Δ EV Variable 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 analysis examines the role of the timing of China's whitelist policy. The table shows the impacts (aggregated during 2013-2025) of a counterfactual whitelist policy on social welfare and EV adoption across regions. This counterfactual policy is assumed to be implemented five years later, during 2021-2024 instead of 2016-2019 (as in the data). The table reports the difference between the two scenarios with and without the counterfactual whitelist policy but holding consumer subsidies in place.

Table 8: 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 impact (aggregated during 2013-2020) of China's consumer subsidies and the whitelist policy with and without LBD incorporated in the simulations. In the scenario without LBD, we set firms' experience as the initial experience in the sample.

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 and Industry Details

A.1 Battery Plant Capacity

Data on battery suppliers' plants are compiled from the 2022 lithium-ion battery gigafactory database by Automotive Logistics (AL) and market 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 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 account for 83.04% of global 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

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

A.2 Income Distribution

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-p50), and (3) the income share of the top 10% (p90-p100). 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:

$$(\text{predicted p0-p50} - \text{observed p0-p50})^2 + (\text{predicted p90-p100} - \text{observed p90-p100})^2.$$

A.3 IV Construction for Battery Experience

We construct the battery experience IV with Equation (9): $IV_{bt} = \sum_{s<t} \sum_j \hat{Pr}_{jbcs}(\mathbf{z}_{jbcs}) \hat{q}_{jcs}(\mathbf{X}_{jcs}, \phi_{jcs})$. This 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. 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 include a dummy variable for China's whitelist 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

[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.

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).

A.4 Battery Supply Agreements

Battery makers sell batteries to EV producers using battery supply agreements. These agreements are confidential and the exact details of the contracts (e.g., the agreed battery price) are not publicly known. Redacted copies of a few contracts, however, have been published by the U.S. Securities and Exchange Commission, including, notably, a 2009 battery supply agreement signed between Tesla and Panasonic in 2009.[3] The Tesla-Panasonic agreement was signed on June 2009 and had an initial end date of December 2010. The end date was automatically extended every year (by one year), unless one of the parties chose to terminate the agreement. The contract specified a linear price per every battery sold; and the quantity (i.e., the number of batteries to order) was chosen on a rolling basis by Tesla, though they were required to provide advance notice to Panasonic, as well as a non-binding, good faith six-month forecast of how many batteries they expect to purchase in the next six months. The 2007 Tesla-Sanyo agreement shared similar features.[4] These features inform some of our modeling choices: (1) battery suppliers and EV producers negotiate linear prices (as opposed to two-part tariffs, or contracts that specify both price and quantity) (2) firms negotiate short-term contracts where the price is only fixed for one year, as opposed to long-term contracts (since in the observed agreements, either party can terminate the contract each year).

B Modeling Details

B.1 Simultaneous Contracting and Pricing

Under the assumption of simultaneous contracting and pricing, bargaining over battery prices and EV price setting happen simultaneously. Let $d^{v,\text{Simult}}$ and $d^{b,\text{Simult}}$ denote the disagreement payoffs for EV supplier v and battery supplier b, respectively. Then the equations characterizing the Nash-

[3] See https://www.sec.gov/Archives/edgar/data/1318605/000119312510017054/dex1033.htm.

[4] See https://www.sec.gov/Archives/edgar/data/1318605/000119312510017054/dex1027.htm.

in-Nash bargaining equilibrium (Equation (4)) can be written as:

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

We now describe how we use the above bargaining FOCs as well as the FOCs characterizing downstream EV pricing to derive upstream markups as a function of downstream markups and bargaining weight (equation (5)). This closely follows Draganska, Klapper, and Villas-Boas (2010).

Profits and Disagreement Payoffs The profits for EV producer v and battery supplier b can be written as:

$$\pi^v(\mathbf{p},\phi) = \sum_{k\in\Omega_v}(p_k - \tau_k - mc_k^v)q_k(\mathbf{p},\phi) = \sum_{k\in\Omega_v} mk_k^v q_k(\mathbf{p},\phi)$$

$$\pi^b(\mathbf{p},\phi) = \sum_{k\in\Omega_b}(\tau_k - mc_k^b)q_k(\mathbf{p},\phi) = \sum_{k\in\Omega_b} mk_k^b q_k(\mathbf{p},\phi)$$

Their disagreement payoffs are:

$$d^{v,\text{Simult}}(\mathbf{p},\phi) = \sum_{k\in\Omega_v}(p_k - \tau_k - mc_k^v)\tilde{q}_k(\mathbf{p},\phi) = \sum_{k\in\Omega_v} mk_k^v \tilde{q}_k(\mathbf{p},\phi)$$

$$d^{b,\text{Simult}}(\mathbf{p},\phi) = \sum_{k\in\Omega_b}(\tau_k - mc_k^b)\tilde{q}_k(\mathbf{p},\phi) = \sum_{k\in\Omega_b} mk_k^b \tilde{q}_k(\mathbf{p},\phi),$$

which embeds that when bargaining breaks down over the battery price for vehicle j (i.e., when there is a disagreement), vehicle j is removed from the market, but all other vehicles are supplied at the same prices as they would be under agreement. Here, note that $\tilde{q}_j(\mathbf{p},\phi) = 0$ (since $\tilde{q}$ denotes the sales when vehicle j is not offered).

Gains from Trade The gains from trade for EV maker v can be written as:

$$\pi^v - d^{v,Simult} = \sum_{k\in\Omega_v} mk_k^v[q_k(\mathbf{p},\phi) - \tilde{q}_k(\mathbf{p},\phi)]$$

Likewise, the gains from trade for battery supplier b can be written as:

$$\pi^b - d^{b,Simult} = \sum_{k\in\Omega_b} mk_k^b[q_k(\mathbf{p},\phi) - \tilde{q}_k(\mathbf{p},\phi)]$$

Profit Derivatives The derivative of EV producer v's profits with respect to the battery price for vehicle j, τ_j, can be written as:

$$\frac{\partial \pi^v}{\partial \tau_j} = -q_j$$

This is because, under simultaneous contracting and pricing, an incremental change in the battery price has no direct effect on downstream EV prices, so the derivatives of downstream EV prices with respect to battery prices are zero. In a similar manner, the derivative of battery supplier b's profits with respect to τ_j can be written as:

$$\frac{\partial \pi^b}{\partial \tau_j} = q_j$$

Upstream Markups We now plug in the above expressions for the gains from trade and profit derivatives into the bargaining FOC for the battery price for vehicle j:

$$(1-\lambda^b)\underbrace{(\pi^b - d^{b,Simult})}_{\text{b's gains from trade}}(-q_j) + \lambda^b \underbrace{(\pi^v - d^{v,Simult})}_{\text{v's gains from trade}} q_j = 0$$

$$\pi^b - d^{b,Simult} = \frac{\lambda^b}{1-\lambda^b}(\pi^v - d^{v,Simult})$$

We now combine this FOC across different vehicles j to obtain the full vector of upstream markups as a function of the vector of downstream markups. To facilitate this, we define a matrix $\mathbf{S}$, whose j,k term equals $q_k(\mathbf{p},\phi) - \tilde{q}_k(\mathbf{p},\phi)$ (where recall that $\tilde{q}_k(\mathbf{p},\phi)$ equals the sales of vehicle k when there is disagreement over the battery price of vehicle j and vehicle j is removed from the set of products offered). Let $\mathbf{T^v}$ denote the ownership matrix for EV producers: $T^v(k,l)$ equals 1 if vehicles k and l are produced by the same EV producer and is 0 otherwise. Similarly, let $\mathbf{T^b}$ denote the ownership matrix for battery suppliers: $T^b(k,l)$ equals 1 if the batteries for vehicles k and l are supplied by the same battery supplier, and is 0 otherwise.

In matrix form, the gains from trade to EV producers and battery suppliers can be respectively written as:

$$\boldsymbol{\pi^v} - \boldsymbol{d^{v,Simult}} = (\mathbf{T^v} \otimes \mathbf{S})\boldsymbol{mk}^v$$
$$\boldsymbol{\pi^b} - \boldsymbol{d^{b,Simult}} = (\mathbf{T^b} \otimes \mathbf{S})\boldsymbol{mk}^b,$$

where $\otimes$ denotes element-by-element multiplication. Plugging these into the above bargaining FOC, we obtain:

$$[\mathbf{T^b} \otimes \mathbf{S}]\boldsymbol{mk}^b = \frac{\lambda^b}{1-\lambda^b}[\mathbf{T^v} \otimes \mathbf{S}]\boldsymbol{mk}^v$$
$$\boldsymbol{mk}^b = \frac{\lambda^b}{1-\lambda^b}[\mathbf{T^b} \otimes \mathbf{S}]^{-1}[\mathbf{T^v} \otimes \mathbf{S}]\boldsymbol{mk}^v,$$

which is the key estimation equation capturing how upstream markups are expressed as a function of downstream markups.

B.2 Sequential Contracting and Pricing

In the sequential contracting and pricing 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 the Nash product:

$$NP_j(\tau_j, \tau_{-j}) = \underbrace{\left(\pi^v - d^{v,Sequential}\right)}_{\text{v's gains from trade}}{}^{(1-\lambda^b)} \underbrace{\left(\pi^b - d^{b,Sequential}\right)}_{\text{b's gains from trade}}{}^{\lambda^b} \tag{A1}$$

and the bargaining FOCs are the same as before. However, two changes arise in Equation (4) due to the timing assumptions:

1. The disagreement profits $d^{v,Sequential}$ and $d^{b,Sequential}$ depend on the new equilibrium downstream EV prices that would arise if EV model j is not offered; that is, downstream EV prices are no longer constant under disagreement. The equilibrium downstream EV prices for all EV models in the case of disagreement need to be re-calculated for every $\{v,b\}$ pair.

2. The derivatives of downstream and upstream profits with respect to battery prices differ from simultaneous contracting and pricing because firms anticipate that any change in the negotiated battery price will result in a change in downstream EV prices.

Disagreement Payoffs The disagreement payoffs for EV producer v and battery supplier b when upstream bargaining and downstream price-setting happen sequentially are:

$$d^{v,\text{Sequential}}(\tilde{\mathbf{p}}, \phi) = \sum_{k \in \Omega_v} (\tilde{p}_k - \tau_k - mc_k^v)\tilde{q}_k(\tilde{\mathbf{p}}, \phi) = \sum_{k \in \Omega_v} \widetilde{mk}_k^v \tilde{q}_k(\tilde{\mathbf{p}}, \phi)$$

$$d^{b,\text{Sequential}}(\tilde{\mathbf{p}}, \phi) = \sum_{k \in \Omega_b} (\tau_k - mc_k^b)\tilde{q}_k(\widetilde{\mathbf{p}}, \phi) = \sum_{k \in \Omega_b} \widetilde{mk}_k^b \tilde{q}_k(\widetilde{\mathbf{p}}, \phi)$$

Here, $\widetilde{q}$, $\widetilde{p}$ and $\widetilde{mk}$ represent the equilibrium EV sales, prices, and markups when product j is excluded from the market.

Gains from Trade The gains from trade for EV maker v from selling vehicle j are

$$\pi^v - d^{v,Sequential} = \sum_{k \in \Omega_v} \left[mk_k^v q_k(\mathbf{p}, \phi) - \widetilde{mk}_k^v \, \widetilde{q}_k(\widetilde{\mathbf{p}}, \phi) \right]$$

Stacking these across vehicle models, we can write down the gains from trade to EV producers as:

$$\boldsymbol{\pi^v} - \boldsymbol{d^{v,Sequential}} = (\mathbf{T^v} \otimes \mathbf{M^v}) \cdot l$$

Here, $\mathbf{M^v}$ captures the changes in profits due to a price change of vehicle k when there is disagreement over the battery price for vehicle j (taking into account that the downstream prices for all other vehicles will be adjusted upon disagreement), $\otimes$ denotes element-by-element multiplication, and l is a vector consisting entirely of ones. Similarly, the gains from trade for battery supplier b from supplying batteries for EV model j are given by

$$\pi^b - d_j^b = \sum_{k \in \Omega_b} \left[mk_k^b(\tau) q_k(p) - mk_k^b(\tau) \widetilde{q}_k(\widetilde{p}) \right]$$

Stacking these across vehicle models, the gains from trade to battery suppliers can be expressed:

$$\boldsymbol{\pi^b} - \boldsymbol{d^{b,Sequential}} = (\mathbf{T^b} \otimes \tilde{\mathbf{S}}) \cdot \boldsymbol{mk}^b$$

The j,k term of $\tilde{\mathbf{S}}$ equals $q_k(\mathbf{p},\phi) - \tilde{q}_k(\tilde{\mathbf{p}},\phi)$. $\tilde{\mathbf{S}}$ therefore represents the changes in sales upon disagreement, similar to the matrix $\mathbf{S}$ defined in the previous Section B.1, except that it takes into account that downstream prices are reset upon disagreement.

Profit Derivatives The derivative of the EV maker's profit with respect to the battery price τ_j is:

$$\frac{\partial \pi^v}{\partial \tau_j} = \sum_{k \in \Omega_v} \frac{d\pi_k^v}{d\tau_j},$$

and in matrix form, this can be written as $(\mathbf{T^v} \otimes \boldsymbol{\Delta}_\tau^{\pi^v}) \cdot l$, where $\boldsymbol{\Delta}_\tau^{\pi^v}$ collects the derivatives of downstream profits with respect to upstream prices. Similarly, the derivative of the battery supplier's profit with respect to the battery price τ_j is given by:

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

which in matrix form becomes $\boldsymbol{q} + (\mathbf{T^b} \otimes \boldsymbol{\Delta}_\tau^q) \cdot \boldsymbol{mk}^b$, where $\boldsymbol{\Delta}_\tau^q$ collects the derivatives of downstream sales with respect to battery prices.

Upstream Markup Then, the bargaining FOC becomes:

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

From this, we can derive upstream markups as follows:

$$\boldsymbol{mk}^b = -\left[\frac{(1-\lambda^b)}{\lambda^b} \cdot \mathbf{X_t} \cdot (\mathbf{T^b} \otimes \tilde{\mathbf{S}}) + (\mathbf{T^b} \otimes \boldsymbol{\Delta}_\tau^q)\right]^{-1} \cdot \boldsymbol{q}, \tag{A2}$$

where $\mathbf{X_t}$ is a diagonal matrix defined as:

$$\mathbf{X_t} = \text{diag}\left(\left[(\mathbf{T^v} \otimes \boldsymbol{\Delta}_\tau^{\pi^v}) \cdot l\right] \oslash \left[(\mathbf{T^v} \otimes \mathbf{M^v}) \cdot l\right] \right).$$

The notation $\oslash$ denotes element-wise division. With the above expression for upstream markups (as a function only of the bargaining weight λ^b and quantities that can be calculated following demand estimation, such as downstream markups) in hand, the supply-side estimation process follows the steps as outlined in Section 4.2.

B.3 Linear Pricing

Here we describe the derivation of upstream markups in the simple linear pricing model (Villas-Boas, 2007). In the first stage of this game, upstream battery suppliers simultaneously choose battery prices; and in the second stage, downstream EV producers simultaneously choose EV prices, after observing the battery prices. Note that this is equivalent to the sequential contracting and pricing model described above when $\lambda^b = 1$, i.e., when upstream battery suppliers can make take-it-or-leave-it offers to downstream EV producers. Setting $\lambda^b = 1$ in Equation (A2), we obtain the following equation for upstream markups in the linear pricing model:

$$\boldsymbol{mk}^b = -(\mathbf{T^b} \otimes \boldsymbol{\Delta}^q_\tau)^{-1} \cdot \boldsymbol{q}. \tag{A3}$$

B.4 Dynamic Bargaining

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 EV firms simultaneously choose EV markups to maximize their profits $\pi^v(\mathbf{p}) = \sum_{j \in \Omega_v}(p_j - \tau_j - mc^v_j)q_j(\mathbf{p}, \phi)$. We make the assumption that EV producers choose *markups* (rather than prices) to ensure that changes in negotiated battery prices directly affect 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' experience and future production costs.[5] In addition, firms assume that future markups remain the same as the equilibrium markups in the current period, as we explain more below.

These assumptions capture the essence of LBD dynamic considerations in which upstream suppliers use low prices to stimulate downstream demand while abstracting away modeling complications that would make the problem intractable (including downstream firms' incentives to manipulate prices). An alternative assumption is that upstream battery price negotiations happen first, followed by downstream EV pricing, i.e., a dynamic extension of the sequential contracting and pricing model presented in Section B.2, but this alternative approach is less tractable.

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

$$NP_t(\tau_{jt}, \tau_{-jt}) = \underbrace{(\pi^v_t - d^v_t)}_{\text{v' gains}}{}^{(1-\lambda^b)} \underbrace{(V^b_t - D^b_t)}_{\text{b' gains}}{}^{\lambda^b}. \tag{A4}$$

The downstream profits π^v_t and deviation payoffs d^v_t are the same as those in Equation (A1). On the other hand, battery suppliers' gains from trade are dynamic value functions that incorporate future profit gains. Battery supplier b's payoff upon agreement V^b_t is defined as:

$$V^b_t = \sum_{k \in \Omega^b_t} mk^b_{kt} \cdot q_{kt}(mk^v_{kt} + mk^b_{kt} + mc_{kt}) + \sum_{s=1}^{\infty} \beta^s \sum_{k \in \Omega^b_{t+s}} mk^b_{kt+s} \cdot q_{kt+s}(mk^v_{kt+s} + mk^b_{kt+s} + mc_{kt+s}), \tag{A5}$$

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-

[5] The preferred bargaining model in the main text ("Simultaneous Contracting and Pricing") assumes that EV firms choose prices (not markups). Under this assumption, battery suppliers have no direct influence on downstream prices or sales, i.e., $\frac{\partial p_j}{\partial \tau_j} = 0$. Consequently, battery firms cannot lower the negotiated battery price today to increase experience tomorrow.

battery vehicle components ($mc^b + mc^v$). The equilibrium quantity q is determined by the final EV price, which is equal to $mk^v + mk^b + mc$.[6] The second term in Equation (A5) is the present 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:

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

where $\widetilde{q}_{kt}$ represents sales when product j is withdrawn from the market in time t.[7] We consider one-period deviations similar to Lee and Fong (2013) and other empirical dynamic papers. 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 impose three simplifying assumptions:

(A1) Battery suppliers believe that the current market structure, consumer preferences, and market size continue indefinitely:

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

(A2) Battery suppliers do not consider the impact of the battery price on future markups:

$$\frac{\partial mk_{kt+s}^v}{\partial \tau_{jt}} = \frac{\partial mk_{kt+s}^b}{\partial \tau_{jt}} = 0 \text{ for all } j, k, \text{ and } s.$$

(A3) Battery suppliers assume future markups to remain the same as the equilibrium markups (mk^*) in the current period:

$$mk_{jt+s}^v = mk_{jt}^{v*} \text{ and } mk_{jt+s}^b = mk_{jt}^{b*} \text{ for all } j \text{ and } s.$$

Adjusting the battery price in the current period affects not only current profits but also the experience gained by battery suppliers, which influences future production costs. The future profits depend on future markups and quantities, and thus, the choice of the current battery price impacts future profits in two ways: (1) by changing future markups and (2) by influencing future sales volumes. Assumption (A2) indicates that battery suppliers do not account for the first channel (the impact on future markups) when negotiating battery prices with automakers. Instead, they focus solely on the second channel (how the current battery prices affect future sales quantities via LBD cost reductions). Lastly, Assumption (A3) suggests that battery suppliers believe future markups remain at the current equilibrium level. Assumption (A2) is a behavioral assumption that makes the dynamic analysis tractable, in spirit similar to Gowrisankaran and Rysman (2012) and Benkard, Jeziorski, and Weintraub (2015).[8]

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

[7] Markups and costs of other EVs remain unchanged by construction.

[8] Gowrisankaran and Rysman (2012) develop a dynamic demand model and assume for tractability that the evolution

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

$$(1-\lambda^b)(V_t^b - D_t^b)\frac{\partial \pi_t^v}{\partial \tau_{jt}} + \lambda^b(\pi_t^v - d_t^v)\frac{\partial V_t^b}{\partial \tau_{jt}} = 0.$$

The derivative of battery suppliers' payoff under agreement with respect to battery price becomes:

$$\frac{\partial V_t^b}{\partial \tau_{jt}} = \underbrace{q_{jt} + \sum_{k \in \Omega_t^b} mk_{kt}^b \cdot \frac{\partial q_{kt}}{\partial p_{jt}}}_{\text{Impact on current profit}} + \underbrace{\sum_{s=1}^{\infty} \beta^s \sum_{k \in \Omega_t^b} mk_{kt}^{b*} \cdot \sum_m \frac{\partial q_{kt+s}}{\partial p_{mt+s}} \frac{dmc_{mt+s}}{d\tau_{jt}}}_{\text{Impact on future profits via LBD}}.$$

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

$$(1-\lambda^b)\left[(\mathbf{T}_t^b \otimes \mathbf{S}_t^+)\cdot \mathbf{mk}_t^b\right] \otimes [(\mathbf{T}_t^v \otimes \mathbf{\Delta}_t)\cdot \mathbf{mk}_t^v] + \lambda^b [(\mathbf{T}_t^v \otimes \mathbf{S}_t)\cdot \mathbf{mk}_t^v] \otimes \left[\mathbf{q}_t + (\mathbf{T}_t^b \otimes \mathbf{\Delta}_t^+)\cdot \mathbf{mk}_t^b\right] = 0,$$

where $\otimes$ is the element-wise multiplication. Note that $\mathbf{T}$ and $\mathbf{S}$ are the same as those defined in Equation 5. The matrix $\mathbf{\Delta}_t$ represents the derivative of EV demand in period t with respect to EV prices. In contrast, $\mathbf{S}^+$ is a deviation matrix that incorporates dynamic terms, with (j,k)-element:

$$S_{jk}^+ = (q_{kt} - \widetilde{q}_{kt}) + \sum_{s=1}^{\infty} \beta^s \cdot (q_{jt+s} - \widetilde{q}_{jt+s}). \tag{A6}$$

In comparison, $\mathbf{S}$ only includes the first term in Equation (A6). Similarly, the $\mathbf{\Delta}_t^+$ also incorporates the derivatives of future EV demand due to changes in future marginal costs through LBD. Specifically, the (j,k)-element of $\mathbf{\Delta}_t^+$ is:

$$\Delta_{jkt}^+ = \frac{\partial q_{kt}}{\partial p_{jt}} + \sum_{s=1}^{\infty} \beta^s \sum_m \frac{\partial q_{kt+s}}{\partial p_{mt+s}} \frac{dmc_{mt+s}}{d\tau_{jt}}. \tag{A7}$$

Note that $\mathbf{\Delta}_t$ only includes the first term in Equation (A7).

Finally, we derive the upstream markup as a function of the downstream markup from the FOCs, similar to the approach in Section 3.2:

$$\mathbf{mk}_t^b = -\left[\frac{(1-\lambda^b)}{\lambda^b}\cdot \mathbf{X}_t \cdot (\mathbf{T}_t^b \otimes \mathbf{S}_t^+) + (\mathbf{T}_t^b \otimes \mathbf{\Delta}_t^+)\right]^{-1} \cdot \mathbf{q}_t, \tag{A8}$$

of the value of purchase follows a simple one-dimensional Markov process. Benkard, Jeziorski, and Weintraub (2015) develop the notion of a partially oblivious equilibrium, where firms only keep track of the states of dominant firms and the long-run industry state instead of keeping track of the state of every single firm in the industry. This simplifying assumption allows the dynamic oligopoly model to remain relatively tractable to compute and estimate.

where $\mathbf{X}_t$ is a diagonal matrix:

$$\mathbf{X}_t := \text{diag}\left([(\mathbf{T}_t^v \otimes \boldsymbol{\Delta}_t) \cdot \mathbf{mk}_t^v] \oslash [(\mathbf{T}_t^v \otimes \mathbf{S}_t) \cdot \mathbf{mk}_t^v] \right).$$

The notation $\oslash$ denotes element-wise division. Given Equation (A8), the estimation process follows the steps as outlined in Section 4.2.

C Counterfactual Analyses and Simulations

C.1 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 likely affects the supply network and shifts 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 at 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 the 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 previous relationships.

C.2 Algorithm for Counterfactual Analyses

For each counterfactual, 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 (4) 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 network, equilibrium prices and sales are recalculated. This process is repeated annually through 2020. Because the link formation process is stochastic, 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.

In the whitelist policy simulations, EV models are allowed to choose a battery supplier in 2016, the policy's beginning year. Hence, in the 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 counterfactuals (Table 7) examines the welfare implications of postponing the whitelist to 2021-2025 after the final sample year. To simulate firm profits 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.

C.3 Environmental Benefits of EV Adoption

This section describes the environmental benefits of EVs relative to gasoline vehicles. Replacing a gasoline vehicle with an electric vehicle (EV) could deliver environmental benefits through reductions in both CO_2 emissions and local 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 Reduction Benefit The carbon reduction benefit reflects the avoided economic damages from reduced CO_2 emissions. A typical gasoline vehicle in the U.S. emits 4.6 tons of CO_2 annually, assuming an average annual vehicle miles traveled (VMT) of 11,500 miles (FHWA, 2022). The average annual VMTs for China, Europe, and South Korea / Japan are 10,000 miles/year (CMT, 2022), 9,500 miles/year (Eurostat, 2020), and 10,200 miles/year (KTI, 2023), respectively. Carbon emission reductions when a gasoline vehicle is replaced with an EV depends on the carbon intensity of electricity grids (International Energy Agency, 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 (due to its moderately clean grid with significant renewables), and 52.5% for South Korea and Japan (due to their mixed reliance on fossil fuels and nuclear energy). Finally, the latest estimate of the social cost of carbon is $185 per ton of CO_2, based on comprehensive global evidence (Rennert,Kevin and Others, 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 local air pollutants such as $PM_{2.5}$, NO_x, and VOCs. These pollutants are shown to cause 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 health benefit is calculated similarly to carbon reduction benefit.

Environmental Benefits The lifetime environmental benefits of replacing a gasoline vehicle with an EV are summarized in Table A2. The benefit ranges from $16,465 (South Korea & Japan) to $19,506 (China) as shown in Column (4). Regional variations reflect differences in annual vehicle miles traveled and grid carbon intensity.

The calculations above are based on the environmental performance of an average gasoline vehicle in the fleet, implicitly assuming that EVs replace an average gasoline vehicle. Xing, Leard, and Li (2021) document that the EVs tend to replace more fuel efficient gasoline vehicles and hybrid vehicles. Therefore, ignoring the non-random replacement of gasoline vehicles would result in overestimating emissions benefits of EVs by 39 percent. To be on the conservative side, we scale down the environmental benefits by half (shown in Column (5) and use these estimates in our welfare analysis.

Table A2: Lifetime Environmental Benefits Of Replacing A Gasoline Vehicle With An EV

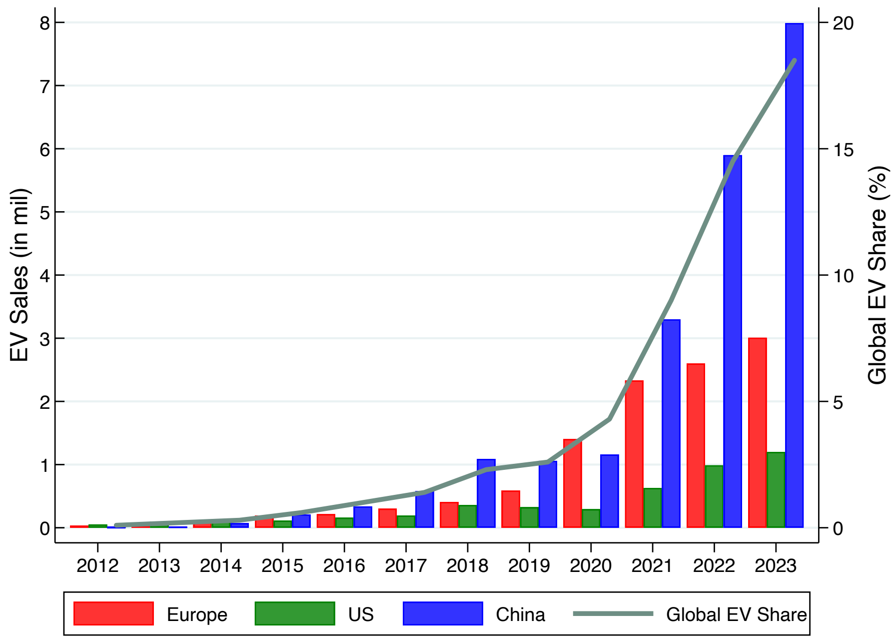
Region	(1) CO_2 Savings (ton/year)	(2) Carbon Benefit ($)	(3) Health Benefit ($)	(4) Total Benefit ($) Upper	(5) Lower
China	2.3	5,106	14,400	19,506	9,753
United States	3.22	7,141	12,000	19,141	9,571
Europe	2.76	6,124	10,800	16,924	9,462
South Korea & Japan	2.42	5,365	11,100	16,465	8,233

Notes: The calculation of environmental benefits assumes 12 years of vehicle lifetime. The lower bound recognizes the fact EVs tend to replace more fuel efficient vehicles than an average gasoline vehicle.

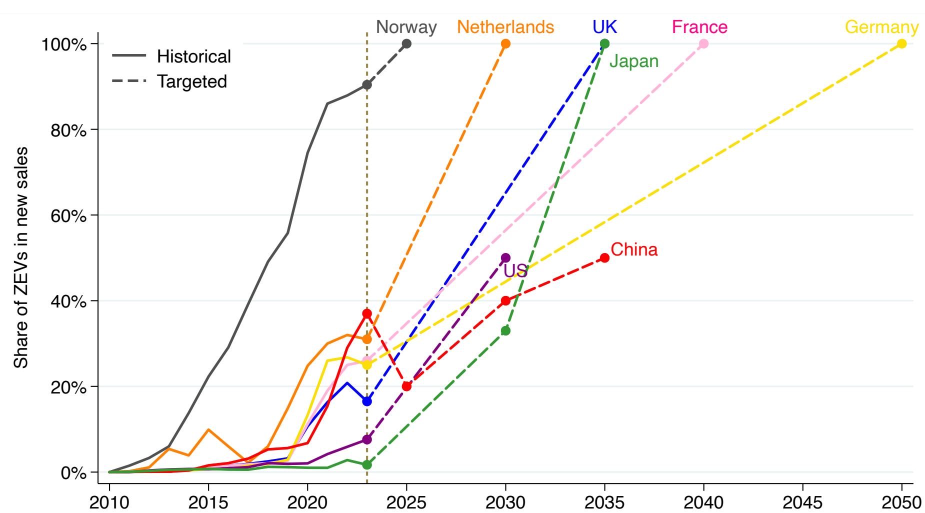
D Appendix Figures

Figure A1: Global EV Diffusion

(a) EV Sales by Region



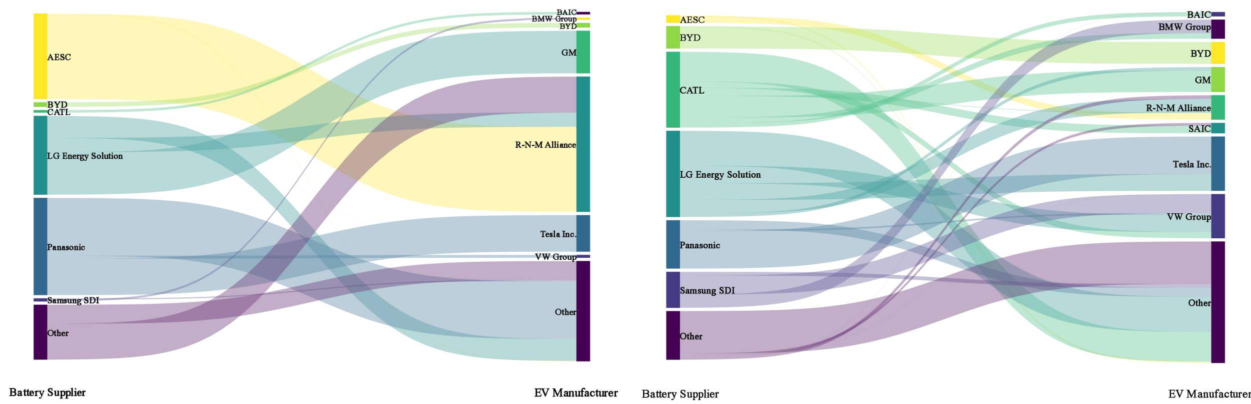
(b) ZEV Targets and Market Shares



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 this 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

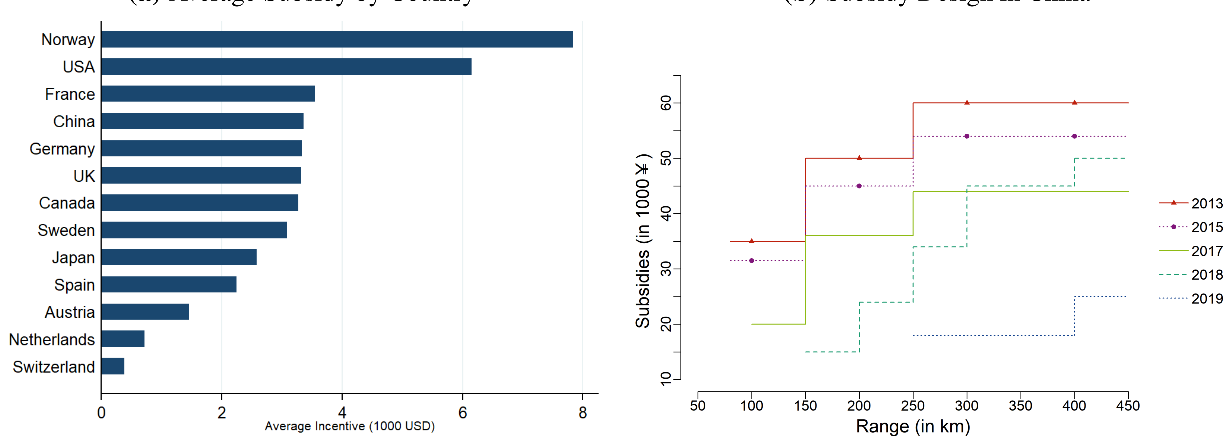
(a) 2013 Network **(b)** 2020 Network



Notes: The graphs depict the vertical relationship between battery suppliers (on the left) and EV producers (on the right) in 2013 (Panel (a)) and 2020 (Panel (b)). The top 6 battery suppliers and top 8 EV producers are shown separately, illustrating an oligopoly market structure in both the upstream and downstream sectors. The thickness of the lines represents the battery sales volume in units.

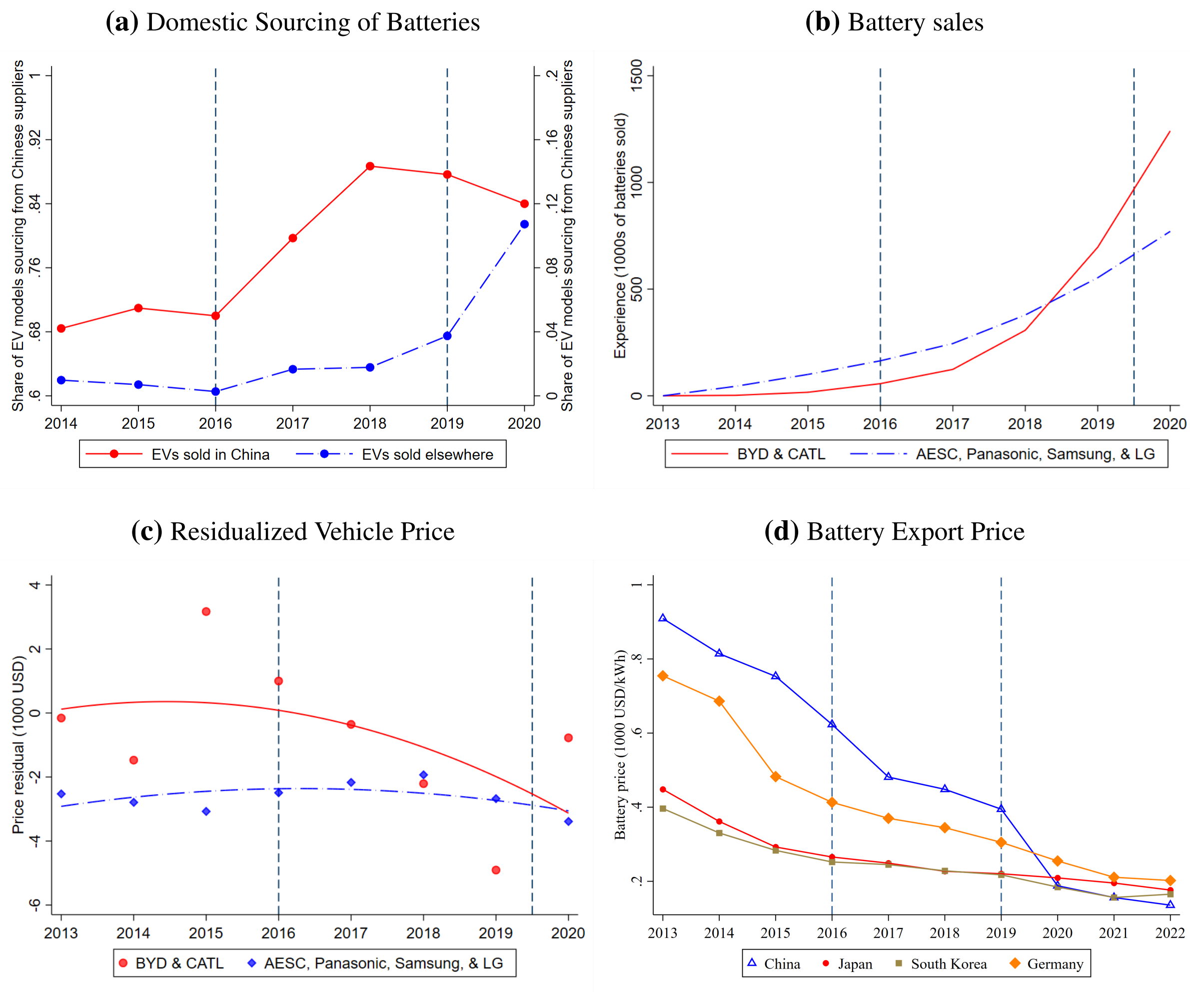
Figure A3: EV Subsidies

(a) Average Subsidy by Country **(b)** Subsidy Design in China



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

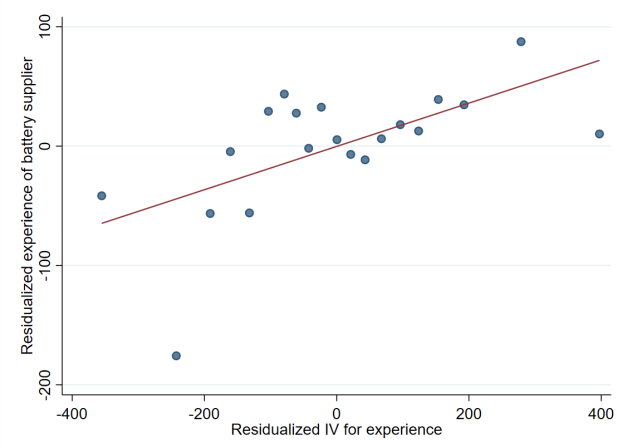
Figure A4: China's Whitelist Policy



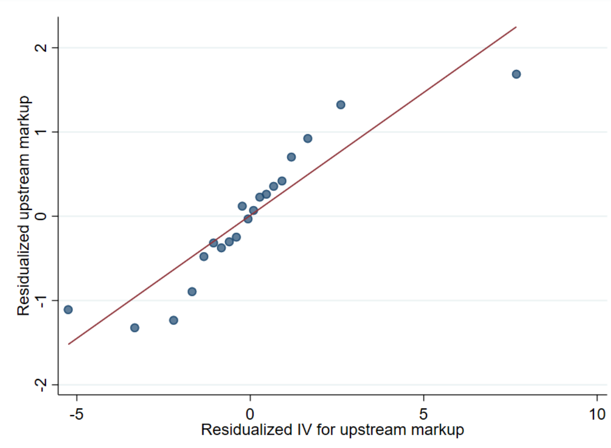
Notes: The two dotted vertical lines depict the timing of China's whitelist policy. Panel (a) shows the share of EV models sourcing from Chinese battery suppliers separately for EV models sold in China (red solid line, left y-axis) and those sold elsewhere (blue dashed line, right y-axis). Panel (b) shows the growth of (average) experience of battery suppliers over time separately for the top two Chinese suppliers (BYD and CATL) and the leading non-Chinese suppliers (AESC, Panasonic, LG, and Samsung). Panel (c) depicts the average EV price by year for the two groups. Panel (d) shows the free-on-board battery price ($/kWh) by country-of-origin from UN Comtrade. The price unit in UN Comtrade was $/liter, which we transform to $/kWh based on the average energy density for each year.

Figure A5: Instruments for Experience and Battery Markups

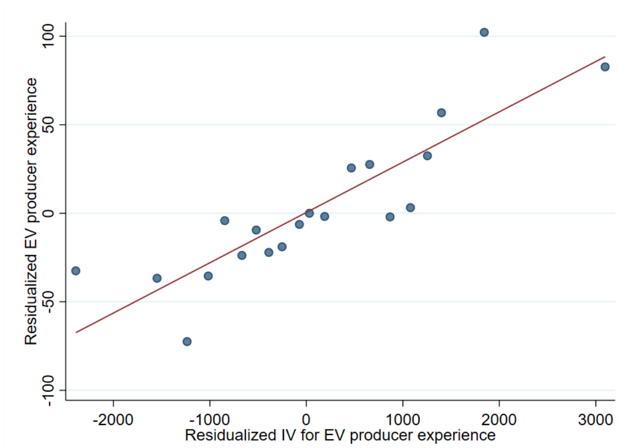
(a) Battery Supplier Experience



(b) Battery Markup

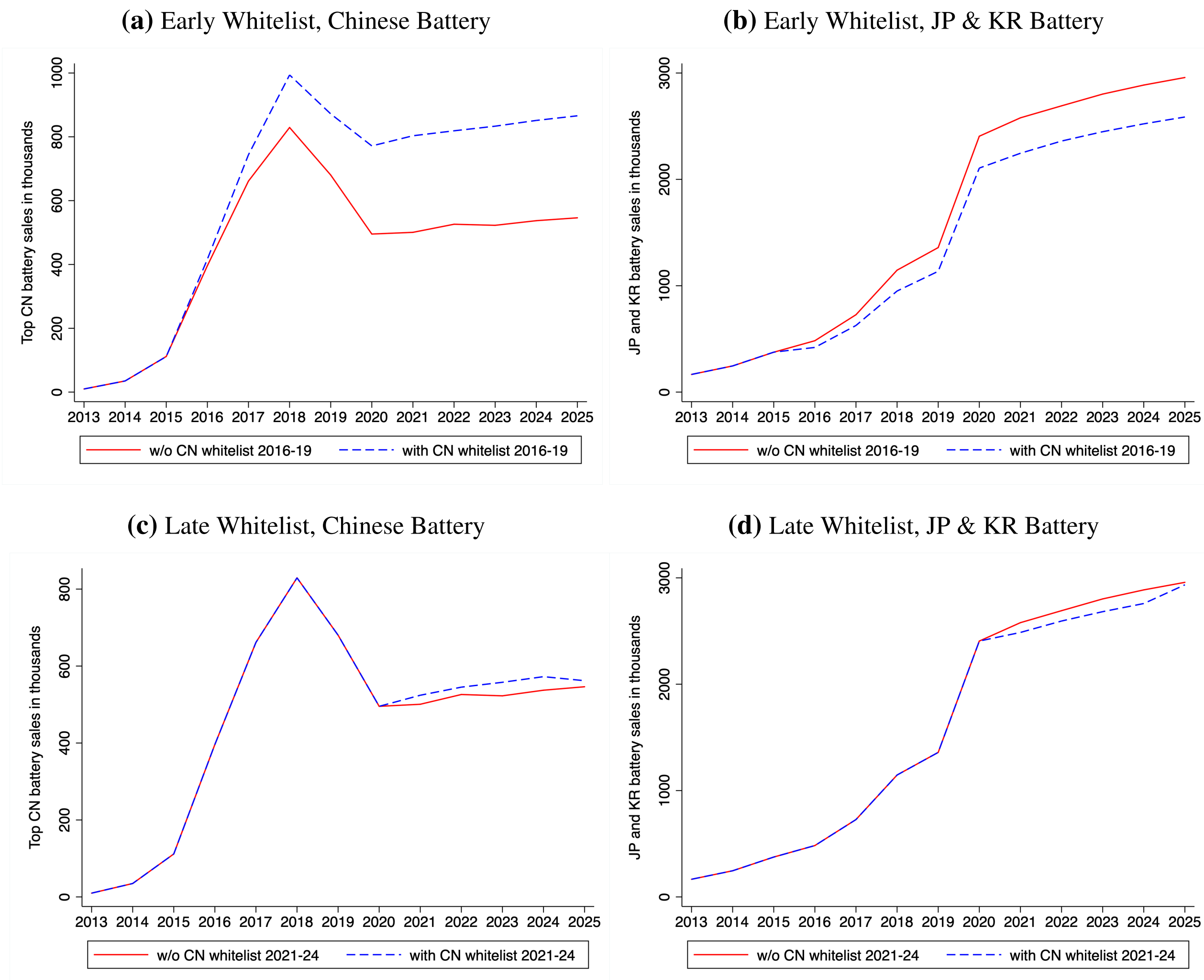


(c) EV Producer Experience



Notes: Binned scatter plots illustrate the strength of the IVs for the experience and markups of battery suppliers (Panels (a) and (b)), as well as the IV for the experience of EV producers (Panel (c)). Residuals are obtained from partialling out vehicle attributes, as well as country, brand, and year fixed effects.

Figure A6: Impact of China's Whitelist Policy (Early and Late) on Battery Production



Notes: Panel (a) illustrates EV battery production by Chinese suppliers under scenarios with and without China's observed whitelist policy in 2016-2019. Panel (b) presents battery production by non-Chinese suppliers under the same scenarios. Panels (c) and (d) repeat the exercise and depict the impact on forward-simulated battery production if the whitelist policy was implemented between 2021 and 2024 instead.

E Appendix Tables

Table A3: LBD Estimation Results With Sequential Contracting and Pricing

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 Parameter 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 contracting and pricing (Appendix B.2), with different values of the bargaining parameter λ^b. Estimation is done analogously as that in Table 3. 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 Parameter 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), with different values of the bargaining parameter λ^b. Estimation is done analogously as that in Table 3. See Table 3 for variable definitions.

Table A5: LBD: Spillovers Across Firms

	(1) No spillovers	(2) Spillovers
Battery Cost Parameters		
Learning Parameter 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 supply-side parameter estimates allowing for within-country across-firm learning spillovers. 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 an estimated parameter θ. We instrument for rival experience using predicted rival experience constructed based on Equation (9). Estimation is done analogously as that in Table 3. See Table 3 for variable definitions.

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

	(1)	(2)
Battery Cost Parameters		
Learning Parameter γ_E	-0.113	-0.116
	(0.052)	(0.054)
γ_0(1000$/kWh)	0.858	0.924
	(0.164)	(0.167)
BK * Time Trend	-0.032	-0.022
	(0.006)	(0.009)
BK * log(Plant Capacity)	-0.078	-0.085
	(0.035)	(0.036)
BK * log(Cumulative Patents)		-0.023
		(0.013)
BK * Battery Chemistry Dummies	✓	✓
BK * Lithium Prices	✓	✓
Vehicle Cost Parameters		
EV Experience	-0.997	-1.196
	(0.421)	(0.411)
PHEV	2.172	1.947
	(1.104)	(1.084)
Horsepower	0.244	0.239
	(0.007)	(0.007)
Volume	0.807	0.723
	(0.232)	(0.226)
Bargaining Parameter		
Bargaining Weight, λ^b	0.275	0.366
	(0.132)	(0.091)
Fixed Effects		
Country	✓	✓
EV Brand	✓	✓
Battery Supplier	✓	✓
Year	✓	✓

Notes: This table reports supply-side parameter estimates controlling for firm innovations. Column(1) is identical to Column (1) from Table 3. In Column (2), we control for firm-level innovation activities by adding the number of cumulative patents (in logarithm) applied for by the battery firm since 2008. We instrument for the patent variable using the battery firm's exposure to industrial policies targeting the EV sector. Specifically, we construct for each firm: (1) a weighted sum of current year industrial policies targeted at the EV sector across countries, and (2) a weighted sum of cumulative EV industrial policies across countries. The weights are the battery firm's predicted sales in a given country, $\hat{q}_{jct}(X_{jcs}, \phi_{jcs})$ (the same predicted sales that are used to construct the IV for experience). We then include both these IVs directly as well as their interaction with battery capacity. The data source and the construction of both the patent and the industry policy variables are discussed in detail in Barwick et al. (2024). Estimation is done analogously as that in Table 3. See Table 3 for variable definitions.

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

	CATL experience			Panasonic experience		
	China	Rest of World	Global	Japan	Rest of World	Global
Δ CATL or Panasonic Profit	1.00	-	1.00	1.00	-	1.00
Δ Other Battery Profit	-0.02	0.00	-0.03	-0.02	-0.02	-0.04
Δ EV Variable Profit	2.53	-0.01	2.53	0.02	2.41	2.43
Δ Consumer Surplus	3.25	0.00	3.25	0.02	2.89	2.91
Δ Expenditure	2.19	0.00	2.19	0.00	1.69	1.70
Δ Welfare	4.57	-0.01	4.55	1.01	3.59	4.60

Notes: This table shows welfare changes resulting from an (exogenous) increase in the experience of CATL or Panasonic starting in 2013 (and continuing thereafter as experience accumulates). We normalize changes in the CATL or Panasonic profits to one. Changes in battery firms' profits in the home country are primarily driven by gains in CATL's and Panasonic's profit. All other values represent changes relative to the CATL or Panasonic profits.

Table A8: Network Formation Model for Counterfactual 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, Home Bias	Yes
Fixed Effects for Top 6 Suppliers	Yes
Supplier Characteristics	Yes
Log-likelihood	-1265.59
Observations	23495

Notes: 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.
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), the beginning year of China's whitelist policy. The eligible subsidy is the subsidy per EV sold, provided the supply relationship meets the eligibility requirement for EV consumer subsidies. From 2016-2019, EVs in China were ineligible for subsidies if their battery supplier was not on the whitelist. We control for the lagged network structure using dummies: one indicating if the supplier-OEM pair had a previous supply relationship, and another if they had a previous supply relationship in the same country.We also include a home bias dummy indicating if the supplier-OEM pair has the same country of origin. We include dummies for all supplier-OEM pairs that are vertically integrated. We also include the age of each supplier, and 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 Including Environmental Benefits

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impact of US Subsidies					
Δ Welfare ($ bn.)	0.55	2.67	5.66	15.32	24.20
Δ Consumer Surplus (+)	0.14	0.96	0.04	13.35	14.48
Δ Battery Variable Profit (+)	-0.21	-	4.59	-	4.38
Δ EV Variable 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 Environ. Benefit (+)	0.06	0.43	0.02	7.23	7.73
Δ EV Sales	6,646	50,224	2,266	754,788	813,925
Panel (b): Impact of European Subsidies					
Δ Welfare ($ bn.)	0.83	9.39	5.52	2.81	18.54
Δ Consumer Surplus (+)	0.15	14.63	0.04	0.89	15.71
Δ Battery Variable Profit (+)	-0.11	-	3.97	-	3.87
Δ EV Variable 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 Environ. Benefit (+)	0.08	6.36	0.03	0.49	6.95
Δ EV Sales	8,650	751,021	2,766	50,749	813,185
Panel (c): Impact of Chinese Subsidies					
Δ Welfare ($ bn.)	56.20	1.30	0.12	1.40	59.02
Δ Consumer Surplus (+)	27.04	0.67	0.01	0.33	28.05
Δ Battery Variable Profit (+)	7.52	-	-0.11	-	7.41
Δ EV Variable 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 Environ. Benefit (+)	26.31	0.25	0.01	0.18	26.75
Δ EV Sales	2,696,916	30,267	732	18,780	2,746,696

Notes: This table shows the impact (aggregated during 2013-2020) of consumer subsidies on social welfare, similar to Table 5, except that the social welfare includes environmental benefits (report in the second to the last row in each panel). The environmental benefits of EV adoption are calculated based on the lower bound estimates of the environmental benefits of replacing a gasoline vehicle with an EV in Column (5) in Table A2. Panel (a) estimates the impact of US subsidies by comparing scenarios with and without US subsidies but holding consumer subsidies in China and Europe fixed. Panels (b) and (c) are obtained similarly.

Table A10: Impact of Consumer Subsidies without Learning

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impact 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 Variable Profit	0.03	-	1.21	-	1.24
Δ EV Variable 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): Impact 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 Variable Profit	0.06	0.01	1.13	0.00	1.19
Δ EV Variable 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): Impact 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 Variable Profit	1.66	0.00	0.19	0.00	1.85
Δ EV Variable 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 impact (aggregated during 2013-2020) of consumer subsidies on social welfare, similar to Table 5, except that it shuts down LBD. Panel (a) estimates the impact of US subsidies by comparing scenarios with and without US subsidies but holding consumer subsidies in China and Europe fixed. Panels (b) and (c) are obtained similarly.