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

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November 2024

Abstract

Electric vehicle (EV) battery costs have declined by over 90% in the past decade. This study investigates the role of learning-by-doing (LBD) in battery production in driving this sharp reduction while accounting for technological advancements, accumulated experience in EV assembly, and economies of scale. The magnitude of LBD is pivotal to understanding the effects of two prominent classes of government policies – consumer subsidies and local content requirements – on industry structure. Leveraging rich data on product attributes and battery suppliers for EV models sold across 13 leading EV markets, we develop and estimate a structural model of the global EV industry that incorporates heterogeneous consumer choices, EV manufacturers' pricing strategies, and bilateral bargaining between EV makers and battery suppliers. The model allows us to recover battery costs for each EV model and quantify the extent of LBD. Battery production achieved an LBD rate of 8.6% during our sample period. LBD magnified the effectiveness of consumer subsidies on EV adoption by six times and led to positive complementarity among subsidies across countries. European and U.S. subsidies benefited other regions more than Chinese subsidies, largely due to higher import shares and a greater extent of sourcing from foreign battery suppliers. China's whitelist policy, which restricted EV subsidies to vehicles using domestically produced batteries, benefited domestic

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battery suppliers at the expense of foreign suppliers and domestic EV producers and consumers while inhibiting the positive global spillovers from consumer subsidies.

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

JEL Classification: F13, L52, L62, Q48

1 Introduction

Electrifying passenger transportation through the widespread adoption of electric vehicles (EVs) and simultaneously transitioning to a cleaner electricity grid is a crucial strategy in mitigating climate change. Many countries have set ambitious targets for transportation electrification and implemented policies to support the adoption of EVs. However, the high upfront cost of EVs, largely driven by the expensive lithium-ion batteries they use, constitutes a major barrier to broader adoption. While the cost of EV batteries has decreased by almost 90% between 2010 and 2020 (Bloomberg NEF, 2020), additional reductions are necessary if EVs were to become widely affordable. Industry experts recognize learning-by-doing (LBD) as a key factor in the significant reduction of battery costs.[1] As experience accumulates, unit production costs decrease, driven by reductions in scrap rates and improvements in production efficiency. Other factors, such as technological progress and changing supply conditions, might also have played a role in the decline in battery costs.

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

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

Second, the preferential treatment of domestic battery producers has become part of a growing spectrum of industrial policies in recent years. During 2016-2019, China implemented a whitelist policy that restricted EV subsidies to vehicles using batteries from government-approved (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 North America or free-trade-agreement partners. The broad implications of local content requirements hinge crucially on the size and scope of LBD. If LBD predominantly occurs within firms (i.e., internal LBD) and concentrates among industry leaders, these policies could accelerate LBD by consolidating production in a smaller set of firms. This would result in reduced EV battery prices but may come at the cost of increased market concentration. Conversely, if policies across countries erect regional barriers and redirect production toward domestic (and potentially less efficient) producers, they might slow down global LBD and hinder the further penetration of EVs. The overall impact on both domestic and global EV adoption is ambiguous and necessitates empirical investigation.

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

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

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

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

Our empirical analysis delivers four key findings. First, the learning rate is estimated to be 7.5% after controlling for technological advancements, experience in EV assembly, and economies of scale. This implies that doubling battery production experience would reduce unit production costs by 7.5%. From 2013 to 2020, LBD accounted for a sizable 35.4% of the overall decline in battery costs. Technological advancements accounted for 52% of the cost reduction, with the remaining explained by changes in battery chemistry and plant capacity (economies of scale). There is suggestive evidence of learning spillover: firms benefit from the production experience of others within the same country, albeit to varying extents. On average, the learning benefit derived from other firms' production is 4.4% of that from their own experience. Smaller producers, constrained by limited production experience, derive most of their learning from others, whereas leading battery producers gain predominantly from their own experience. When spillover effects are incorporated, LBD explains 49% of the overall battery cost reduction during the sample period.

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 30% 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. Once we account for the snowball effect of LBD, subsidies boosted cumulative global sales by an astounding 184%, six times as large as the effect without LBD. 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 by one country generate global spillovers through LBD in battery

production, but the extent of spillovers hinges critically on the supply chain network and trade patterns. For example, the estimated $13.2 billion of U.S. subsidies generated $16.6 billion in global welfare gains, measured as the sum of consumer surplus and firm profit on a global scale minus subsidy expenditure. U.S. (and Canada) captured 54% of these global welfare gains, as the interaction between subsidies and LBD significantly lowered vehicle prices for domestic consumers and reduced input costs (batteries) for domestic EV producers. U.S. subsidies also indirectly benefited battery suppliers in Japan and South Korea, which together captured 26% of the global welfare gains. EV producers and consumers in Japan and South Korea also benefited from cheaper EV batteries, enabling the two countries to capture a combined 32% of global welfare gains. Similarly, EV producers and consumers in Europe and China benefit from U.S. subsidies, although China captured only 3% of the global gains. This relatively modest share reflects China's limited imports from foreign EV producers and almost non-existent exports of Chinese EV batteries (in contrast to batteries produced in Japan and South Korea) during our sample period.

In a similar manner, European governments invested $16.3 billion in EV purchase subsidies, resulting in $11.52 billion in global welfare gains, of which only 35% were captured by the EU. This relatively low domestic capture is driven by Europe's higher import share of EVs and the widespread use of uniform subsidies, the latter of which was less effective in generating consumer surplus compared to the battery capacity-based subsidies in the U.S. (Barwick, Kwon, and Li, 2023). In contrast, China captured 93% of the global welfare gains from its subsidies. This high capture rate is due to China's limited EV imports and the fact that the majority of its EV producers source batteries domestically.

Lastly, China's whitelist policy benefited domestic battery suppliers at a cost to other countries. The EU, Japan, South Korea, and the U.S. collectively incurred $3.8 billion in welfare loss due to the policy. This was driven by a shift in global battery production from more efficient Korean and Japanese battery suppliers to (at the time) higher-cost Chinese suppliers, which inflated EV prices and slowed global EV adoption. Within China, while battery suppliers reaped gains, domestic EV producers faced higher input costs, and consumers bore the burden of increased EV prices. Notably, 70% of the profit gains by Chinese battery suppliers were offset by losses to domestic EV producers and consumers. These findings highlight the important tradeoffs inherent in protective policies that distort market forces.

Our study is related to the following strands of literature. It adds to the growing economics literature to understand consumer adoption of EVs (Li et al., 2017; Li, 2023; Springel, 2019; Muehlegger and Rapson, 2022; Remmy, 2022; Barwick, Kwon, and Li, 2023). 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 analysis and, as a result, could underestimate the longer-term impact 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.

This study also contribute to the literature on LBD that has been documented in a variety of industries (Argote and Epple, 1990; 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 good, 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 final goods (i.e., EVs) and information on the vertical links between final good producers and intermediate input suppliers. The methodology is well suited to estimate LBD in the production of intermediate inputs (i.e. batteries).

This paper is related to studies that analyze vertical relationships between manufacturers and input suppliers (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). It contributes to that literature by developing a framework that leverages the vertical relationships to study LBD among the upstream suppliers.

Finally, the paper analyzes consumer purchase subsidies and local content requirements, two classes of commonly used industrial policies in the automobile sector. There has been a wave of recent studies on industrial policies that blend modern identification techniques with carefully chosen historical contexts (see Juhász, Lane, and Rodrik (2024) for an excellent review). Our paper contributes to this literature by analyzing the global implications of these domestic industrial policies and highlights the importance of considering spillovers across country borders in analyzing the broad policy effects.

The rest of the paper proceeds as follows. Section 2 describes the data and presents descriptive evidence. Sections 3 and 4 present the model and estimation strategy. Section 5 discusses estimation results. Section 6 uses counterfactual simulations to analyze the global welfare implications of consumer subsidies and local content requirements. Section 7 concludes. The appendices contain more details and additional analyses.

2 Data and Descriptive Evidence

2.1 Data Description

The research relies on four comprehensive data sets on global EV and EV battery industries.

EV Sales and Attributes The first data set contains annual EV sales, vehicle attributes, and prices by model for each of the 13 countries that had the largest EV sales from 2013 to 2020. These countries include Austria, Canada, China, France, Germany, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the UK, and the US, which collectively accounted for 95% of global EV sales during the data period.

Figure 1 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 zero-emissions vehicle (ZEV) target by country in Panel (b). Since the introduction of mass-market EV models in 2010, worldwide passenger EV sales have grown to reach 14.2 million units, or 15.8% of the passenger vehicle market in 2023. There is a large variation across countries in EV penetration. China became the largest EV market in 2015 and accounted for 59% of global new EV sales in 2023. In terms of the market share in the new vehicle market, Norway has by far the highest share of nearly 90.4% in 2023, while it was 34% in China, 21.4% in Europe, and 9.4% in the US, respectively.

Battery Suppliers The second data set contains information on battery suppliers such as location and production capacity. It also 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 the vertical relationships between upstream battery suppliers and downstream EV producers. We construct the experience variable (i.e., cumulative production) for each battery supplier in each year based on the vertical relationship together with data on EV sales. Finally, we also separately collected data on the battery cell production plants owned by each supplier, which includes information on the production capacity, start-up year and location of each plant (see Appendix A).

Figure A1 shows the supply network in 2013 in Panel (a) and in 2020 in Panel (b). The left side of the figure displays the top six battery producers, while the right side reports the top eight EV producers. The thickness of the lines represents the battery sales volume in units. Both EV production and battery manufacturing are concentrated, illustrating a two-sided duopoly market structure. In addition, EV producers often source from multiple battery supplies while battery suppliers sell to multiple EV producers, except for BYD and AESC, which are vertically integrated firms. These features inform our use of a bargaining model to characterize the vertical relationship.

EV Incentives The third data set contains financial and non-financial EV incentives offered in different countries. Consumer subsidies for EV purchases vary across countries and over time. Importantly, there is considerable cross-model variation within a given country and year due to the fact that the amount of subsidies is often based on vehicle attributes. For example, in the U.S., the amount of subsidy that an EV model is eligible for is \$2500+\$415*(kWh-4), with a minimum battery capacity of 4 KWh and a maximum subsidy of \$7500 during out data period.[2] EV subsidies in China are based on vehicle driving range with a notch design (Barwick, Kwon, and Li, 2023). The wedges in EV subsidies serve as a crucial exogenous source of variation in the experience of different battery suppliers, thereby identifying the extent of LBD — the impact of experience on production costs.

Figure A2 reports the average EV subsidy (from the central government) by country during 2013-2020 in Panel (a) and the subsidy design over time in China in Panel (b). Norway has the most generous consumer 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.

Demographics and Surveys The fourth data set contains socio-economic variables for each country as well as household surveys on vehicle ownership in China, US and France. Information on vehicle ownership links household demographics with vehicle attributes, providing useful moment conditions to identify consumer preference heterogeneity for vehicle demand.

Table 1 shows summary statistics for key variables used in the analysis.

2.2 Descriptive Evidence

Before presenting the descriptive data pattern that is used to inform our identification of LBD and policy impacts, we first provide a primer of EV bateries, and discuss how LBD arises in the battery production process. Batteries used in BEVs and PHEVs are lithium-ion batteries which feature lithium as one of the key minerals used in cathodes and graphite as the key material in anodes. The chemical composition of the cathode is a major determinant of battery performance. There are three main types of lithium-ion batteries based on cathode chemistries: NMC (Nickel Manganese Cobalt), NCA (Nickel Cobalt Aluminum), and LFP (Lithium Iron Phosphate).[3] The global market

[2]The subsidy phases out following a pre-set schedule when the EV manufacturer hits a cap of 200,000 subsidy-qualifying vehicle. By quarter six after the cap was reached, the subsidy is completely phased out for that EV manufacturer (Lohawala, 2023).

[3]NMC batteries have higher energy density and are most expensive due to the high cost of manganese and cobalt. They are the preferred type by American and European automakers. NCA batteries are mainly used by Tesla sourced from Panasonic, particularly in its higher-end models. Chinese automakers, such as BYD, are major adopters of LFP

share of the three types (by battery capacity) based on new EV sales in 2023 were 71%, 21% and 6% in 2020 (International Energy Agency, 2021). The share of LFP batteries has grown rapidly during last few years due to its cost advantage and reached 40% globally in 2023 while that of NCA batteries has dropped to 8%.

Battery packs used in EVs consist of multiple interconnected modules, each made up of tens to hundreds of battery cells, which account for about 70-80% of the battery pack's cost (Bloomberg NEF, 2023). The production process of battery cells involves three stages, each comprising multiple steps: electrode production, cell assembly, and cell finishing. Battery production has at least three key features that could contribute to LBD. First, the production process is highly complex and automated with hundreds of parameters to be set. The inter-connected system needs to be constantly fine-tuned and optimized to achieve efficiency. Second, the process is very sensitive in that it has strong requirement on materials purity and the production requires clean-room process standards. Tiny amounts of impurities can cause high scrap and low yield rate.[4] Third, the industry has been undergoing continuous change in terms of advances in new chemistry composition and production techniques, which have important implications on production costs. All these features suggest that production know-how by managers and engineers in the plant gained through experience could help improve production efficiency and reduce scrap, leading to a lower cost.[5]

The estimate of LBD is fundamentally informed by the relationship between production experience and the cost of battery production. In the absence of cost data, we examine the extent to which vehicle prices, a significant portion of which is attributed to battery expenses, are correlated with the production experience of battery suppliers.

Figure 2 shows the relationship between vehicle prices at the model level and the experience of battery supplies for the corresponding vehicle model in binned scatter plots. The unit of analysis is a vehicle model by country by year. Panel (a) depicts the raw data pattern, while Panel (b) shows the residualized plot by partialing out vehicle attributes (horsepower, size, driving range, and the PHEV dummy), country fixed effects, brand fixed effects, and year fixed effects. The size of the dots is proportional to the cumulative subsidies received by the battery supplier for the corresponding EV model.

Panel (a) of Figure 2 shows a slight positive relationship between battery supplier experience

batteries due to their lower cos and and thermal stability. Two-thirds of EV sold in China used LFP batteries in 2023 but its share in Europe and the United States remains below 10% (International Energy Agency, 2024).

[4]Even the industry leaders struggle with the issue of high scrap rate in the initial stage of production. For example, the Gigafactory built by Tesla and Panasonic in Nevada in 2017 had a scrap rate as high as 80-90% initially as discussed in this article. It takes several years for the scrap rate to be reduced to 15%.

[5]A report by Boston Consulting Group suggests among the 15 stages of cell production, the most common challenges have to do with yield rate/scrap and efficiency/process time. The report suggests that engineers need to rely on experience, rather than physical correlations, to adjust parameters in order to optimize the production process.

and vehicle prices. This could be driven by the fact that high-end EV models (e.g., Tesla model X) source from more experienced battery suppliers (e.g., Panasonic) for their better quality. After controlling for vehicle attributes and a rich set of fixed effects, Panel (b) exhibits a strong and precisely estimated negative relationship, suggesting that vehicle models that source from more experienced battery suppliers charge lower prices. In addition, the plots show that production experience increases with the cumulative subsidy received in the past by the battery supplier (captured by the size of the dots), motivating a key IV strategy for identifying LBD that we discuss below.

Figure A3 provides some suggestive evidence of the impacts of China's whitelist policy from 2016 to 2019, which requires EV models to use government-sanctioned battery suppliers – all of which are Chinese firms – in order to qualify for subsidies. There were six major battery suppliers during this period: two Chinese firms, BYD and CATL, and four non-Chinese firms, AESC and Panasonic from Japan and LG and Samsung from South Korea. Before the policy was enacted, the Chinese suppliers had less experience, and vehicles that used their batteries sold at higher prices relative to the non-Chinese suppliers.

Panel (a) shows the share of EV models sourcing from Chinese battery suppliers separately for EV models sold in China, and those sold elsewhere. As the policy intended, the share of EV models sold in China sourcing from Chinese battery suppliers increased from about 70% to nearly 90% during the policy period. The share dropped once the policy was scrapped. Panel (b) shows that the sales of the top two Chinese battery suppliers that were on the whitelist increased faster than the top four non-Chinese battery suppliers during China's whitelist policy. As BYD and CATL accumulated production experience, the EV models that sourced batteries from BYD and CATL saw a faster reduction in (residualized) vehicle prices relative to the non-Chinese firms, as shown in Panel (c). This is consistent with the pattern in Panel (a): among the EV models sold elsewhere, the share of models sourcing from Chinese battery suppliers increased slightly during the policy period, but more dramatically after the policy. This large increase could be driven by the fast cost reduction among Chinese battery producers and hence improved competitiveness as a result of the policy. While the descriptive evidence presented here is consistent with LBD, there could be other confounding factors at play. The section below outlines a structural model that allows us to better establish the causal evidence on the size and scope of LBD as well as its implications on government policies.

3 Model

We develop a structural model to characterize consumer EV purchase decisions, EV producer pricing decisions, and battery price negotiations between vehicle producers and battery suppliers. The model allows us to back out the battery cost based on observed data on EV sales and the time-varying vertical relationships between EV producers and battery suppliers. The model is used for two purposes. The first is to estimate LBD by examining the relationship between recovered battery cost and the production experience of battery suppliers. The second purpose of the model is to understand the broader impacts of various government policies based on counterfactual simulations while taking into LBD into account. We first outline the key elements of the model, and then discuss the estimation strategy in the following section.

Here are the key notations: 1) EV producer v, producing a set of vehicles Ω_v; 2) battery supplier b, supplying batteries for a set of vehicles Ω_b; 3) consumer is denoted by i, vehicle model j; 4) country is denoted by c, time/year t; and 5) vehicle price before subsidies is denoted by p_{jct}, consumer subsidy ϕ_{jct}, and battery price τ_{jct}.

Consumer demand The first component of the structural model is a random coefficient discrete choice model of EV demand following Berry, Levinsohn, and Pakes (1995). In each period t, consumer i in county c chooses among all the available EV models, as well as an outside option representing the choice of not buying a new EV. The utility of consumer i from buying vehicle j is:

$$U_{ijct} = \alpha_i \hat{p}_{jct} + X_{jct}\beta_{\mathbf{i}} + \xi_{jct} + \varepsilon_{ijct}. \tag{1}$$

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

EV supply We assume a Bertrand-Nash game among EV producers (or Original Equipment Manufacturers, OEMs) in a country that choose EV prices to maximize profit in a country in a year. An OEM or automaker can own multiple brands (e.g., Toyota owns Lexus and Toyota brands), and we

assume joint profit maximization across brands within an OEM.[6] Producer v's profit is (suppressing country and time indices)

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

where the battery cost for vehicle j is denoted as τ_j; firm v's marginal cost of producing non-battery components is mc_{vj}; and the per-unit markup is $p_j - \tau_j - mc_{vj}$.

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

$$q_j + \sum_{k \in \Omega_v} \underbrace{(p_k - \tau_k - mc_{vk})}_{\text{Vehicle markup, } mk_{vk}} \frac{\partial q_k}{\partial p_j} = 0. \tag{2}$$

Note that $\frac{\partial q_k}{\partial p_j}$ is known after demand estimation. Inverting the system of FOCs in Equation (2) yields a vector of vehicle markups $\boldsymbol{mk}^v$.

Bargaining Motivated by the two-sided duopoly observed in the vertical relationship between battery suppliers and EV producers, we use the Nash-in-Nash bargaining model (Horn and Wolinsky, 1988) to characterize the negotiation of battery prices between EV producers and battery suppliers, with the exception of BYD and AESC.[7] We assume that the bargaining and vehicle price setting are simultaneous, following Draganska, Klapper, and Villas-Boas (2010); Ho and Lee (2017).

For the base specification, we assume that 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 its battery is supplied by b) to maximize the Nash product of their net gains from trade, taking as given the battery prices chosen for other vehicles:

$$NP_{vb}(\tau_j, \tau_{-j}) = \underbrace{(\pi^v - d^v_{vb})}_{\text{v' gains}}^{(1-\lambda^b)} \underbrace{(\pi^b - d^b_{vb})}_{\text{b' gains}}^{\lambda^b},$$

where $\lambda^b \in [0, 1)$ is the bargaining weight of battery supplier b and $\lambda^b = 0$ implies zero markup for battery suppliers. We use π^v and π^b to denote the profit of EV producer v and battery supplier b, respectively, and d^v and d^b to denote the *disagreement* payoff, i.e., profit if negotiations fail. The battery supplier's profit is similar to that for the EV producer, except that battery prices do not affect downstream demand q_j conditioning on retail prices: $\pi^b(\tau) = \sum_{j \in \Omega_b} (\tau_j - mc_{bj}) q_j(p, \phi)$. Supplier b's cost of producing the battery used in vehicle j is denoted as mc_{bj}, and $\tau_j - mc_{bj}$ is

[6] Joint ventures (JVs) are common in China, and we assume JVs are separate OEMs from local partners who often own their domestic 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 it sells Chevrolet, Buick, and Cadillac brands. SAIC which own domestic brands such as Roewe and Maxus is considered a separate profit maximizer.

[7] BYD is vertically integrated, and neither buys nor sells batteries. AESC produces batteries only for Renault-Nissan-Mitsubishi alliance.

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. The FOC for battery price τ_j is:

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

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

$$\begin{aligned}\underbrace{\boldsymbol{mk}^b}_{\text{Battery markup}} &= \frac{\lambda^b}{1-\lambda^b}[\boldsymbol{T}^b * \boldsymbol{S}]^{-1}[\boldsymbol{T}^v * \boldsymbol{S}] \underbrace{\boldsymbol{mk}^v}_{\text{Vehicle markup}} \\ &= \frac{\lambda^b}{1-\lambda^b} \underbrace{\overline{\boldsymbol{mk}}^b}_{\text{Battery markup when } \lambda^b = 0.5} \end{aligned} \tag{3}$$

where $\mathbf{T}^v$ and $\mathbf{T}^b$ are ownership matrices for EV producer v and battery supplier b, respectively. Matrix $\boldsymbol{S}$ denotes how market shares of all products change upon disagreement. That is, the $\{j,k\}$ term of $\boldsymbol{S}$ captures how much the market share of product k *changes* when v and b disagree over the battery price for vehicle j. Ownership matrices are observed and $\boldsymbol{S}$ can be derived from the demand model after estimating consumer preferences. The vector of vehicle markups $\boldsymbol{mk}^v$ is backed out from Equation (2). Consequently, the battery supplier's markup if its bargaining weight is 0.5, denoted as $\overline{\boldsymbol{mk}}^b$, is known after demand estimation. Therefore, Equation (3) suggests that battery markups can be recovered up to the bargaining parameter λ^b after the demand estimation.

Our approach for recovering downstream and upstream markups follows Draganska, Klapper, and Villas-Boas (2010). Intuitively, upstream markups depend both on the bargaining parameter and responsiveness of the battery supplier's sales to changes in the battery price. For example, if increases in the battery price lead to a large reduction in battery sales, then equilibrium upstream markups will tend to be smaller. Once the demand system has been estimated and downstream markups recovered, we can infer how battery suppliers' sales respond to changes in the battery price, which allows us to pin down the magnitude of upstream markups (up to the bargaining parameter, which we discuss and estimate below).

An advantage of this approach is that it allows us to estimate the structural model without direct information on battery production costs or battery prices, so long as we have detailed information on downstream EV prices, sales, and EV and battery characteristics. A caveat of this approach is that the estimated markups depend on the supply-side assumptions, i.e., that negotiations between EV producers and battery suppliers follow Nash-in-Nash bargaining and that EV producers engage in Bertrand-Nash competition. We explore alterative modeling assumptions below in our robustness checks.

4 Estimation

The estimation 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 bargaining weight as well as the parameters that govern LBD.

4.1 Demand Estimation

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

$$\alpha_i = \alpha_1 + \frac{\alpha_{c(i)}}{y_i} + \sigma_p \nu_i^p. \tag{4}$$

Price sensitivity is inversely related to income y_i. We divide countries into four groups based on income per capita, allow the coefficient on income $\alpha_{c(i)}$ to vary by country groups.[8] If $\alpha_{c(i)}$ is positive, low-income households tend to be more price sensitive than high-income households. σ_p captures the dispersion of price sensitivity across consumers due to unobserved demographics ν_i^p, which is assumed to follow the lognormal distribution. The income y_i is simulated from a log-normal distribution with distribution parameters $\hat{\mu}_{ct}$ and $\hat{\sigma}_{ct}$. We estimate $\hat{\mu}_{ct}$ and $\hat{\sigma}_{ct}$ for each country c and year t using the following information: the average household income, the top 10% income share, and the bottom 50% income share for each year and each country 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 the top 6 battery supplier dummy variables. They capture the fact that batteries with higher capacity are most costly to produce, and these costs vary across suppliers (Li et al., 2021). The second set is the BLP instruments using the three exogenous product characteristics: vehicle size, horsepower, and driving range. In total, we use nine excluded IVs, Z_{jct}, in addition to the exogenous attributes X_{jct} to construct the following aggregate moment conditions:

$$E[\xi_{jct}|X_{jct}, Z_{jct}] = 0. \tag{5}$$

Micro-moments We construct two types of micro-moments to facilitate the identification of preference parameters. Based on household survey data, the first type of micro-moments matches the observed average income of households that purchased a given EV model with the predicted income from the demand model. From the survey data in China and U.S., we obtain average income

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

for 50 popular EV models in China from 2016 to 2020 and for 33 popular EV models in the US in 2018, giving us a total of 88 micro-moments for Chinese and U.S. EV buyers. The second type of micro-moments matches the share of EV buyers in an income bracket to the 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), and four in the Netherlands (2019). Since these income groups are mutually exclusive, we drop one group for each country, leaving us a total of 21 micro-moments for the second type. We follow Conlon and Gortmaker (2023) to construct the variance-covariance matrix and gradients of the aggregate moments and micro-moments.

4.2 Battery Cost

To estimate LBD, we decompose vehicle prices into four terms that consist of the marginal costs (mc) and the markups (mk) for battery suppliers and EV producers (now bringing back the country and time subscripts for clarity):

$$p_{jct} = \underbrace{mc_{vjct} + mk^{v}_{jct}}_{\text{Non-battery cost}} + \underbrace{mc_{bjct} + mk^{b}_{jct}}_{\text{Battery cost}}, \tag{6}$$

where vehicle markup mk^{v}_{jct} is known after demand estimation, and battery markup $mk^{b}_{jct} = \frac{\lambda_b}{1-\lambda_b}\overline{mk}_{bjct}$ is known up to λ_b following the discussion of Equation (3). The marginal cost for non-battery components is specified as a function of vehicle attributes, such as vehicle weight and horsepower, and a rich set of fixed effects. Similarly, the marginal cost of battery is specified as the product of battery capacity (in kWh) and the cost associated with producing each kWh.[9]

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

where BK_{bjct} is battery capacity (in kWh). E_{bt} is a battery supplier's experience, defined as the past cumulative production of all models in all countries and years that source batteries from supplier b:

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

where q_{jcs} is the sales of vehicle j at country c and year s, and $\{I_{hbcs} = 1\}$ denotes the set of vehicle models at country c and year s that source battery from supplier b. The key parameter of interest is the learning coefficient γ^E, which determines the rate at which the cost of manufacturing a kWh

[9]The manufacturing of EV batteries typically begins with the production of small battery cells through a chemical process. These cells are then interconnected to create modules, and these modules are further assembled into battery packs through a mechanical assembly process.

of battery decreases as experience in production doubles.[10] γ^0 captures the baseline cost without learning. CH_{bjct} reflects the battery's chemical type (such as NMC or LFP) and PK_{bt} is a battery plant's capacity in GWh that captures economies of scale. η_t are year fixed effects that control for industry-wide technological progress over time.

Combining Equations (3), (6), and (7), the LBD estimating equation is defined as follows:

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

where the set of fixed effects includes country fixed effects, EV brand fixed effects (e.g. Tesla), battery supplier fixed effects (e.g. LG), and year fixed effects. The residual ω_{jct} captures the unobserved cost shocks.

4.3 Empirical Challenges

There are two challenges in estimating Equation (9). First, the experience variable defined in Equation (8) is likely to be endogenous. For example, past EV sales q_{jcs} could be correlated with serially correlated cost shocks ω_{jct}. Additionally, the supply network that partially determines past sales could be endogenous in that productive battery suppliers might supply more EV models. To address the endogeneity of experience, we predict past experience using exogenous variation and use predicted experience as an IV.

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

where $\hat{Pr}_{jbcs}$ is the predicted probability of vehicle model j sourcing from battery supplier b. It is specified as a discrete choice model of supplier choices determined by a set of exogenous variables, z_{jbcs}, that are unlikely to be correlated with unobserved cost shocks ω_{jct}. These exogenous variables include controls for home bias (to capture the fact that EV producers are more likely to source from domestic battery suppliers), as well as China's White List policy. We also control for EV characteristics, battery supplier characteristics that are predetermined in the initial year that we observe them (their age, initial battery size, initial battery chemistry etc.), and the initial EV producer - battery supplier network structure.

$\hat{q}_{jcs}(\boldsymbol{x}_{vjcs}, \phi_{jcs})$ is the predicted sales based on our demand model as a function of observed vehicle attributes $\boldsymbol{x}_{vjcs}$ and EV subsidies ϕ_{jcs}. The predicted sales exploits variation in EV sub-

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

sidy policies across countries and models as well as over time which leads to variation in demand for EVs and hence batteries produced by different suppliers. The subsidies serve as powerful instruments because they greatly affect demand for EVs and, hence, the production of batteries by different suppliers. For example, a battery supplier that sells batteries to EV models eligible for more generous EV subsidies will gain experience more quickly.

The key identification assumption is that China's whitelist policy and variation in EV subsidies are not correlated with vehicle and battery costs shocks ω_{jct}. As discussed above, EV subsidies are often based on vehicle attributes. For example, the notched design based on driving range in China shown in Figure A2 lends to a RD-type of identification strategy in that the amount of subsidy changes discretely along the range cutoffs but unobserved vehicle and battery costs are unlikely to change discretely among the cutoffs. We also assume that the *initial* network structure, and the initial characteristics of battery suppliers, are uncorrelated with subsequent realizations of the cost shocks ω_{jct}.[11]

Our IVs are shift-share IVs in nature in that the shift is predicted sales $\hat{q}_{jcs}(\boldsymbol{x}_{vjcs}, \phi_{jcs})$, and the share is $\hat{Pr}_{jbcs}$. Intuitively, variation in subsidies shifts predicted sales for each EV model, and the whitelist policy or variation in home bias and initial network structure shifts the probability any given battery supplier is chosen. This means that subsidies differentially affect experience accumulation across different battery suppliers.

The second challenge in estimating Equation (9) is that battery markups $\overline{mk}^{b}_{jct}$ might be endogenous. The battery markups are a function of vehicle markups, which could be correlated with cost shocks ω_{jct} because EV firms' optimal pricing strategies and equilibrium markups depend on their costs. We follow the same strategy as above and construct an IV of predicted battery markups using only observed attributes and subsidies. To do so, we first regress EV prices on observed attributes, subsidies, and fixed effects, to obtain predicted prices for each vehicle model. We then use predicted prices to re-calculate market shares, vehicle markups, and battery markups. By construction, the predicted battery markups are exogenous to cost shocks ω_{jct} and serve as valid IVs.

[11] Note that this permits for the possibility that subsequent adjustments to the supply network respond endogenously to ω_{jct}; for example, if a battery supplier experiences a long-term productivity improvement, and is therefore more likely to be chosen as the supplier when EV producers release new models.

5 Estimation Results

5.1 Demand Results

Table 2 reports parameter estimates for the EV demand model from there specifications. All columns include country fixed effects, brand fixed effects, 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 BLP IVs based on observed vehicle attributes. As common in the demand literature, the OLS coefficient estimate on vehicle price in column (1) is much smaller in magnitude than that from the 2SLS in column (2) due to the positive correlation between unobserved product attributes and prices. The coefficient estimate on vehicle volume (i.e., length by width by height) is counter-intuitive from OLS. All coefficient estimates from 2SLS are intuitively signed: consumers dislike higher price but prefer larger size and horsepower. Interestingly, consumers prefer longer driving range but that preference is much weaker for PHEVs.

Column (3) reports results from our preferred specification, the random coefficient model with heterogeneous preferences. As in Column (2), all parameter estimates are intuitively signed. 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 consumer preference heterogeneity. All the random coefficient estimates are estimated precisely though the magnitude for those on vehicle attributes appear to be modest relative to the mean preference parameters.

Figure 3 plots the implied price elasticities of demand in Panel (a) and semi-elasticities by country group in Panel (b). Across all EV models in our sample, the average price elasticity is -3.51, and the sales-weighted average is -2.67, with a standard deviation of 1.53. These estimates are in line with those from the EV demand literature (Li et al., 2017; Li, 2018; Xing, Leard, and Li, 2021; Muehlegger and Rapson, 2022; Springel, 2019). Panel (b) depicts the price semi-elasticities: the percentage change in sales for a $1,000 reduction in own prices. The sales increase in percentage terms is larger for cheaper vehicles, implying the demand being more price sensitive.

5.2 Supply Side Results

IV Construction. The focus of the supply side is to estimate the parameters in Equation (9). Before the estimation, we first construct IVs for the three endogenous variables: battery supplier

experience, battery markups (with equal bargaining weight), and EV producer experience. To construct the IV for battery supplier experience as shown in Equation (10), we first estimate a conditional logit model of network formation to capture the relationship between battery suppliers and EV producers. The unit of analysis is a battery supplier and EV model pair by country-year. The outcome variable is a dummy variable that equals one if the battery supplier in question was chosen by the OEM to supply batteries for that EV model, and zero otherwise. We assume that the EV maker selects a battery supplier (from a choice set that includes all suppliers active in that country) during the year when the EV model is first released, and maintains the same battery supplier in subsequent years when the same model is sold (since we rarely observe switches in the data). The model is reduced-form in nature with the goal of generating the predicted network, which in turn is used as an input to construct the predicted battery experience. Since the purpose of the model is to construct instrumental variables, we only include variables that are likely uncorrelated with cost shocks ω_{jct}, such as China's White List policy, the initial supplier network structure, and initial supplier characteristics.[12]

Table A1 reports the estimation results. The key variable of interest is a dummy variable for China's White List that equals one if the supply relationship meets the eligibility requirement for consumer subsidies: 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 not eligible for subsidies. The coefficient estimate is large in magnitude and statistically significant. This is consistent with the fact that the policy incentivized Chinese EV producers to shift to domestic battery suppliers as shown in Panel (a) of Figure A3. We also find evidence of home bias, with EV producers more likely to procure batteries from domestic battery suppliers.

We then used the estimated demand model to construct predicted EV sales over time, which together with the predicted supply network generate predicted experience for each battery supplier in each year. Panel (a) in Figure A4 depicts a strong positive correlation between the observed battery supplier experience against the predicted experience after partialing out vehicle attributes and the rich set of fixed effects (country, brand and year). Similarly, we construct predicted battery markups as a function of exogenous variables based on demand estimation as an IV for the recovered battery markups (with equal bargaining weight) as shown in Equation (9). Panel (b) in Figure A4 also shows a strong positive correlation between the two variables. The two plots provide suggestive evidence validating the strength of the instruments.

Coefficient Estimates. Table 3 reports the estimation results from GMM for Equation (9) that characterizes the marginal cost of battery and vehicle production. We categories the parameters into

[12]Later when we carry out counter-factual simulations, we use a richer network formation model.

four groups: (1) the bargaining weight, (2) parameters associated with battery costs as a function of battery attributes and LBD, (3) parameters associated with vehicle costs (exclusive of battery) as a function of vehicle attributes, and (4) fixed effects to control for unobserved cost shocks in both battery and vehicle production.[13]

The bargaining weight λ_b being zero implies no bargaining power and hence zero markup among upstream battery suppliers, while λ_b being 0.5 implies the same bargaining weight and the same profit between battery suppliers and EV producers. The experience of battery suppliers, the experience of EV producers, and vehicle markup (corresponding to the bargaining weight parameter) are instrumented in all columns as discussed above.

Columns (1) to (3) have different controls to illustrate the role of important confounding factors: overall technology progress captured by the time trend, economies of scale captured by the plant capacity, and potential learning in vehicle manufacturing stage captured by the experience of EV producers. Column (4) is our preferred specification with most controls and the estimates are used for subsequent counterfactual analysis.

Column (1) does not control for time trend, plant capacity, and EV producer experience. The bargaining weight is estimated to be 0.503 and the learning coefficient is estimated to be -0.203, suggesting a learning rate of 13%. While the learning rate estimate falls into the range in the literature, the bargaining weight estimate seems to be very high as it would imply upstream markups of about \$180/kWh, relative to battery pack prices \$200-\$600/kWh during our data period. γ_0 captures the baseline battery cost, i.e., in the absence of learning, and its estimate suggests a baseline cost of \$1,095/kWh in 2013, higher than the industry average of about \$700 reported by the Bloomberg New Energy Finance.

Column (2) controls for industry-wide technological progress in battery production with time trend. The estimate on time trend suggests a \$24/kWh reduction in battery cost per year. Intuitively, the learning coefficient reduces from -0.203 to -0.135, suggesting that technology progress at the industry level could confound LBD estimates. Column (3) further attempts to control for economies of scale by including plant capacity but the coefficient estimate is imprecise and counter-intuitive.

Column (4) adds the experience of EV producers to capture potential learning in automobile manufacturing. The coefficient estimate suggests that the unit cost of EV production reduces by \$997 (or about 2%) for every doubling of the EV manufacturing experience. While there are differences between EV production and gasoline vehicle production, there are a lot of similarities. The low learning rate is consistent with the fact that auto manufacturing is a mature industry. Nevertheless, controlling for EV manufacturing experience leads to several notable changes in the

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

estimation results.

First, the bargaining weight estimates drops from about 0.5 in the first three columns to 0.28 in Column (4). This suggests upstream markups to be about \$100/kWh, a plausible estimate compared to battery pack prices of \$200-\$600/kWh during the data period. It is also consistent with markups reported by CATL. Equal bargaining weight is unlikely to be realistic given that batteries on average account for about one-third of the cost of EV production during our sample period.

Second, the learning coefficient is further reduced to 0.112 in column (4), implying the learning rate (or the Spence coefficient) being 7.5%. That is, the marginal cost of battery is expected to reduce by 7.5% on average for a doubling of experience. Our estimate is much lower than the 20-28% estimates from industry reports or studies using aggregate data (Ziegler and Trancik, 2021) without adequately control for industry-wide technology progress and other cost shocks. The learning rate in some well-know economic studies is found to be in the range of 20-30%. For example, it is estimated to be 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), about 30% in aircraft manufacturing using data from 1970-1984 (Benkard, 2000), and in wind turbine production from 2000 to 2019 (Covert and Sweeney, 2022). Nevertheless, there is a large variation in the learning rate estimates across the literature driven by multiple factors including the nature of industries (capital intensive versus labor intensive), knowledge stock depreciation (or organizational forgetting) from employee turnover, as well as the failure to control for other factors such as economies of scale when estimating learning curve (Argote and Epple, 1990; Thompson, 2012).

Third, γ_0 estimate falls to about \$850/kWh, close to the industry data. The time trend estimates suggest that the battery cost reduces by \$32 per year or about 4% of the baseline cost during our data period, implying a significant technology progress in EV battery production. Interestingly, the coefficient estimate on plant capacity becomes intuitively signed and precisely estimated, suggesting economics of scale to be about 8%.

Size of LBD. To better understand the size of LBD and its contribution to the overall cost reduction observed during the past decade, we simulate the predicted battery costs from 2014 to 2020 under different scenarios as shown in Figure 4. Panel (a) depicts the role of LBD as well as the time trend in explaining the overall cost reduction. The bottom line is the battery price index from Bloomberg NEF (2020) while the second line from the bottom shows the predictions from our model.[14] The top line shows the predicted cost with only the time trend. The coefficient estimate on the time trend suggests that the battery cost reduced by \$32/kWh per year on average due to for

[14]Given that we cannot separately identify the level of battery cost and the level of vehicle cost, we calibrate the level of battery cost to the Bloomberg price index in the base year in 2014. The bottom two lines show that our model fits the overall cost decline well.

example technological progress. Overall, the time trend accounted for 52% of the cost reduction during the period. The second line from the top captures the cost reduction from both LBD and the time trend. The difference between the top two lines suggests that LBD contributed to 34.5% of the reduction in battery cost from 2014 to 2020.

Panel (b) of Figure 4 shows the cost reduction of battery suppliers for China, Japan and South Korea separately. The average battery cost was nearly $800/kWh among Chinese suppliers in 2014, relative to less than $650/kWh among Japan and South Korean suppliers. However, Chinese suppliers have caught up with South Korean suppliers by 2020.

Scope of LBD Our analysis so far has focused on internal LBD, i.e., learning within the firm. Ongoing policies such as the local content requirements on EV subsidies in IRA critically hinges on the scope of learning. The extent to which these requirements favor local battery producers is positively correlated with how strong LBD is internal instead of external. For example, if LBD has no or a weak external component, the experience accumulation among local suppliers due to these requirements would have no or small spillover benefit to other suppliers. Therefore, the scope of learning has important policy implications. Nevertheless, identifying the scope of learning poses additional empirical challenges as it requires additional variation and exogenous shocks.

We first explore learning across firms within the same country by assuming the effective experience of a battery supplier is the sum of own experience and the experience of rival firms in the same country scaled by a parameter θ to be estimated. θ being zero implies no learning spillover from rival firms, while being one implies complete spillover: learning from rival experience is as effective as from own experience. We instrument the effective experience variable with the predicted own experience and predicted rival experience based on exogenous variables as shown in Equation (10).

Table 4 presents the estimation results to explore learning across firms. The estimate on θ is 0.044, suggesting that learning from one unit of rival experience is equivalent to only 4.4% of learning from one unit of own experience. However, the estimate is imprecise due to limited variation in rival experience across firms especially for small battery suppliers. If we take the estimate at the face value, learning from rivals constitutes a small share of overall learning for top-6 battery suppliers, but learning from rivals accounts for up to two-thirds of overall learning for smaller firms.

We also explore differential learning across chemistry types within the same firm. We construct own experience variable by chemistry type and define effective experience as the sum of the own experience of the same type and the own experience of other types scaled by a parameter θ. The θ estimate is small in magnitude and imprecise: more than 80% of the battery suppliers produce only

one chemistry type, leading to limited variation. Similarly, we explore global LBD by allowing learning spillover across countries but there is a lack of variation for identification too.

6 Policy Simulations

We conduct counterfactual simulations to examine the broad impact of two types of government policies prominent in the EV industry while accounting for LBD: (1) consumer subsidies; and (2) domestic content requirements. For each of the counterfactual simulations, we proceed by (1) constructing new supply relationship between EV producers and battery suppliers based on a logit model to characterizes the network formation; (2) solving for new battery prices, vehicle price and new sales; and (3) updating battery supplier experience and battery production costs.

For the counterfactual simulations, we use a richer network formation model than the one we used to construct IVs. We now include richer controls for the lagged network structure and control for fixed effects for top 6 suppliers. Give our interest in domestic content requirements, we allow EV makers to choose from an expanded choice set that includes all top 15 battery suppliers in the world, even those that were not previously active in that country. We also allow EV makers to choose a new battery supplier for each EV model in the year 2016 (even for existing models), since some of our counter-factual simulations involve unexpected policy shocks in the year 2016. Table A2 reports the estimation results. Eligible subsidy is the 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. 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 not eligible for subsidies. The coefficient estimate is large in magnitude and statistically significant.

6.1 Consumer subsidies

Our first set of counterfactuals explores the impact of consumer subsidies on EV adoption and social welfare. Table 5 shows the impacts of consumer subsidies separately for four regions: China, Europe, Japan and South Korea, and US and Canada. Panel (a) presents the impacts of US subsidies while holding fixed the subsidies in other regions. With $13.24 billion in total spending, consumer subsidies in the US increased social welfare by $8.98 billion during 2013-2020. Both US consumers and EV producers benefited significantly. EV sales increased by 0.77 million units. Interestingly, US subsidies benefited Japan and South Korea most significantly because US EV production mainly source battery from Japan and South Korea battery suppliers. Consumers and

EV producers in all the other regions benefited from the US subsidies due to accelerated learning and battery cost reduction. The positive spillover is much smaller to Europe than to China because EVs sold in Europe also sourced heavily from Japan and South Korea battery suppliers while EVs sold in China mostly rely on domestic battery suppliers.

Panel (b) shows that the impacts of European subsidies are broadly similar to those from US subsidies. There are large welfare gains for consumer and EV producers. Japan and South Korea benefited significantly because EVs sold in Europe sourced batteries mainly from those two countries. The spillover benefit to the US is stronger than to China due to the fact that EVs sold in Europe and those sold in US source from the same battery suppliers. Panel (c) presents the impact of Chinese subsidies, which amounted to over $21 billion. the subsidies generated over $26 billion social welfare gain in China, benefiting consumers, battery supplier and EV producers. EV sales increased by over 2.5 million units during 2013-2020. Although the subsidies generated some spillovers to other regions, they are small relative to those from US and Europe subsidies.

The top panel of Figure A5 shows changes in EV prices in the US and Europe, respectively due to US subsidies. The subsidy pass-through and the reduction in downstream markup are the two largest components in EV price reduction in the US. In comparison, the reduction in upstream markup and the decrease in battery marginal costs are relatively small. However, the EV price reduction in Europe as a result of US subsidies was mostly driven by the decrease in battery marginal cost, which amounts to $150-200. Similar patterns emerge in Panel (b) of Figure A5 which shows the channels of price reduction due to European subsidies. Panel (c) show the price changes due to Chinese subsidies. The price reduction in other regions outside of China became more significant overtime as EV sold in those regions sourced more batteries from China, thus benefiting more from the reduced battery cost as a results of accelerated learning among Chinese battery suppliers.

Table 5 highlights two important findings. First, consumer subsidies in one country generate spillovers to other countries due to LBD as well as the linkage in battery supply networks. Both of these factors are important for significant cross-country spillovers to emerge. Second, the extent of spillovers crucially hinges on the overlap of the battery supply networks. Consumer subsidies in China generated smaller spillovers to other regions because EVs sold in China mainly rely on domestic battery producers. The strong spillovers between US and EU to each other arise because of EVs sold in these two regions use the same battery suppliers from Japan and South Korea. Table A3 confirms that the cross-country spillover effect from subsidies are much smaller in the absence of LBD. In addition, the spillovers from US or European subsidies to China are nearly non-existent because of limited overlap in battery suppliers between EV producers in the US and Europe and those in China.

6.2 Domestic content requirements

To explore the impact of domestic content requirements, we begin by evaluating China's whitelist policy that was implemented in the middle of our sample period. We compare outcomes with and without the whitelist. The comparisons help us understand a) the overall impact on global EV adoption, which depends on the cost differentials between the battery suppliers on the whitelist and the others; and (b) the extent to which the policy propelled some Chinese battery suppliers to rise to the top in the industry.

Panel (a) of Table 6 presents the impacts of the Whitelist policy itself while holding the subsidies fixed. The whitelist policy increases the profit of battery producers in China by over $2 billion while hurting both consumers and EV producers. While the overall welfare impact is positive in China, the protectionism policy had negative spillovers to other regions, leading to global welfare loss. In addition, it slowed EV adoption everywhere.

In order to take advantage of consumer subsidies in the presence of the whitelist policy, some EV producers in China had to switch from Japanese and South Korean battery suppliers to Chinese suppliers which had higher costs. Figure 5 shows that the Whitelist policy significantly benefited Chinese battery suppliers (such as CATL), with sales of Chinese battery suppliers increased by 59% as a consequence of this policy. This came at the expense of non-Chinese battery suppliers, whose sales reduced by 43% relative to a scenario with no White List policy.

The higher battery costs under the policy resulted in high EV prices and lower EV sales in China. Japanese and South Korean battery suppliers saw reduced demand and hence profit loss. This also slowed down LBD among these battery suppliers, which hurt downstream EV producers in Europe and US who source from them, leading to slower EV adoption in both regions. The bottom panels in Figure 5 shows that the policy reduced global EV sales by 12%, as it shifted sales from low-cost to high-cost suppliers. The policy led to a 16% reduction in EV sales in China and a 4% reduction in EV sales in the rest of the world.

These results point to Chinese battery suppliers being the only winner of the whitelist policy. Consistent with our simulation results, the policy was scrapped in 2019 amid opposition from both Chinese EV producers and non-Chinese battery producers. Nevertheless, the policy may have achieved the intended consequences by accelerating experience accumulation among Chinese battery suppliers especially CATL and BYD, as shown in Figure A3. This then increased their global competitiveness, which led to the growth of their market share even after the policy ended.

Panel (b) of Table 6 presents the combined effect of the whitelist policy and consumer subsidies in China. While the whitelist policy slightly increased overall welfare gain from consumer subsidies to China, it reduced and even reversed the positive cross-country spillovers from the subsidies.

The IRA of the Biden administration put into place local content requirements for batteries as part of the eligibility rules for consumer subsidies. While a policy simulation of the local content requirements under IRA is out of sample of our study, our analysis suggests that the policy will likely generate welfare impacts across consumers, battery suppliers, and EV producers in the US that are qualitatively similar those observed under the whitelist policy in China. To the extent that the production cost of battery will be higher at least initially, the switch to batteries produced in North America from cheaper batteries made elsewhere will lead to loss in consumer surplus, reduced profit among EV producers as well as slower EV adoption in the U.S. and elsewhere.

6.3 LBD and Policy Interactions

To examine the role of LBD, and how it interacts with consumer subsidies, we simulate market outcomes for the top 13 EV countries during 2013-2020 under four scenarios as shown in Figure 6: (1) no consumer subsidies and no LBD; (2) with consumer subsidies but without LBD; (3) without consumer subsidies but with LBD; and (4) with both consumer subsidies and LBD.

The difference between the first and third scenarios (i.e., the bottom line and the second line from the top) captures the effect of LBD itself (absent any subsidies): the cost reduction from LBD increased global EV sales by 2.99 million unit (or 121%) during 2013-2020 relative to a baseline scenario with no LBD. In addition, LBD greatly amplifies the effect of consumer subsidies through the feedback loops: in the absence of LBD, consumer subsidies would have increased sales by 24.7% (or 0.61 million units) during 2013-2020; whereas in the presence of LBD, subsidies are estimated to have increased sales by 49% (or 2.69 million). The combined effect of LBD and consumer subsidies (the difference between the top and bottom lines) is 5.68 million units during 2013-2020, or 231% of the baseline sales. This combined effect is nearly 60% larger than the sum of the individual effect, suggesting strong complementarity between LBD and consumer subsidies. Table A3 shows the welfare impacts of consumer subsidies by region in the absence of LBD. The global impacts from subsidies as well as the impacts on the source region are only about one fifth to one third of the baseline estimates presented in Table 5 with LBD. The cross-country spillover is also much weaker.

To further illustrate how LBD interact with policies, we simulate the impacts of Chinese consumer subsidies and the whitelist policy in the absence of LBD. Table 7 presents the welfare impacts of the two policies with and without LBD. Welfare gain and positive cross-country spillovers from consumer subsidies without LBD are less than 20% of those with LBD. Likewise, negative spillovers from China's whitelist policy to the rest of the world are much smaller as well in the absence of LBD. These findings underscore the critical importance of taking LBD into account in

understanding the cost-effectiveness and broad impacts of policies to promote EVs.

7 Conclusion

The transportation sector is a significant contributor to global greenhouse gas (GHG) emissions. Electrifying transportation stands out as a crucial strategy adopted by many countries to combat climate change. Despite substantial growth in the EV market during the last decade, further reductions in battery costs and ultimately EV prices remain imperative for the ultimate success of this strategy. The paper aims to offer valuable insights into the process of cost reduction in this key clean energy technology. In addition, it seeks to shed light on important government policies to promote this technology, notably the funding provisions in both the IRA and IIJA. The research findings would enhance our understanding of how LBD interacts with policies and the comprehensive impacts of these policies on the cost reduction for batteries and electric vehicles (EVs), firm market share dynamics, and the global diffusion of EVs in the future.

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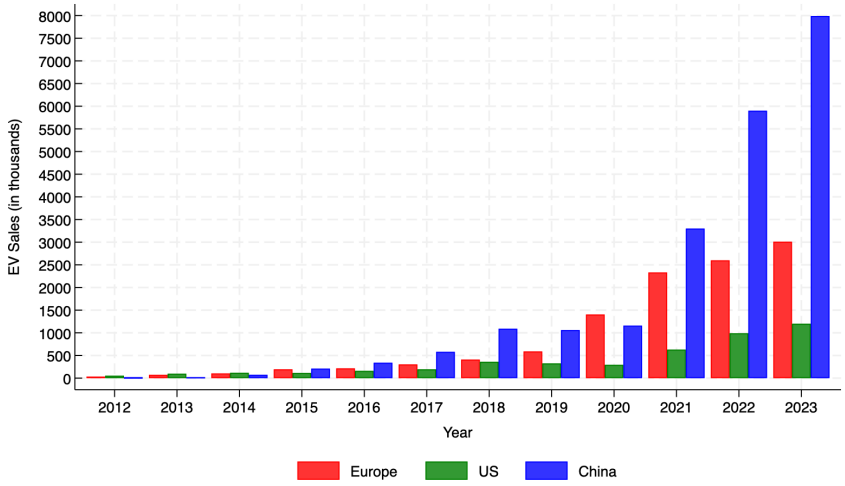
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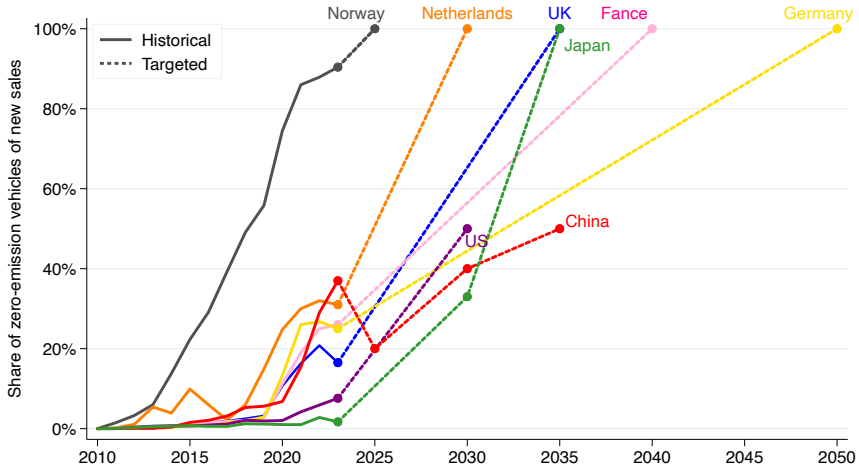
Figures & Tables

Figure 1: Global EV Diffusion

(a) EV Sales by Region



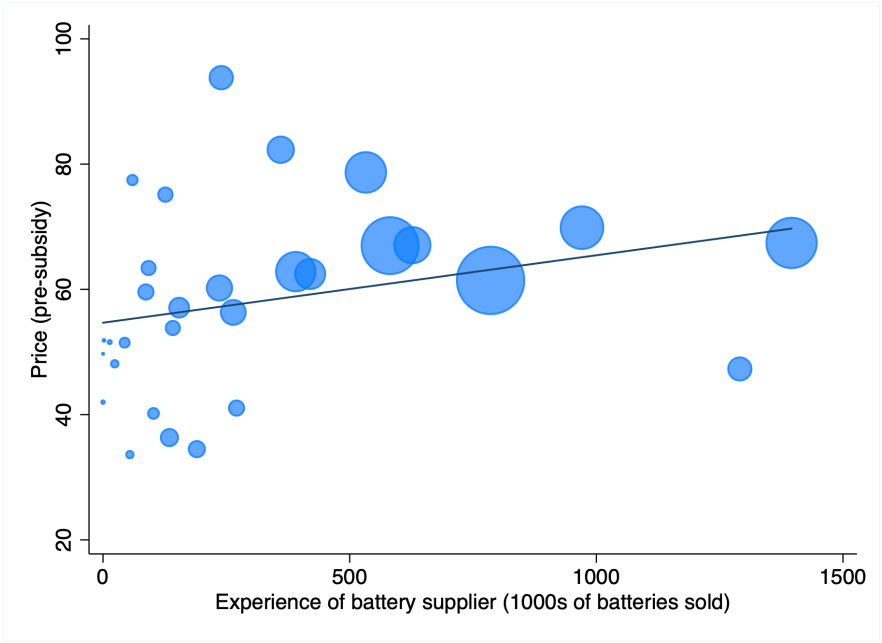
(b) ZEV Targets and EV Shares



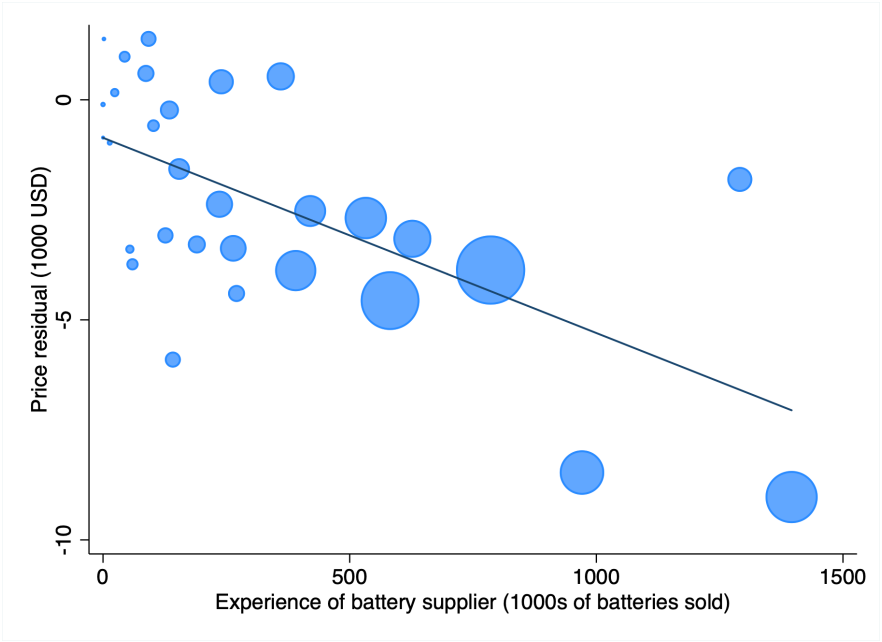
Notes: Panel (a) shows the annual sales of new EVs (including both BEVs and PHEVs) by region from 2012 to 2023. China, Europe and the U.S. accounted for over 95% of global EV sales during the data period. Source: International Energy Agency. Panel (b) depicts the zero-emission vehicle (ZEV) targets and the market share of ZEVs over time by country. ZEVs include EVs and fuel cell vehicles but have been predominantly EVs. Source: International Energy Agency and the International Council on Clean Transportation.

Figure 2: Vehicle Price vs. Battery Supplier Experience

(a) Raw Prices



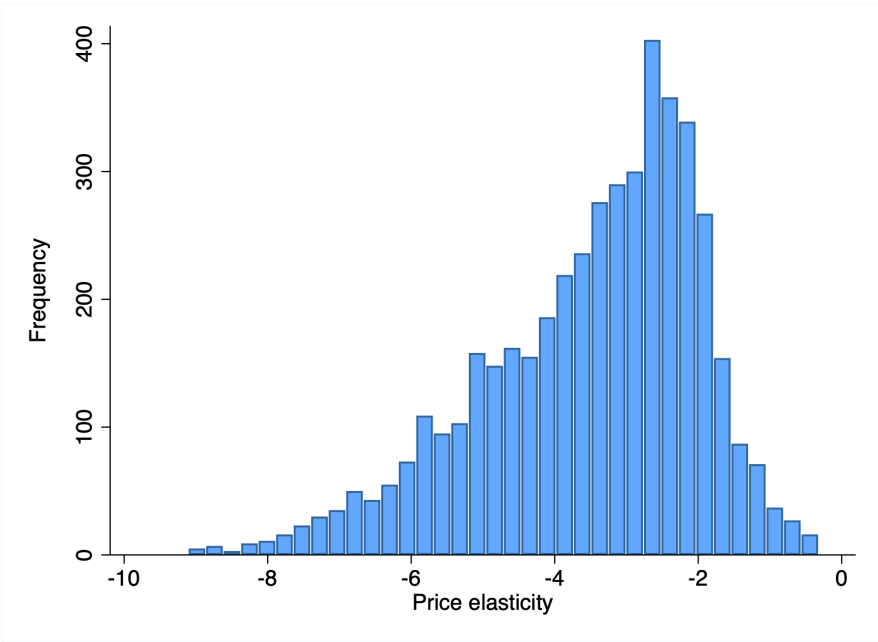
(b) Residualized Prices



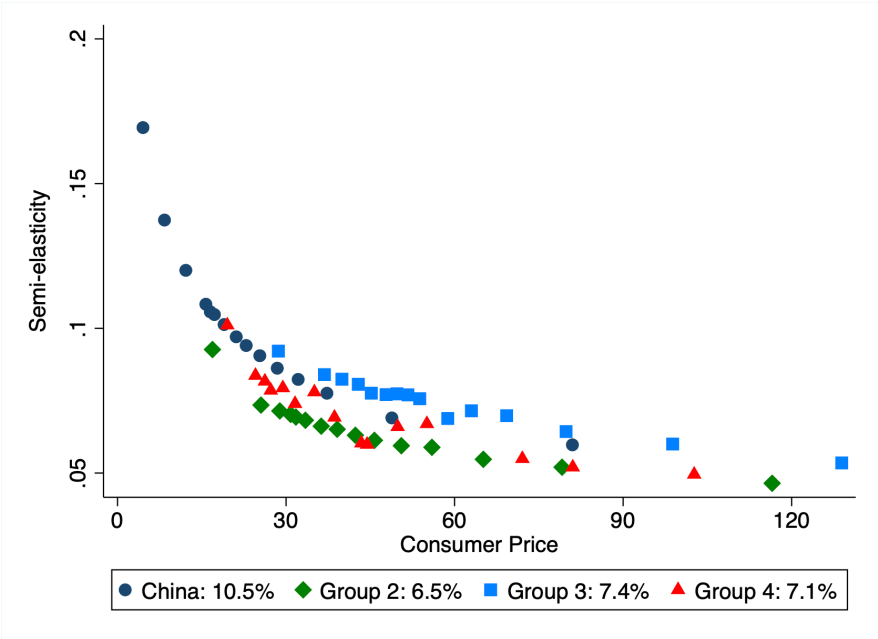
Notes: The binned scatter plot in Panel (a) shows the raw correlation between vehicle price and the experience of the battery supplier for the corresponding EV model. Panel (b) shows the residulized prices after partialing out vehicle attributes (horsepower, size, driving range, and the PHEV dummy), country fixed effects, brand fixed effects, and year fixed effects. The size of the dot is proportional to the cumulative subsidy received by the battery supplier.

Figure 3: Implied Demand Elasticities

(a) Elasticity



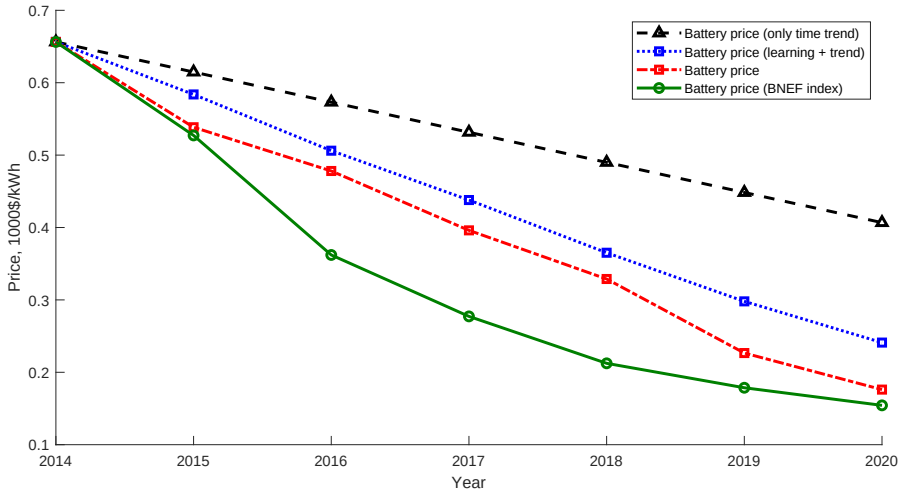
(b) Semi-elasticity ($1000 ↓)



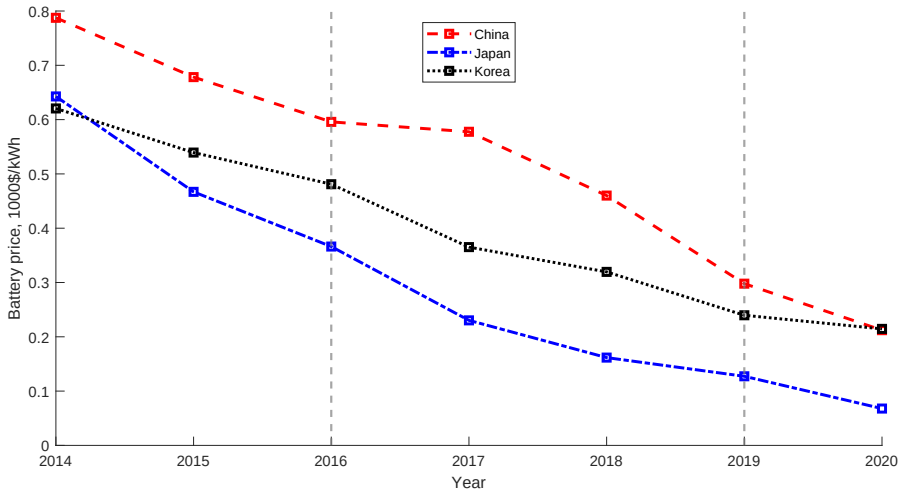
Notes: Panel (a) shows the histogram of price elasticities of demand with the average being 3.51. Panel (b) depicts the binned scatter plot for semi-elasticities (the percentage change in sales for a $1,000 reduction in own prices) by country group. The increase in the percentage of sales is more pronounced for cheaper vehicles, implying more sensitive demand.

Figure 4: LBD and Cost Reduction

(a) Decomposing Cost Reduction

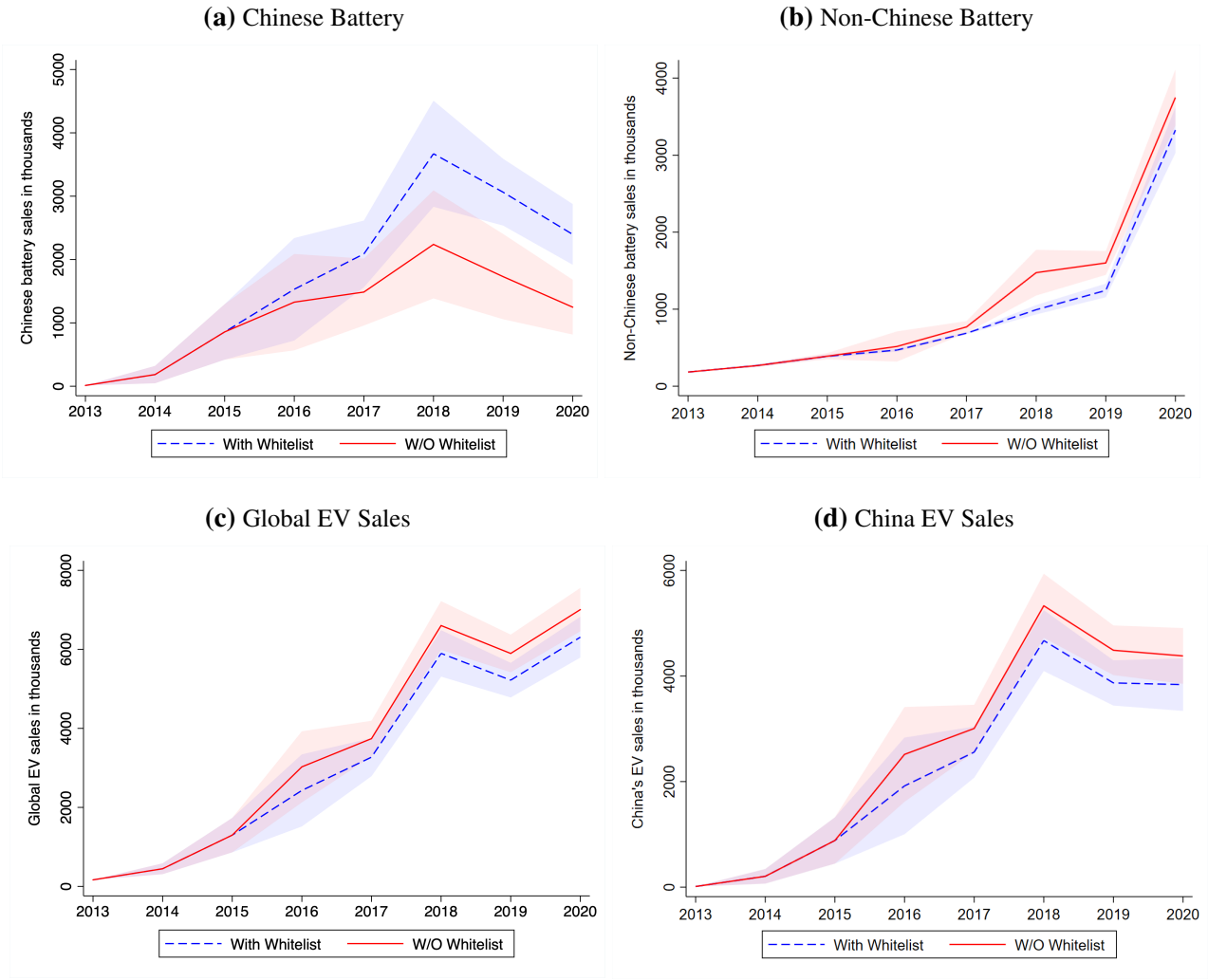


(b) Cost Reduction across Countries



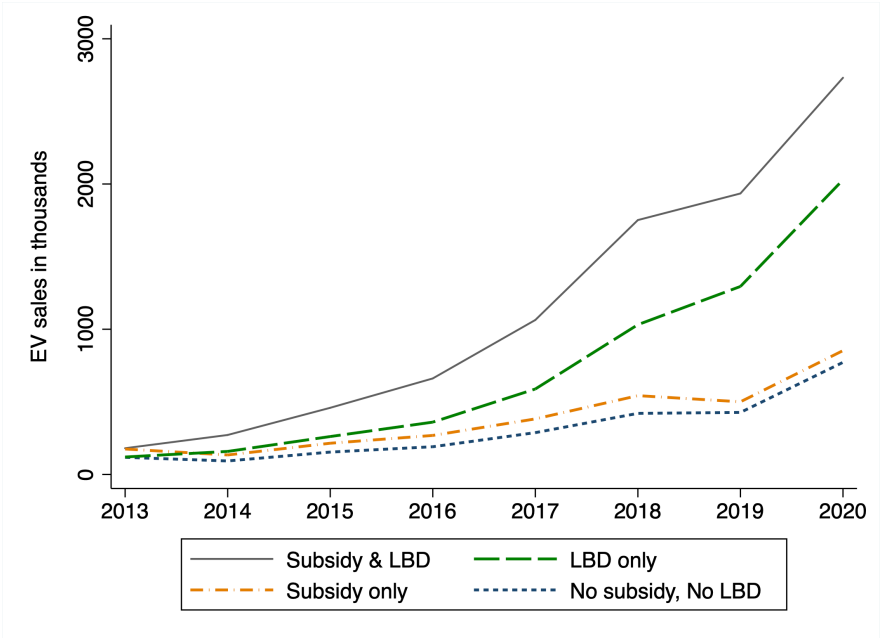
Notes: These plots show the reduction of battery cost over time from 2014 to 2020. Panel (a) decomposes the cost reduction into two components: learning and time trend. The bottom green line shows the battery price index from the Bloomberg New Energy Finance while the red line from the second to the bottom depicts the predictions of our model. Panel (b) shows the cost reduction for battery suppliers from China, Japan, and Korea respectively. Chinese battery suppliers started at a high cost level but experienced a faster reduction over time.

Figure 5: Impact of China's Whitelist policy on battery production and EV Sales



Notes: Panel (a) shows EV battery production by Chinese suppliers with and without China's Whitelist policy. Panel (b) depicts battery production by non-Chinese suppliers under the two scenarios. Panels (c) and (d) show EV sales globally and in China, respectively.

Figure 6: Effect of Subsidies on Global EV Sales



Notes: The figure depicts total EV sales from top 13 EV countries under various scenarios. The top line shows the observed EV sales with LBD and consumer subsidies in place while the bottom line shows the sales with neither of the two factors. The difference between the bottom two lines shows the effect of subsides without LBD while that between the top two lines captures the impact of the effect of subsidies in the presence of LBD. LBD greatly amplifies the 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						
Experience	204	86,672	199,272			
Production Capacity (GWh)	204	10.51	18.49			
Panel D: Market-level information						
HHI, downstream	104	2,731	1,616			
HHI, upstream	104	2,961	788			

Notes: The sample covers 13 countries which have the largest EV sales in the world from 2023 to 2020. NMC: Nickel Manganese Cobalt; LFP: Lithium iron phosphate; NCA: Nickel Cobalt Aluminum Oxide.

Table 2: Demand Estimation Results

	(1) OLS logit		(2) IV logit		(3) Full model	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Linear parameters						
Consumer price (α_1)	-0.016	0.002	-0.057	0.010	-0.017	0.009
PHEV	4.763	0.898	4.787	0.911	4.402	0.958
log(volume)	-0.744	0.245	0.749	0.417	1.346	0.413
log(HP)	0.285	0.154	1.217	0.277	1.191	0.274
log(range)	1.229	0.163	0.918	0.184	1.025	0.192
log(range) x PHEV	-0.780	0.209	-0.868	0.214	-0.638	0.219
Non-linear price coefficients (α_{2c}/y_i)						
α_2 for China	-	-	-	-	0.318	0.013
α_2 for JP/SP/FR/DE	-	-	-	-	0.220	0.020
α_2 for UK/NL/AT/SE	-	-	-	-	1.221	0.111
α_2 for CA/NO/US/CH	-	-	-	-	0.616	0.026
Random coefficients (σ)						
Constant	-	-	-	-	0.330	0.038
log(volume)	-	-	-	-	0.077	0.013
log(HP)	-	-	-	-	0.032	0.004
log(range)	-	-	-	-	0.014	0.006
Consumer price	-	-	-	-	0.123	0.009

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

Table 3: LBD Estimation Results

	(1)	(2)	(3)	(4)
Bargaining weight λ^b	0.503	0.484	0.488	0.275
	(0.074)	(0.08)	(0.08)	(0.132)
Battery Cost Parameters				
Learning para. γ_E	-0.203	-0.135	-0.137	-0.112
	(0.048)	(0.044)	(0.044)	(0.052)
γ_0(1000$/kWh)	1.095	1.071	1.082	0.856
	(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)			0.025	-0.081
			(0.045)	(0.036)
*BK**battery chemistry dummies	✓	✓	✓	✓
Vehicle Cost Parameters				
EV Experience				-0.997
				(0.421)
PHEV	11.741	10.998	11.231	2.163
	(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	-2.600	0.808
	(0.647)	(0.657)	(0.678)	(0.232)
Fixed Effects				
Country	✓	✓	✓	✓
EV brand	✓	✓	✓	✓
Battery supplier	✓	✓	✓	✓
Year	✓	✓	✓	✓

Notes: This table reports the parameter estimates for Equation (9). All specifications use GMM estimation with battery supplier experience, battery markup (the variable corresponding to bargaining weight), and EV producer experience being instrumented. The marginal cost of battery pack is specified as: $BK_{bjct}\left(\gamma_0 E_{bt}{}^{\gamma_E} + CH_{bjct}\gamma_1 + PK_{bt}\gamma_2 + \eta * t\right)$. *BK* is battery capacity; γ_E is the learning parameter; and γ_0 capture the baseline cost. The regression has three sets of controls. The first set includes the variables specified in the battery marginal cost: battery capacity interacting with battery chemistry (NMC, NCA, LFP), battery capacity interacting with time trend to capture industry-wise technological progress or cost shocks, and battery capacity interacting with production capacity of the firm to capture economies of scale. The second set includes vehicle attributes such as vehicle fuel type (BEV or PHEV), vehicle size, horsepower, and EV producer experience (i.e., cumulative EV production by each EV producer in logarithm) to capture LBD in automobile manufacturing. The third set of controls include country fixed effects, EV brand fixed effects, battery supplier fixed effects, and year fixed effects.

Table 4: LBD: Spillovers Across Firms

	(1) No spillovers	(2) Spillovers
Bargaining weight, λ^b	0.275	0.274
	(0.132)	(0.133)
Battery Cost Parameters		
Learning para. γ_E	-0.112	-0.173
	(0.052)	(0.093)
γ_0(1000$/kWh)	0.856	1.027
	(0.164)	(0.37)
*BK**Time Trend	-0.032	-0.022
	(0.006)	(0.006)
*BK**log(Plant Capacity)	-0.081	-0.065
	(0.036)	(0.018)
Within-country spillover, θ		0.044
		(0.131)
*BK**battery chemistry dummies	✓	✓
Vehicle Cost Parameters		
EV Experience	-0.997	-1.032
	(0.421)	(0.412)
PHEV	2.163	2.058
	(1.104)	(1.102)
Horsepower	0.244	0.243
	(0.007)	(0.007)
Volume	0.808	0.878
	(0.232)	(0.23)
Fixed Effects		
Country	✓	✓
EV brand	✓	✓
Battery supplier	✓	✓
Year	✓	✓

Notes: This table reports the parameter estimates for Equation (9). Column(1) is identical to Column (1) from Table 3. In Column (2), we include the experience of rival firms in the same country scaled by a parameter θ that we estimate; we instrument for rival experience using predicted rival experience constructed based on Equation (10).

Table 5: Impact of Consumer Subsidies

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of US Subsidies					
Δ Welfare ($ bn.)	0.44	1.83	5.31	8.98	16.57
Δ Consumer surplus (+)	0.27	0.90	0.04	13.48	14.69
Δ Battery profit (+)	0.07	-	4.27	-	4.34
Δ EV profit (+)	0.14	1.29	1.00	8.74	11.18
Δ Gov't expenditure (-)	0.04	0.35	0.01	13.24	13.64
Δ EV sales	18,156	46,202	2,968	770,844	838,171
Panel (b): Impacts of European Subsidies					
Δ Welfare ($ bn.)	0.63	4.03	4.70	2.18	11.52
Δ Consumer surplus (+)	0.26	14.65	0.06	0.79	15.75
Δ Battery profit (+)	0.15	-	3.46	-	3.63
Δ EV profit (+)	0.23	5.70	1.18	1.72	8.83
Δ Gov't expenditure (-)	0.01	16.34	0.01	0.33	16.69
Δ EV sales	16,359	753,690	3,900	45,781	819,730
Panel (c): Impacts of Chinese Subsidies					
Δ Welfare ($ bn.)	26.08	0.45	0.69	0.80	28.01
Δ Consumer surplus (+)	24.71	0.45	0.01	0.28	25.45
Δ Battery profit (+)	6.07	-	0.64	-	6.72
Δ EV profit (+)	16.44	0.17	0.04	0.63	17.28
Δ Gov't expenditure (-)	21.15	0.17	0.00	0.11	21.43
Δ EV sales	2,566,694	20,830	775	15,948	2,604,246

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

Table 6: Impacts of China's Whitelist Policy

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of China's Whitelist itself in the presence of subsidies					
Δ Welfare ($ bn.)	1.70	-0.46	-2.61	-0.69	-2.07
Δ Consumer surplus (+)	-1.12	-0.39	-0.01	-0.26	-1.79
Δ Battery profit (+)	2.15	-	-2.54	-	-0.40
Δ EV profit (+)	-0.40	-0.22	-0.06	-0.54	-1.21
Δ Gov't expenditure (-)	-1.07	-0.15	0.00	-0.11	-1.33
Δ EV sales	-81411	-20270	-921	-15203	-117805
Panel (b): Impacts of China's policy combination: Whitelist and Subsidies					
Δ Welfare ($ bn.)	27.77	-0.02	-1.92	0.11	25.95
Δ Consumer surplus (+)	23.59	0.05	0.00	0.02	23.66
Δ Battery profit (+)	8.22	-	-1.90	-	6.32
Δ EV profit (+)	16.04	-0.05	-0.02	0.10	16.07
Δ Gov't expenditure (+)	20.07	0.02	0.00	0.01	20.1
Δ EV sales	2485283	559	-146	745	2486441

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

Table 7: LBD and Policy Interactions

($ bn.)	World	China	Rest of World
With LBD			
Δ Welfare, Chinese subsidies	28.01	26.08	1.93
Δ Welfare, Whitelist	− 2.07	1.70	− 3.77
Without LBD			
Δ Welfare, Chinese subsidies	5.21	+ 4.97	+ 0.24
Δ Welfare, Whitelist	− 0.27	0.45	− 0.72

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

Online Appendix

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

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

A Data Construction Appendix

The battery cell plant database is constructed based on the 2022 lithium-ion battery gigafactory databaseof Automotive Logistics (AL), and analysis report from Markline. The AL dataset presents the main characteristics of each plant by year and region, including manufacturing start date, current capacity in 2022, predicted capacity from 2023-2030, and city-level location. For 2022, the dataset contains 204 cell plants in Asia Pacific with 703 GWh, 73 cell plants in Europe with 160 GWh and 48 cell plants in North America with 95 GWh. The analysis report of Markline presents the 2018-2021 production capacity of top10 Chinese cell suppliers (CATL, LG, Panasonic, Findreams/BYD, EVE, CALB, Gotion High-tech, Farasis Energy, SVOLT, and Sunwoda), which account for 60% global market share.

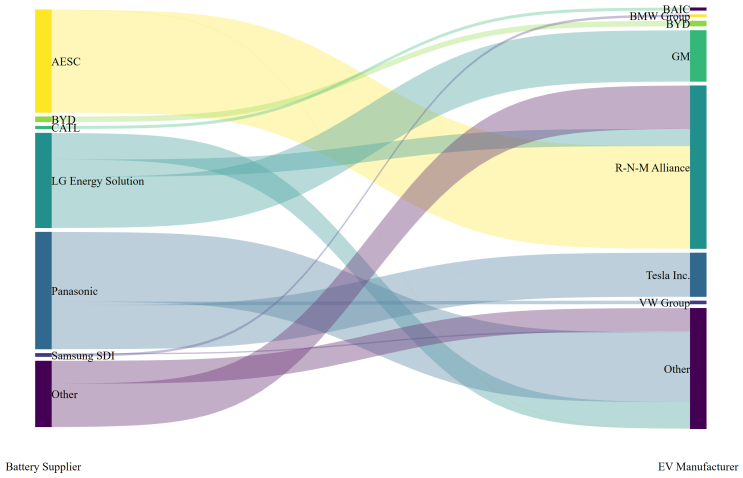
To combine the two data sources, we made detailed improvements by merging the plants and completing the capacity before 2022 using a manual search approach.

There appear to have significant discrepancies between our manually collected data and those from reports, especially plants that starts after 2020. The discrepancies mainly come from 2 aspects. First, online news report only show the date for signing the contract, which is usually earlier than the date of factory construction. Second, online news report only show the maximum capacity, thus it is necessary to estimate the exact annual production by using a lag, where we define as a 2-year time-to-build, and a 2-year ramp-up. This assumption is intuitively natural, as the average year for plants in our dataset to reach their maximum capacity production is 1.8. We find our data consistent with some of the major media reports, including International Energy Agency (IEA) and Bloomberg.

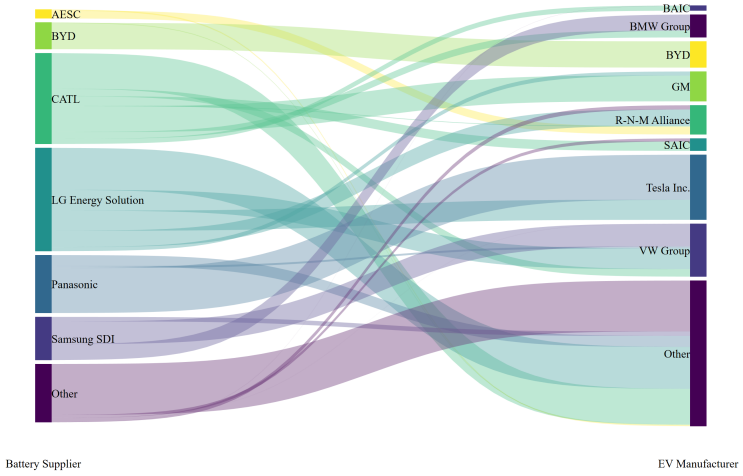
B Appendix Figures

Figure A1: Battery supplier network

(a) 2013 network



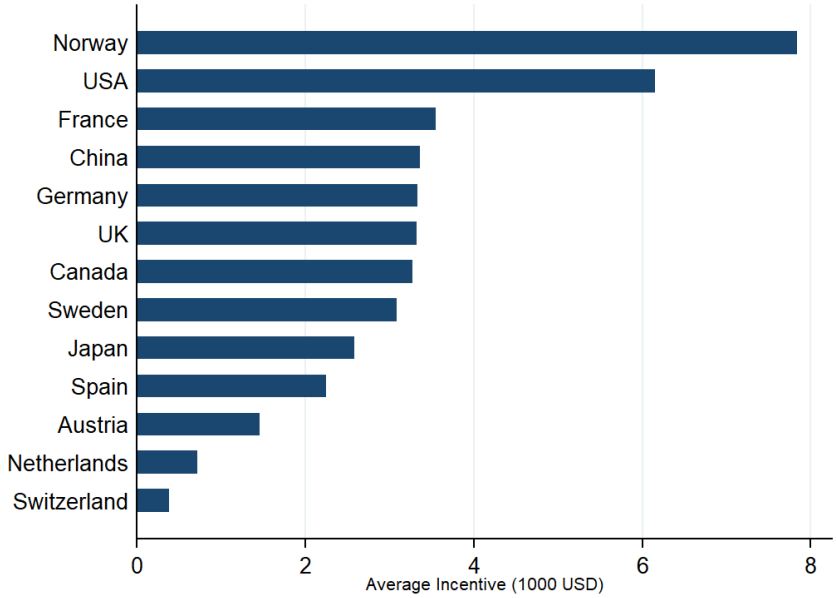
(b) 2020 network



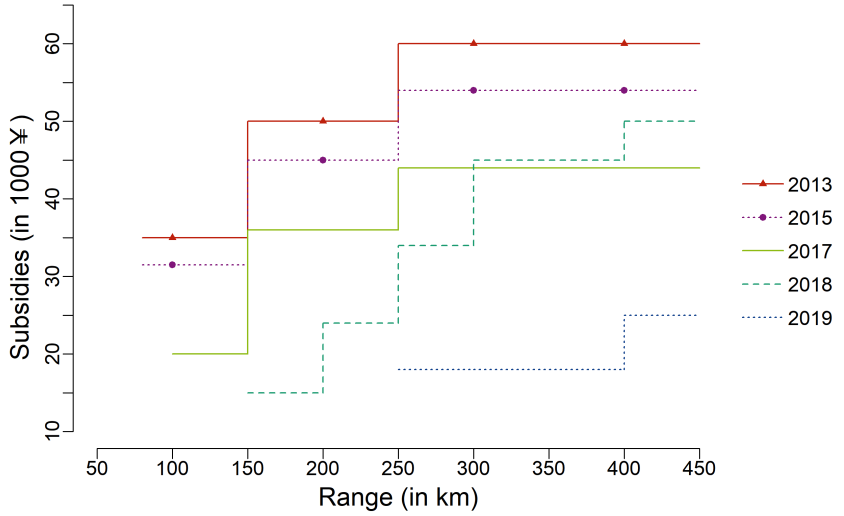
Notes: The figure depicts the vertical relationship between battery suppliers (on the left) and EV producers (on the right). The top 6 battery suppliers and top 8 EV producers are shown separately, illustrating a two-sided duopoly market structure. The thickness of the lines represents the battery sales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

Figure A2: EV Subsidies

(a) Average subsidies by country



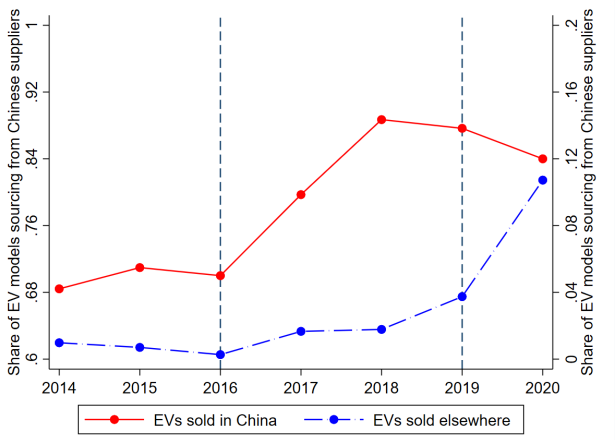
(b) Subsidy design in China



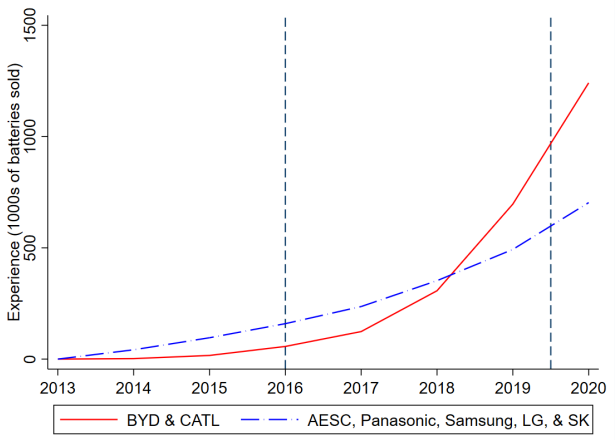
Notes: Panel (a) shows the average federal subsidy per eligible EV by country during 2013-2020 while Panel (b) shows the subsidy schedule for BEVs in China where the amount of subsidy is based on driving range.

Figure A3: China's whitelist policy

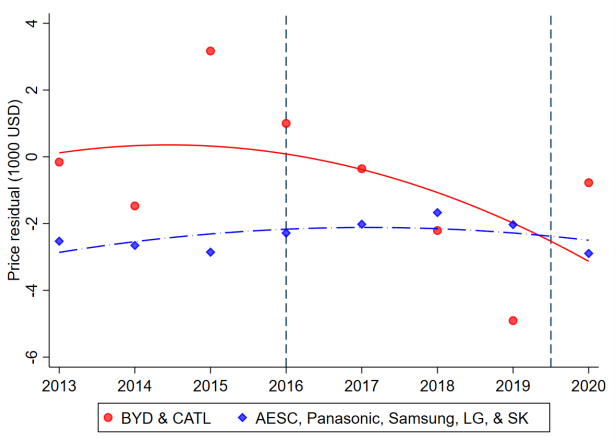
(a) Domestic sourcing of batteries



(b) Battery sales



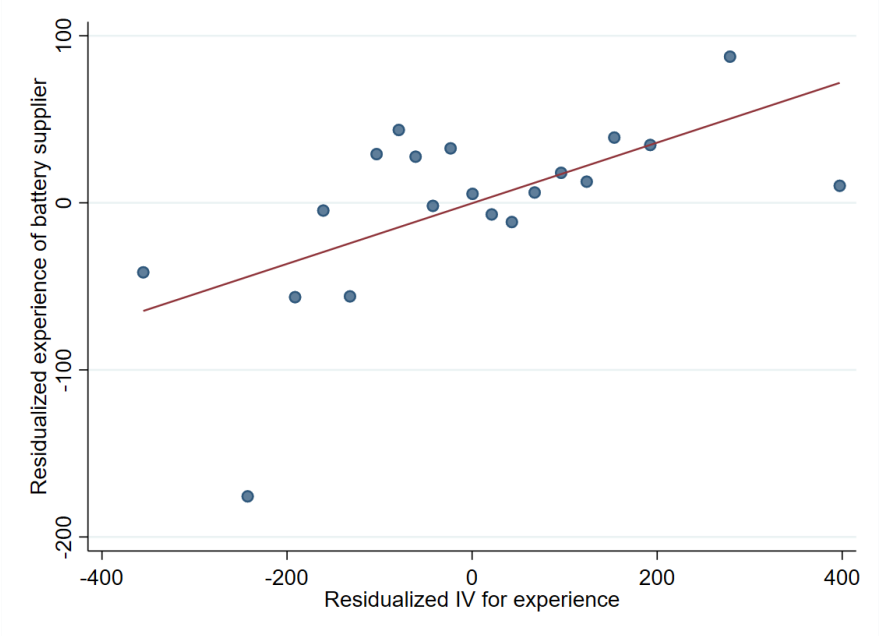
(c) Vehicle price



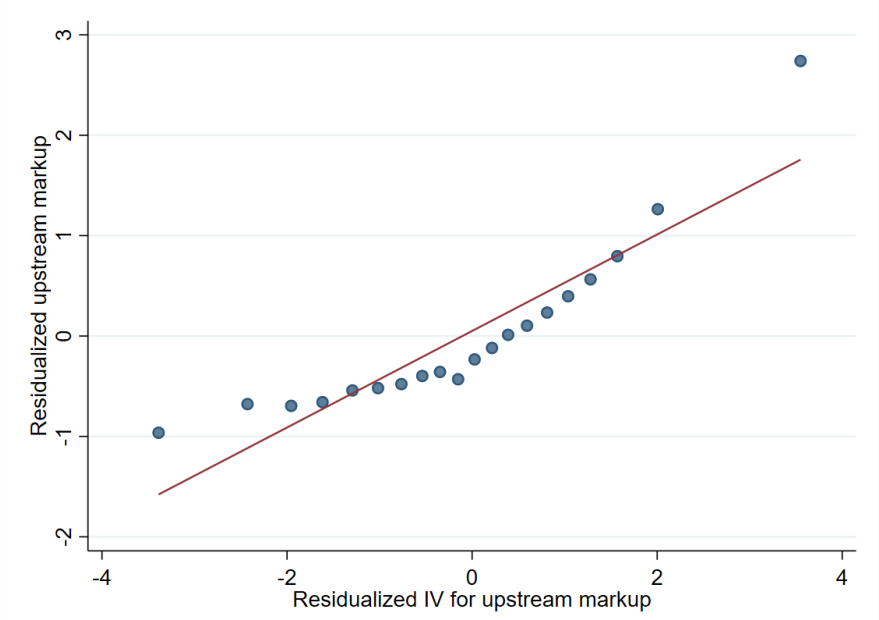
Notes: Panel (a) shows the share of EV models sourcing from Chinese battery suppliers separately for EV models sold in China, and those sold elsewhere. Panel (b) shows the growth of (average) experience of battery suppliers overtime separately for the top-two Chinese suppliers, and the top-four non-Chinese suppliers. Panel (c) depicts the average EV price by year for the two groups. The two dotted vertical lines defines China's whitelist policy.

Figure A4: Instruments for Experience and Battery Markups

(a) Experience



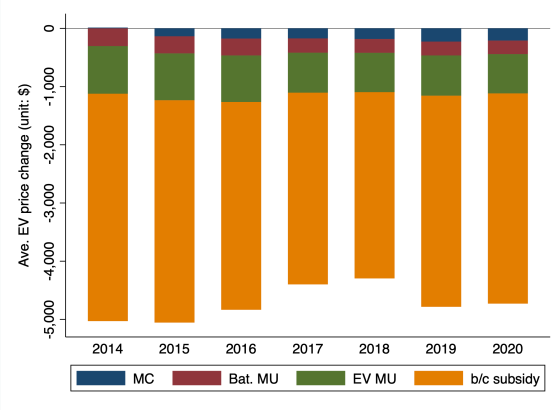
(b) Battery markup



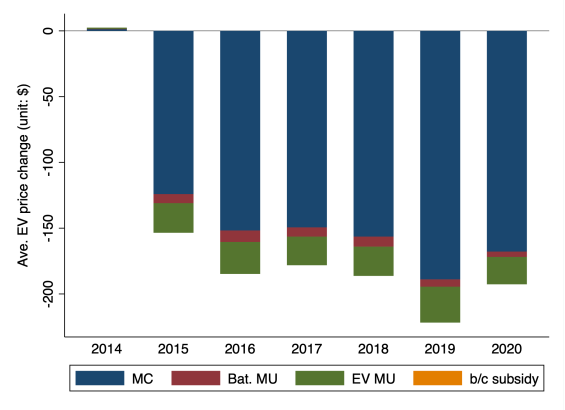
Notes: Binned scatter plots to illustrate the strength of the IVs for the experience and markups of battery suppliers. Residuals are obtained from partialing out vehicle attributes, as well as country fixed effects, brand fixed effects, and year fixed effects.

Figure A5: Price Changes due to Subsidies

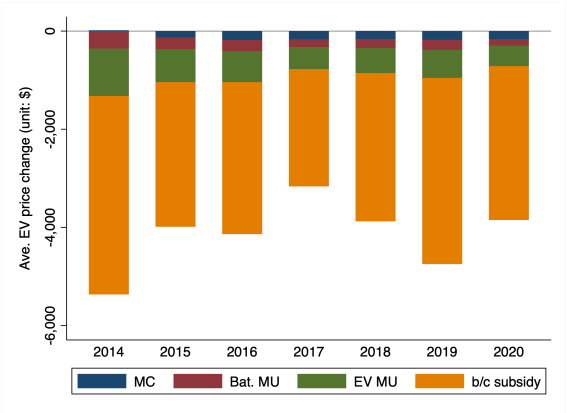
(a) In US & CA from US subsidies



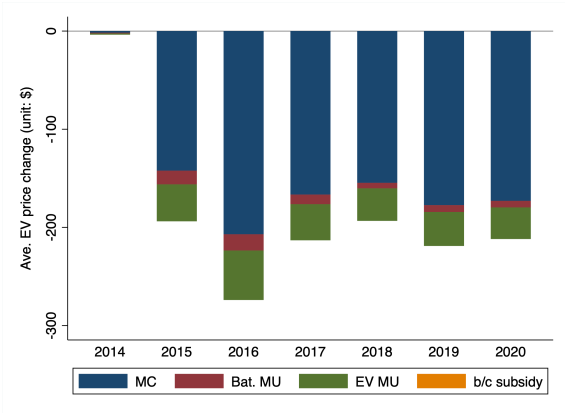
(b) In Europe from US subsidies



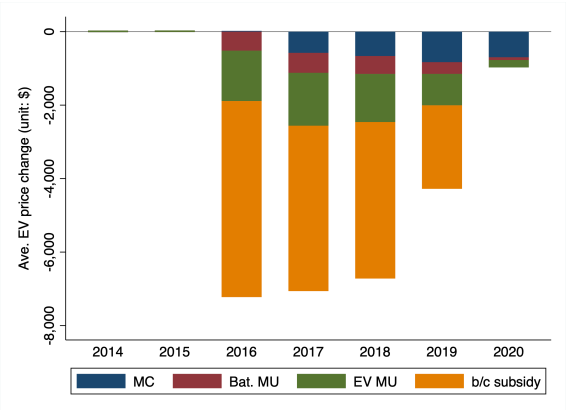
(c) In Europe from European subsidies



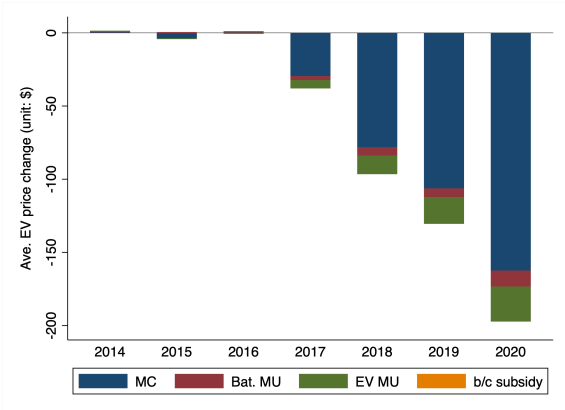
(d) In US & CA from European subsidies



(e) In China from Chinese subsidies



(f) Outside China from Chinese subsidies



Notes: These figures show the subsidy-induced changes in different components of consumer prices: battery marginal cost (MC), upstream markup (bat. MU), downstream markup (EV MU), and subsidy pass-through (b/c subsidy). The top panel shows the price changes in the US & CA, and in Europe from US subsidies; the middle panels shows the price changes in the US & CA, and in Europe from European subsidies; the bottom panel shows the price changes in China and outside of China from Chinese subsidies.

C Appendix Tables

Table A1: Network Formation Model for IV Construction

	Dep. var.: Link formed
White List China (2016 - 2019)	2.683***
	(0.834)
Home Bias	2.666***
	(0.421)
Initial links	Yes
Dummies for vertically integrated firms	Yes
Supplier characteristics	Yes
Initial links*Supplier characteristics	Yes
EV attributes*Supplier characteristics	Yes
EV attributes*Initial links	Yes
Log-likelihood	-846.44
Observations	8179

Note: The unit of analysis is a model-country-year-battery supplier combination. The dependent variable is one if the EV producer (i.e., OEM) for that EV model sources battery from a given battery supplier, and zero otherwise. The results are from a conditional logit regression. We assume the choice set for each OEM includes every battery supplier that was already active in that country. EV makers choose battery suppliers the year when the EV model is first released. Standard errors are clustered at the country - OEM level.
"White List China (2016 - 2019)" equals 1 for EVs in China during China's whitelist period 2016-2019, if the supplier is Chinese, and 0 otherwise. Home bias is a dummy variable being one if the supplier-OEM pair has the same country-of-origin. Other controls include dummies for all supplier-OEM pairs that are vertically integrated: namely, BYD - BYD and AESC - RNM alliance. We control for the initial network structure by including a dummy variable that equals one if the supplier-OEM pair had an initial supply relationship at the beginning of our data period, and another dummy variable for whether the initial supply relationship was in the same country as the one where the EV is produced. We also include the age of each supplier, as well as the following *initial* characteristics of the supplier: the average battery capacity, the most common chemistry of batteries initially supplied, and the average number of models for which the firm was a battery supplier. Finally, we include interaction terms between initial links, supplier characteristics, and EV characteristics (volume, horsepower, battery capacity, range, and battery chemistry).

Table A2: Network Formation Model for Counter-factual Simulations

	Dep. var.: Link formed
Eligible Subsidy	0.432***
	(0.109)
Supplier-OEM lagged link	2.964***
	(0.195)
Supplier-OEM lagged link, same country	0.491***
	(0.131)
Dummies for vertically integrated firms	Yes
Initial link or home bias	Yes
Fixed effects for top 6 suppliers	Yes
Supplier characteristics	Yes
Log-likelihood	-1280.69
Observations	23495

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

Table A3: Impact of Consumer Subsidies without Learning

	China	Europe	JP & KR	US & CA	Global
Panel (a): Impacts of US Subsidies					
Δ Welfare	0.00	0.61	1.87	1.88	4.36
Δ Consumer surplus	-0.01	0.00	0.00	3.89	3.88
Δ Battery profit	0.00	-	1.25	-	1.25
Δ EV profit	0.00	0.61	0.61	2.00	3.22
Δ Gov't Expenditure	-0.01	0.00	0.00	4.02	4.01
Panel (b): Impacts of European Subsidies					
Δ Welfare	0.07	2.07	1.74	0.24	4.12
Δ Consumer surplus	0.00	5.28	0.00	0.00	5.28
Δ Battery profit	0.04	0.01	1.17	0.00	1.18
Δ EV profit	0.02	2.25	0.57	0.24	3.08
Δ Gov't expenditure	0.00	5.47	0.00	0.00	5.47
Panel (c): Impacts of Chinese Subsidies					
Δ Welfare	4.97	0.03	0.14	0.07	5.21
Δ Consumer surplus	4.69	0.00	0.00	0.00	4.69
Δ Battery profit	1.29	0.00	0.14	0.00	1.43
Δ EV profit	3.66	0.03	0.00	0.07	3.76
Δ Gov't expenditure	4.67	0.00	0.00	0.00	4.67

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