# Capability, Consumption, and Competition: China's Leapfrogging in Electric Vehicles Industry

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**Abstract**

This study unpacks China's electric vehicles (EV) industrial policies over the past two decades through three sequential stages: Capability, Consumption, and Competition (the *3C strategy*). We first empirically document the structured and phased policy approach backed by nine major instruments. We then theorize and quantify the impact of policies with a two-country, two-technology industry-equilibrium model with directed and step-by-step innovation. We find that (i) China's initial EV technology gap with foreign is much smaller than the GV gap, making EVs the profitable direction for Chinese firms and rationalizing rapid lane-switching; (ii) the policy bundle delivers long-run welfare gains at Home and positive global spillovers through consumer surplus and global emissions benefits, despite substantial short-run costs; (iii) different types of policy are complements, and policy sequencing is critical to overall effectiveness. Taken together, China's low opportunity cost and well-designed policy package fueled its leapfrogging in EV industry.

**JEL classification:** O25, O30, O38, Q55, Q58

**Keywords:** Electric Vehicles, Industrial Policy, Directed Technical Change, International Competition

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# 1 Introduction

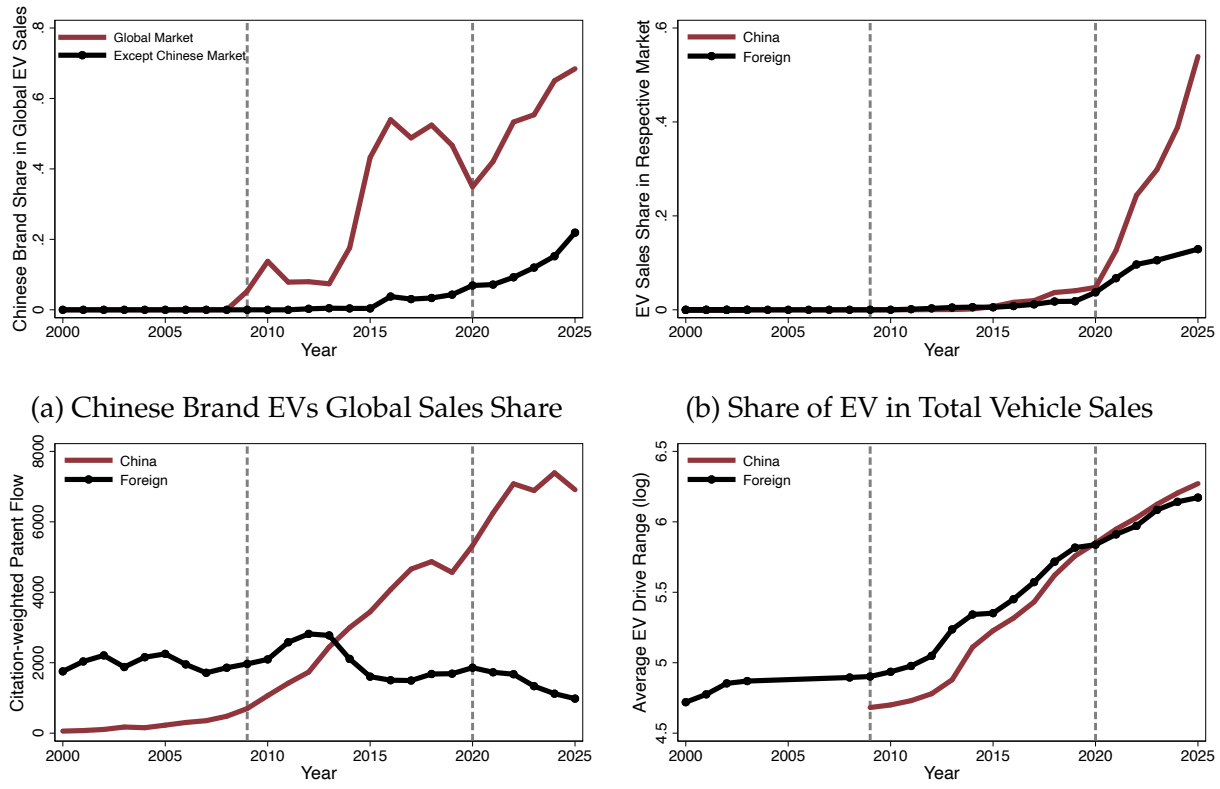
Ever since economic development has become inseparable from the problem of catch-up, economists have studied, debated, and often contested the role of government policy in narrowing the technological gap and promoting industrial growth in latecomer economies (List, 1841; Gerschenkron, 1962; Amsden, 1989; Lin, 2012). In practice, many developing-country governments have pursued industrial policies with the aim of enhancing economic sophistication and fostering globally competitive domestic industries. Yet, few have succeeded. Despite substantial targeted support, domestic firms often continue to lag behind global technology leaders, scaling-up efforts frequently falter, and the resulting market competition remains insufficient.

China's experience in the electric vehicle (EV) sector offers a notable exception. Beginning with the 10th Five-Year Plan (2001–2005), the Chinese government deployed sustained policy support for over two decades, aiming to build up domestic technological base and *leapfrog* over the incumbent GV technology. Although a few advanced economies have historically dominated the global automobile industry, two decades of sustained policy efforts have catapulted Chinese manufacturers to the forefront in the transition toward EV technologies.

As Figure 1.1 illustrates, Chinese brands are now important players in the global market, accounting for over 60% of worldwide EV sales in 2024 and rapidly expanding their export to the rest of the world (Panel a). Domestically, the Chinese market is accelerating the transition away from gasoline vehicles (GVs). EVs now capture over 50% of total new vehicle sales in China as of 2025, standing in contrast to the slow market penetration observed in most advanced economies (Panel b).[1] In addition to this market expansion, Chinese EV manufacturers have rapidly converged to the global technology frontier. As Panel (c) demonstrates, Chinese patent filings in EV technologies has exceeded those of traditional auto powerhouses. This rapid accumulation of innovation is also evident in the growth in product quality: the average electric driving range of Chinese EVs has quadrupled in just fifteen years and surpassed Foreign producers in recent years (Panel d).

How did China's EV industry evolve over time? What role did industrial policy play in

[1]For international comparison, we construct a benchmark "foreign country," defined as the weighted combination of five traditional auto powerhouses (the United States, Japan, Germany, South Korea, and France). The weights for sales and prices are based on total vehicle sales in each of the five countries, while the weights for patents are based on global vehicle sales by automobile firms headquartered in each country. The annual weights are reported in Table A.3.




(a) Chinese Brand EVs Global Sales Share

(b) Share of EV in Total Vehicle Sales

(c) Number of EV Patent Filing

(d) Average EV Model Quality

Figure 1.1: Trends in China's EV Industry Performance

*Note:* This figure shows the performance of Chinese EV producers and EV market (data source: Marklines, Autohome, ORBIS IP). Panel (a) plots the share of Chinese-brand electric vehicles (EVs) in the total quantity of EVs sold globally (solid blue line) and the share of Chinese-brand EVs in total EV sales outside of the Chinese market (dashed red line) from 2000 to 2024. Panel (b) displays the market penetration of EVs, calculated as the share of new EVs in total vehicle sales, for the Chinese market and the Foreign market. "Foreign" is constructed as a weighted average of the five major automobile powerhouses: the United States, Japan, Germany, South Korea, and France. Weights are based on total vehicle sales in each country. EVs include battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), and fuel cell vehicles (FCV). Panel (c) shows the annual patent filing flow of Chinese applicants and Foreign applicants in global patent offices. Patents are identified as GV and EV technology according to Main IPC codes in Appendix A, and are citation-weighted and counted by patent families. Panel (d) shows the logarithm of average drive range of Chinese brand and Foreign brand EVs by model release year.

driving China's rise from a latecomer into a global EV powerhouse? And more importantly, what general lessons can global policymakers draw from this case? In this study, we unpack the development of China's EV industry and the impact of industrial policy both theoretically and quantitatively. We first bring together new evidence on the two-decade evolution of China's EV industrial policy, drawing on detailed product- and firm-level microdata for both downstream vehicles and upstream components of the global automobile industry, alongside a comprehensive dataset of central and local policies in China. Our evidence suggests that this leapfrogging was backed by a highly structured and sequenced approach with nine major instruments through three sequential stages—what we summarize as the *3C model*: *Capability*, *Consumption*, and *Competition*.

In the initial *Capability* phase, government policy front-loaded R&D through public research grants, R&D subsidies for both state-owned enterprises (SOEs) and private firms, and joint venture (JV) requirements designed to build up domestic technological capacity in EVs. Around 2010, policy shifted to the second *Consumption* phase. This stage focused on jump-starting demand through public fleet procurement, private purchase subsidies, nationwide investments in charging infrastructure, and local content requirements (LCRs) on batteries that further scaled the market size for domestic upstream producers. Around 2020, policy transitioned into the *Competition* phase. The government scaled down protectionist measures, and gradually phased out purchase subsidies. and introduced Tesla, the leading global EV producer, to enter the domestic market without a JV partner. This marked a shift toward relying on market competition to sustain innovation incentives among domestic incumbents.

To theorize and quantitatively evaluate the role of these industrial policies in China's EV development, we build a two-country, two-technology dynamic industry-equilibrium model featuring directed and step-by-step innovation. The key feature of the model is the coexisitence of two dimensions of competition: EV-GV technology competition and within technology Home-Foreign competition. Households consume two imperfectly substitutable EVs and GVs, with the latter generating greater negative environmental externalities. Each final good comprises a continuum of segments, within which a Home and a Foreign leading firm compete in both markets. Firms face tariff and non-tariff barriers when exporting. Both EV and GV producers undertake internal, quality-improving innovation. As in the standard step-by-step innovation framework (Aghion et al., 2001), the international quality gap shapes firms' innovation incentives: smaller effective technological gaps intensify "escape-competition" incentives for both sides. New entrants must determine whether to direct their innovation toward a GV or an EV product line.

For both EV and GV technologies, final goods are produced with a continuum of technology-specific intermediate inputs. Each technology-specific intermediate good is supplied by either a Home or a Foreign firm with different productivity levels. As with final goods, intermediate producers face trade barriers when accessing Foreign markets. Innovation by intermediate firms lands randomly on a domestic production line and raises the productivity of that line by one step as in Klette and Kortum (2004). In this framework, R&D and consumption subsidies may raise welfare owing to the cumulative nature of technological progress and the presence of environmental externalities (Acemoglu et al., 2012, 2016), while pro-competition policies may be optimal given the strategic interactions among innovating firms (Akcigit et al., 2025).

We embed the nine policy instruments documented in our empirical section directly into this framework. In the Capability stage, these include public basic-research grants, mandated SOE R&D, private R&D subsidies, and JV requirements. In the Consumption stage, the instruments encompass public procurement, purchase subsidies and tax exemptions, charging infrastructure investments, and LCRs. Finally, the Competition stage models the lifting of entry barriers on foreign producers. Two additional features are worth noting. First, among the continuum of EV segments in Home, a fraction is initially operated by SOEs, which innovate at government-mandated rates. These SOE-operated segments gradually shrink over time through creative destruction by private entrants. Second, households' willingness to purchase EVs depends on both the ratio of the existing EV stock to the GV stock and the ratio of public chargers to the EV stock. The former captures social learning and belief formation based on others' adoption behavior, while the latter reflects the importance of supporting infrastructure.

In the quantitative analysis, we map the Home country to China and the Foreign country to the weighted average of five advanced automobile powerhouses (the US, Japan, Germany, France, and South Korea). We also include a Rest of the World (ROW) region as an exogenous market. We map the first 24 years of the model's transition toward a long-run equilibrium to observed data from 2001 to 2024. The initial technology gap in final goods is inferred from empirical differences in product quality (i.e. driving range and horsepower), while the gap in intermediate goods is backed out from historical patent stock differences following (Acemoglu et al., 2016; Akcigit et al., 2025). This calibration reveals a large initial international gap in GV technology in 2001, with China lagging far behind, but a relatively small gap in the nascent EV technology. This asymmetry implies that the opportunity cost of transitioning to EVs was relatively low for China both socially and privately.

We internally calibrate the model parameters to match empirical patterns using firm- and product-level data. Among other targets, we select the step sizes for final and intermediate goods to match the observed growth rates in EV driving range and intermediate-good prices. Furthermore, we set the within-segment elasticity of substitution between Home and Foreign firms to replicate a Difference-in-Differences (DiD) estimate that captures the effect of Tesla's entry on domestic producers' product quality. The calibration performs well on non-targeted moments. In particular, the full distribution of international technology gaps in both final and intermediate goods in the simulation closely aligns with the empirical distribution observed in the data. Moreover, the model successfully reproduces the impact of the "Tesla shock" on vehicle prices, closely matching our reduced-form em-

pirical results. The fiscal cost of policies generated in the model is also consistent with external estimates. From 2001 to 2024, our model-generated policy expenditures account for an average of 17.5% of annual EV sales revenue in China.

We measure aggregate welfare as the sum of consumer surplus, producer surplus, and environmental benefits, net of policy fiscal costs. Our results indicate that in the short term (through 2025), sizable fiscal costs dominate the welfare impact, resulting in a net domestic welfare loss. However, over the long term (through 2050), China's EV industrial policies generate substantial benefits. The policy bundle raises the present value of domestic welfare as a fraction of EV sales by approximately +5.52%, while Foreign welfare increases slightly by +0.16%. The policies generated loss of Foreign incumbent automakers' profits, but these were outweighed by positive consumer surplus and environmental benefits in Foreign markets. A decomposition of the welfare impacts shows that policies implemented in the Capability stage drive the largest long-term welfare gains, and the contribution of Consumption stage policies is nearly as critical. A more granular decomposition of individual policy instruments reveals that, over the long horizon, EV R&D subsidy and private purchase subsidy deliver the largest absolute welfare gains, followed by charging infrastructure investments. However, in terms of cost-effectiveness (benefit-to-cost ratio), public research grants and joint venture requirements rank as the most efficient interventions.

We then utilize counterfactual exercises to discuss general lessons for industrial policy design. Our findings yield three main conclusions. First, the effectiveness of industrial policy is shaped by opportunity costs. In our empirical setting, these costs are determined by China's initial technological position in the GV sector. Transitioning to EVs inevitably comes at the expense of incumbent GV rents; the larger these rents, the greater the cannibalization cost of an EV shift. China's starting point, however, is characterized by a substantial lag behind the foreign frontier in GV technology—a context that makes the opportunity cost of reallocating innovation efforts toward EVs relatively low. In a counterfactual world where China initially holds a lead in GV technology, the same policy package yields significantly lower welfare gains, because the associated cannibalization effect is much stronger.

Second, policy sequencing is crucial. We demonstrate the economic rationale behind the progression from Capability to Consumption to Competition. The effectiveness of consumption subsidies is shaped by both GV–EV technology competition and within-technology international competition. Subsidies are more effective when the relative price

of EVs is not too high. Moreover, when domestic technology lags substantially behind the foreign frontier, consumption subsidies risk "leaking" to foreign producers—a leakage that would further amplify foreign leads and dampen domestic innovation incentives. Capability-stage policies reduce the relative price of EVs and narrow international technology gaps, thereby enhancing the effectiveness of subsequent Consumption-stage policies. In turn, the Capability and Consumption stages together strengthen domestic firms' technological capabilities and further close the international gap. By doing so, they amplify the pro-competitive effects of introducing foreign competition in the final stage, ultimately boosting overall welfare gains.

Finally, we emphasize that effective policy intervention requires both timeliness and an appropriate duration, yet must be designed for eventual phase-out. The cumulative nature of innovation renders delay costly, making sustained support imperative. However, given that such interventions entail fiscal costs, they should be withdrawn once market mechanisms are sufficient to fulfill the transition.

**Contribution to literature.** Our paper contributes to several strands of literature. On the theoretical side, our model integrates elements from three classes of innovation and growth models: step-by-step innovation (Aghion et al., 2001, 2005; Acemoglu and Akcigit, 2012; Akcigit et al., 2025), directed technical change and its applications to environmental economics (Acemoglu et al., 2012, 2016), and innovation with firm dynamics (Klette and Kortum, 2004; Acemoglu et al., 2018; Akcigit and Kerr, 2018). Our framework is most closely related to Acemoglu et al. (2016), which models competition between dirty and clean technologies in a closed economy, and Akcigit et al. (2025), which develops a step-by-step innovation model in an open economy. Our model combines both EV-GV technology competition (through prices) and within technology international competition. Moreover, we apply the framework to study policies in a specific industry.[2]

The second strand of related literature is the rapidly growing body of empirical work on the effectiveness and welfare impacts of industrial policy. Earlier research on industrial policy often emphasized market frictions arising from externalities, coordination failures, and economies of scale.[3] More recent structural work examines specific industries fea-

[2]Our work also connects conceptually to Brezis et al. (1993), who propose a model in which major technological paradigm shifts enable lagging nations to "leapfrog" established leaders. This occurs because the new technology does not initially appear advantageous to leading nations, which possess extensive accumulated experience and sunk costs in the old technologies alongside high domestic wages.

[3]See Juhasz et al. (2024) and Harrison and Rodriguez-Clare (2010) for excellent surveys of the traditional industrial policy literature.

turing such frictions to precisely assess the impacts of targeted policy interventions (e.g., Kalouptsidi, 2017; Bai et al., 2022; Barwick et al., 2025b; Gerarden et al., 2025). We contribute to this literature by developing a unified, dynamic framework that can jointly analyze a comprehensive and evolving sequence of policy instruments.

Lastly, this paper contributes to the empirical studies evaluating China's EV industrial policies (e.g., Li et al., 2017; Barwick et al., 2024a,b; Wang and Xing, 2024; Barwick et al., 2025a). Most existing research in this space focuses on the effects of a single policy (usually demand-side policies) designed to promote EV adoption within a static setting. Several recent studies discuss the impact of policy on technological progress in the EV industry. In particular, Barwick et al. (2025a) investigates the effects of consumer EV subsidies and China's local content requirement on domestic producers. We differ from this literature by taking a holistic, structural view of the entire industrial policy bundle rather than isolating a single instrument. By embedding these policies in a dynamic framework, we are able to evaluate the transitional dynamics of the industry and calculate both short-run fiscal burdens and long-run aggregate welfare effects.

The rest of the paper is organized as follows. Section 2 provides the institutional background and summarizes the empirical facts regarding the development of China's EV industry. Section 3 introduces the theoretical model. Section 4 parametrizes the baseline model and quantitatively validates the model mechanisms. Section 5 examines the aggregate welfare impacts of the various policies and derives broader implications for industrial policy design. Section 6 concludes.

# 2 Evolution of 3Cs in China's EV Industrial Policy

Since the early 2000s, the Chinese government has continuously supported domestic EV development through a comprehensive set of targeted interventions aimed at enhancing the industry's competitiveness. In this section, we document three stages in the evolution of China's EV industrial policy, along with the major instruments adopted by central and local governments over the past 25 years.[4] Figure 2.1 illustrates the approximate timing and magnitude of nine major policy instruments, spanning the *Capability*, *Consumption*, and *Competition* stages, which we elaborate on below.

[4]Our industrial policy measures are drawn from official documents compiled in the NEV Yearbook, with sources including the State Council, the Ministry of Science and Technology (MOST), the Ministry of Industry and Information Technology (MIIT), the National Development and Reform Commission (NDRC), the Ministry of Finance (MOF), and provincial government announcements. Details of the data construction are provided in Appendix A.

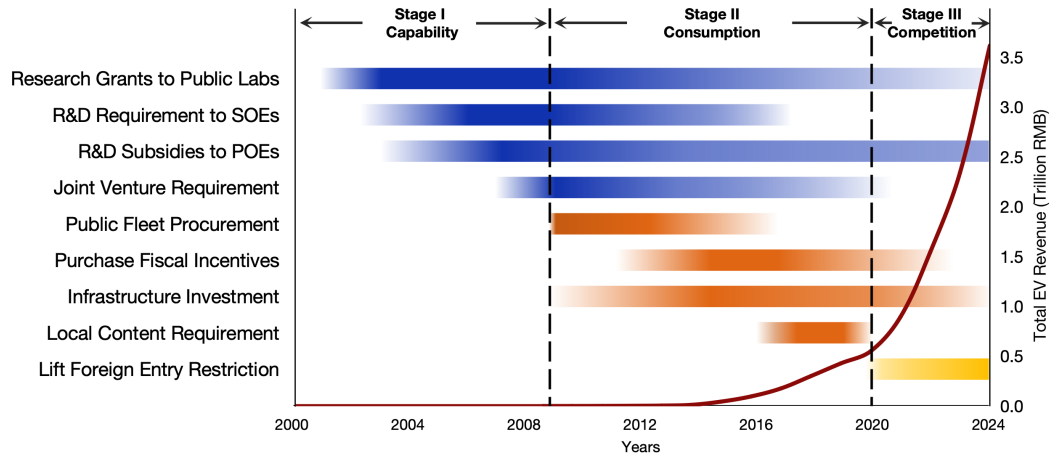



Figure 2.1: Evolution of China's EV Industry and Industrial Policy

*Note:* The figure illustrates the timeline and intensity of the nine major policy instruments employed by the Chinese government. We group the policies across three development stages: Capability, Consumption, and Competition. The red solid line shows the trend in China's EV industry sales revenue in trillion RMB. For each policy, the bar indicates the starting time and phase out time, and the color shading indicates the relative intensity of the policy instrument in total EV revenue.

## 2.1 Data and Measurement

To empirically characterize the evolution of the 3C stages, we assemble a multi-layer dataset covering the EV and GV market and key components supply chain for China, advanced economies, and the rest of the world (ROW) from 2001 to 2024. Details on sample selection, data cleaning, and variable construction are reported in Appendix A.

**Industrial policy.** Our primary data source for tracking the evolution and intensity of China's EV industrial policy is the *Energy Saving and New Energy Vehicle Yearbook* (hereafter referred to as the *NEV Yearbook*) from 2010 to 2024. Published as an official and authoritative compendium for the sector by the Ministry of Industry and Information Technology (MIIT) of China, the *NEV Yearbook* provides comprehensive and granular data encompassing firm-level vehicle production, deployment volumes in pilot demonstration cities, supply quantities for key upstream components (such as batteries, electric motors, battery management system), and the rollout of public charging infrastructure. Crucially for our policy analysis, the publication systematically documents and categorizes all relevant policy directives, subsidy schedules, and regulatory standards issued by both central and local governments. By aggregating these official policy texts, the *NEV Yearbook* enables us to precisely map the timeline, scale, and specific instruments of China's EV industrial interventions over our sample period.

**Product-level sales, prices, and attributes**. We combine global vehicle sales data for both EV and GV from Marklines database, which reports the monthly counts of vehicle sold in

each country, and we merge this data with retail prices and technical attributes for vehicle models obtained from Autohome, and supplement the Chinese sales data from China Automotive Technology and Research Center (CATARC). For upstream components, we combine the key EV component supplier-client information from the *NEV Yearbook*, which includes detailed supply quantity and technical attributes. For the GV and for Foreign EV side, we supplement this with supplier information provided by Marklines.

**Firm-level innovation, R&D, and sales.** We measure firms' innovations using patent applications from ORBIS Intellectual Property and PatSnap, which includes all major patent offices. Patents are mapped to EV and GV technology domains for final goods and intermediate components based on IPC/CPC subgroups. We count patent families for firms and institutions weighted by the number of forward citations. For listed global automakers and component manufacturers, we assemble firm-year time series on R&D expenditures, employment, operating revenue, ownership (SOE/private) from CNRDS. We further obtain the JV involvement for Chinese firms from the NEV Yearbook. Lastly, we assign the product-level sales to vehicle firms based on the brands.

**Sector-level sales and infrastructure**. We combine sectoral aggregate data from China Association of Automobile Manufacturers (CAAM), The International Organization of Motor Vehicle Manufacturers (OICA), and International Energy Agency (IEA). These datasets cover sales and production quantity, global EV and GV fleet stocks, number of public charging infrastructure, and average carbon emissions of vehicles.

## 2.2 Capability Stage

The development of China's EV industry traces back to the "863 Program" (National High Technology Development Program) during the 10th Five-Year Plan period (2001–2005), which served as the key agenda for advancing EV-related technologies. The *Outline of the National Medium- and Long-Term Program for Science and Technology Development (2006–2020)* further identified EV as a key priority area and a strategic science and technology objective at the national level, underscoring that the initial stage focused on strengthening domestic innovation capabilities and achieving technological breakthroughs.

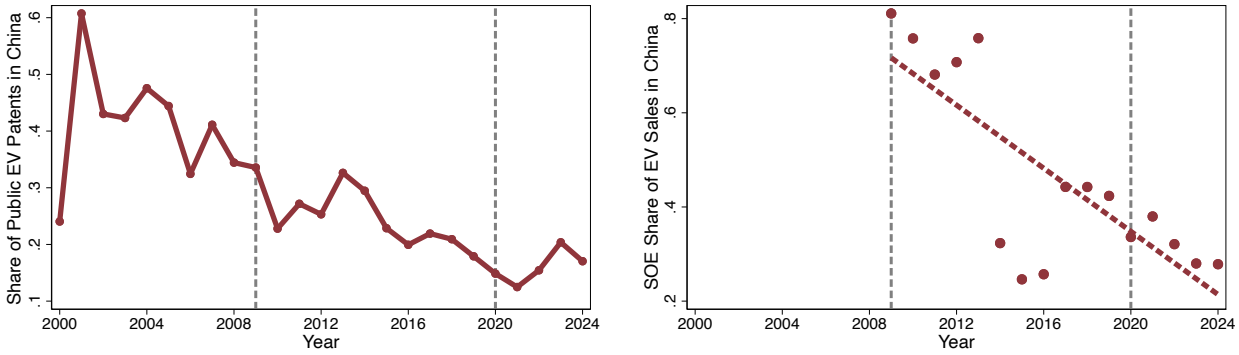
**Research Grants to Public Institutes** In 2001, the Ministry of Science and Technology (MoST) allocated sizable, multi-year grants for basic EV technology research under the "863" program. Leading universities and research institutes (e.g., Tsinghua University, China Academy of Sciences, Beijing Institute of Technology) were engaged alongside in-

dustry partners to develop the "Three-by-Three R&D Strategy" (three vehicle technology pillars and three core component technology pillars). The funding of basic research was followed by National Key Science and Technology programs in the following decades[5]. Panel (a) of Figure 2.2 shows the public-institute patent application share in EV technology fields filed with the China National Intellectual Property Administration (CNIPA). It started at above 70% in the early 2000s, while falling gradually below 10% in recent years as private innovation scales up.

**SOE EV R&D Requirements** Major state-owned automakers (e.g., FAW, Dongfeng, SAIC) were key industry partners in the early "863" EV projects and were tasked with leading technology alliances for prototype development and demonstration. Policy guidance emphasized building internal R&D capacity within incumbent automakers, including dedicated R&D centers and pilot production lines, to accelerate progress along hybrids, fuel-cell, and early battery-electric buses. Consistent with this emphasis, Dongfeng Motor Corporation (an SOE headquartered in Wuhan) developed and field-tested the first domestic hybrid electric bus prototype in 2003. Panel (b) of Figure 2.2 shows the evolving role of SOEs in the development and production of EVs in China. The share of SOEs' total EV production has decreased from over 60 percent initially to around 25 percent in recent years.

**R&D Subsidy and Tax Exemption** Starting in 2006, China began offering direct R&D subsidies that covered up to 50% of research and development spending on EV technologies. These grants supported privately owned automakers such as BYD and Geely in developing their own early EV products, and subsidized core EV component producers—including current market leaders CATL, BAK Power, and Optimum Nano—in advancing battery and motor technologies. Since 2008, EV manufacturers have also been eligible for certification as High and New Technology Enterprises (HNTEs), which grants firms a double amount reduction in corporate income tax for qualified R&D spending.

[5]According to the Ministry of Finance and Ministry of Science & Technology, the first '863' Program in 2001 invested RMB 880 million (USD 135 million), and the project scale for EV R&D expanded in the 11$^{th}$ FYP, with the total funded projects under the National Science and Technology Plan exceeding RMB 1.16 billion (USD 172 million), that prompts local governments and social forces to invest a total of RMB 11 billion (USD 1.7 billion) in R&D and supporting facilities. During the 12$^{th}$ and 13$^{th}$ FYPs, an additional RMB 1.4 billion (USD 214 million) was allocated to subsidize R&D for the development of battery technology, and an additional RMB 4 billion (USD 612 million) as special funding to support the R&D of prototype EVs and other key components.




(a) Public Lab's EV Patent Share in China

(b) SOEs Sales Share of EVs in China

Figure 2.2: China's EV Industrial Policy in Capacity Stage

*Note:* This figure shows the trend in Chinese market related to China's Capability stage policies. The starting years of second and third stage are denoted by the vertical dashed lines. Panel (a) shows the share of new EV patents filled by public institutions and universities in total EV patents filled by Chinese entities in each year (citation-weighted and counted invention patents by patent families). Patents are identified as EV technology according to Main IPC codes in Appendix A. Panel (b) shows the share of state-owned enterprise (SOE) brands in total quantity of EVs sold in the Chinese market in each year. Before 2007 there is no available Chinese brand EV in the market.

**Joint Venture R&D Cooperation** Since 2007, the government encouraged domestic OBMs to sign joint R&D agreements and form joint ventures (JVs) with global leaders to accelerate technology catch-up. For instance, since 2009, BYD and Volkswagen signed a series of R&D cooperation agreements in developing battery technologies for EVs. In the same year, Chinese SOE Lishen Battery and U.S.-based Miles Electric Vehicles formed a JV in Tianjin to produce lithium-ion power batteries for EVs. More collaborations and JVs were established in the following years.

To examine the dynamic response in the domestic firms' innovation after forming joint ventures and R&D collaborations with foreign leading firms, we conduct a Difference-in-Differences (DiD) event study using Poisson (PPML):

$$Patent_{it} = \sum_{\tau=\{-4,\ldots,4\}\setminus\{-1\}} \beta_\tau \left(Treated_i \times \mathbf{1}\{t - T^{\text{JV}} = \tau\}\right) + \gamma \ln PatentStock_{i,t-1} + \text{FE}_i + \text{FE}_t + \epsilon_{it},$$

where $Patent_{it}$ is the number of patent application of Chinese domestic firms in the main IPC group $i$ at year $t$ (weighted by citations), $T^{\text{JV}}$ indicates the year of joint venture patent filing, $Treated_i$ is the dummy variable indicating an IPC group has patent application from joint ventures, $\ln PatentStock_{i,t-1}$ is the logarithm of patent stock in the IPC group $i$ in year $t-1$. We include the IPC group fixed effects ($\text{FE}_i$) and year fixed effects ($\text{FE}_i$). The results is reported in Figure 2.3. The event study shows the gap in number of patent filings between the treated IPCs and their control group. Domestic EV firm's patenting in the technology fields with foreign partner's patent filings increased significantly relative

to the technology fields without such patents, indicating the knowledge diffusion from early stage foreign presence to domestic firms.[6]

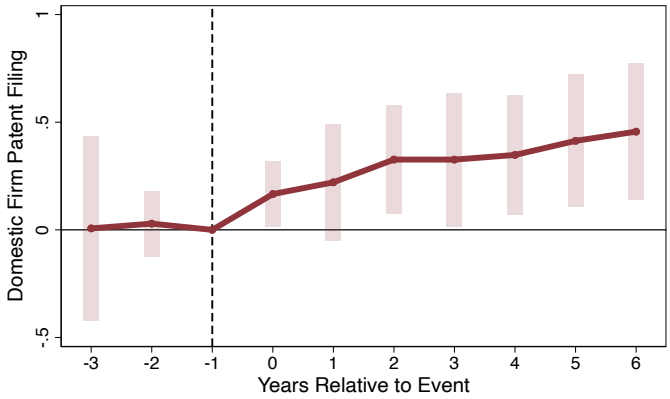



Figure 2.3: Event Study on Joint Venture Technology Diffusion

*Note:* This figure presents the event study results of technology diffusion from joint venture with foreign leading firms to Chinese firms. The treatment group is the technology fields (IPCs) with foreign joint venture patent filings, and the control group is the technology fields without foreign joint venture patent filings. The x axis denotes the year relative to the the event year of joint venture patent filing in China. All coefficients are relative to the year before the event year. Standard errors are clustered at the IPC group levels.

## 2.3 Consumption Stage

Starting in late 2009, China shifted its policy emphasis from capability building toward demand creation and market formation. This reorientation was later stated in the *Development Plan for the New Energy Vehicle Industry (2012–2020)*, which stresses that "scaling up adoption requires a coordinated policy package—combining the guiding role of government procurement with fiscal incentives to stimulate private demand".

**Public Fleet Procurement** The "Ten Cities, Thousand Vehicles" demonstration program launched in 2009 was aimed at deploying more than 1,000 EVs per pilot city each year for three years, primarily within public fleets (such as buses, sanitation and mail trucks, and taxis). The program later expanded beyond the original pilot cities and was scaled nationwide over the following two years. As shown in Panel (a) of Figure 2.4, government procurement accounted for as much as 85% of total domestic EV sales in the program's early years, but this share declined sharply after 2014.

**Charging Infrastructure Investment.** Since late 2009, the central government has been investing in the construction of charging points and stations for EVs. In 2015, support

[6]We report the synthetic Difference-in-Difference (DiD) estimation result in Appendix B.

grew as national guidelines were introduced to encourage the development of public EV charging infrastructure to enhance user convenience. Subsequently, in 2018, the NDRC and MIIT jointly released the *Action Plan for Improving the Charging Support Capacity of New Energy Vehicles*, which aimed to optimize the spatial layout of charging stations and significantly enhance network connectivity. As shown in Panel (b) of Figure 2.4, China's public charging infrastructure stock expanded rapidly through 2024.

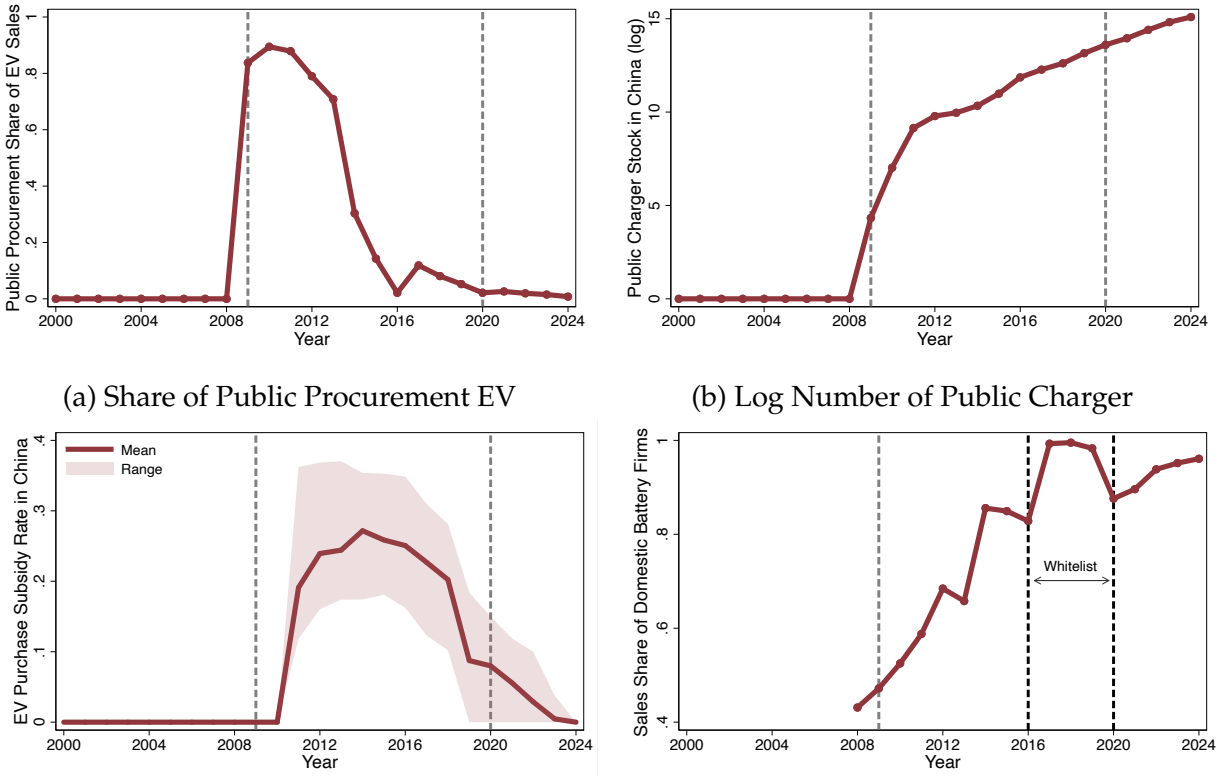
**Purchase Subsidy and Tax Exemption.** Pilot programs aimed at promoting private EV adoption were launched in late 2010 and subsequently expanded into a nationwide subsidy scheme in 2013. Importantly, the government announced from the outset that these subsidies would be gradually phased out. As shown in Panel (c) of Figure 2.4, combined national and local consumer subsidies accounted for roughly 30% of a vehicle's MSRP on average during 2013–2016, and then declined by about 2.5% per year until they were fully eliminated in 2023.[7] In parallel, in 2014, the Ministry of Finance issued the *Notice on Exempting New Energy Vehicles from Vehicle Purchase Tax*, which exempted qualifying EVs from the Vehicle and Vessel Tax as well as the 10% Vehicle Purchase Tax from 2014 through 2025.

**Local Content Requirement of EV Battery** In late 2015, MIIT issued the *Management Rules on Market Entry of New Energy Vehicle Manufacturers and Products*, which tied purchase-subsidy eligibility to EV battery packs sourced from suppliers on a government "whitelist," excluding the majority of foreign producers. Starting in 2015, China also imposed foreign-equity restrictions in EV battery and component manufacturing, effectively preventing majority foreign ownership in these segments. As shown in Panel (d) of Figure 2.4, the foreign battery producers' market share in China fell from close to 20% in 2015 to almost 0% in 2017.

## 2.4 Competition Stage

With domestic demand for EVs scaling up, China's industrial policy pivoted around 2020 from consumption expansion toward greater market discipline and greater openness to global frontier competition. In the *New Energy Vehicle Industry Development Plan (2021–2035)*, this transition is framed explicitly as a move to improve the overall effectiveness of resource allocation and market competition.

[7] Several cases of subsidy fraud were reported between 2013 and 2015. However, the actual financial loss was limited because a time lag existed between subsidy claims and disbursements. In response, the government tightened the technical requirements for subsidy-eligible vehicles starting in 2016.




(a) Share of Public Procurement EV

(b) Log Number of Public Charger

(c) Purchase Subsidy Rate

(d) Sales Share of Domestic Batteries

Figure 2.4: China's EV Industrial Policy in Consumption Stage

*Note:* This figure shows the trend in Chinese market related to China's Consumption stage policies. The starting years of second and third stage are denoted by the vertical dashed lines. Panel (a) shows the share of public fleet procurement in total EV sales in China, which include sales in public services, public transportation and taxi fleets. Total EV sales include both light duty vehicles and (LDV) and heavy duty vehicles (HDV). Panel (b) shows the total number of public charging points in China in logarithm. Panel (c) shows the average intensity (solid line) and the 75 and 25 percentile (red area) of purchase subsidy rate. Purchase subsidy included both central and local government subsidies, and is calculated as the amount of subsidy divided by the MRSP of each vehicle model in the particular year. Panel (d) shows the sales share of domestic brand EV batteries in the Chinese market including LDV and HDV, and in the years of "whitelist" the share approaches 100%.

**Lifting Foreign Entry Restrictions.** In late 2018, China announced the removal of the foreign-equity cap for EV manufacturing. Tesla's localized production and rapid scaling in China is the salient event marking the intensified competitive pressure on domestic incumbents. Locally produced Tesla vehicles by its wholly-owned Gigafactory in Shanghai entered the Chinese market in January 2020. The market share of domestic EV brands declined sharply in the segments directly overlapping with Tesla's locally produced models, as shown in Figure 2.5. Nevertheless, the competition brought by Tesla triggered a *pro-competition effect* that spurred domestic incumbents to accelerate R&D efforts, leading to rapid improvement in quality and recovery in domestic market share[8]. Figure B.1 dis-

[8]Hu et al. (2024) estimate the impact on EV prices around domestic Tesla's availability in 2020 with a Diff-in-diff strategy and find that incumbent manufacturers lowered EV model prices after Tesla's entry. They further show the price response is larger for BEVs than for PHEVs, consistent with Tesla posing more

plays the price–quality (driving-range) distributions of Chinese domestic original brand manufacturers (OBMs) before (2019) and after (2023) Tesla's entry.

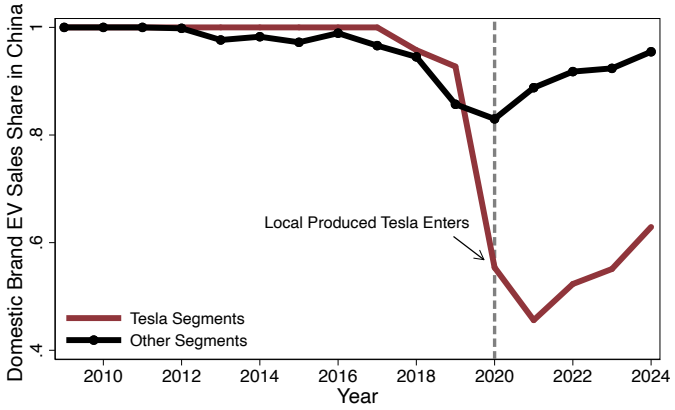



Figure 2.5: Sales Share of Domestic EVs in China by Segment

*Note:* This figure shows the sales share of domestic brands in Chinese market for two groups of segments. The red line denotes the Tesla segment, which indicate the segments of Tesla's Model 3 and Model Y. The blue line denotes all other light duty vehicle (LDV) segments. The year before Tesla's product delivery in Chinese market is denoted by the vertical dashed line.

To estimate the impact of Tesla's entry into China's EV market (the "Tesla shock") on the innovative activity of Chinese firms, we leverage the fact that Tesla's Model 3 and Model Y compete head-to-head with Chinese EV models in specific vehicle segments, while competition is more limited in other segments. We conduct TWFE DiD event studies at the firm-segment-year level to compare EV models that are directly exposed to Tesla's entry with those that are not:

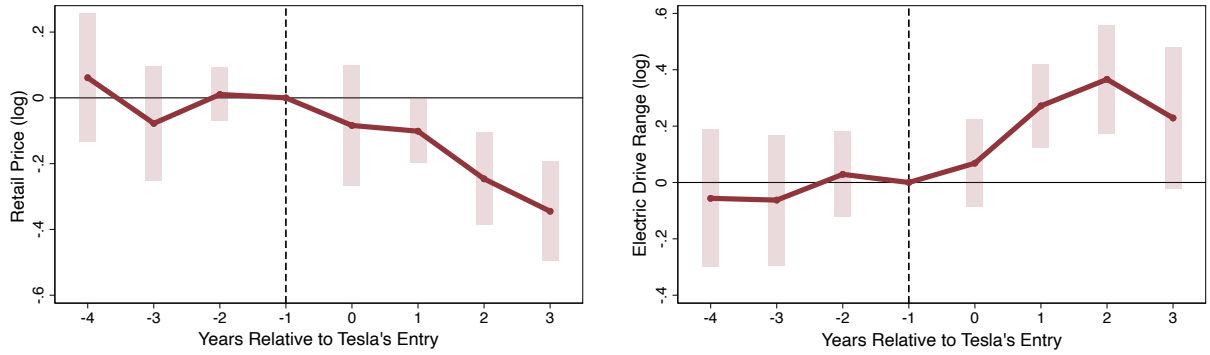
$$Y_{f,s,t} = \sum_{\tau=\{-4,\dots,3\}\setminus\{-1\}} \beta_\tau \left(Treated_s \times \mathbf{1}\{t - 2020 = \tau\}\right) + \gamma\, X_{f,s,t} + \mathrm{FE}_f + \mathrm{FE}_t + \epsilon_{f,s,t},$$

where $Y_{f,s,t}$ is the variable of interest for EV models produced by firm $f$ in segment $s$ in year $t$. $Treated_s$ is an indicator variable equal to one for the same segments that include Tesla's products, and we include a set of year dummies in each year relative to the event. $X_{f,s,t}$ is a set of control variables including the average battery capacity, the average horsepower, and average car weight. $\mathrm{FE}_f$ and $\mathrm{FE}_t$ are the firm and year fixed effects.

Figure 2.6 presents the estimated coefficients and confidence intervals. The left panel shows the event study for retail prices, where relative to other segments, the treated segments experienced a sharp decrease in price over time. The right panel shows the result for product quality proxied by the average electric drive range. The pre-entry coefficients are statistically indistinguishable from zero, suggesting no strong differential pre-trends

direct competitive pressure to similar models.

between treated and comparison groups. In contrast, post-entry coefficients become positive and increase over the first one to two years after entry, indicating that domestic producers improve EV range after the Tesla shock. We report the robustness check results with alternative control groups in Appendix B.2.




(a) Effect on EV MRSP

(b) Effect on EV Drive Range

Figure 2.6: Event Study on "Tesla Shock"

*Note:* This figure presents the event study result on "Tesla shock". The sample only includes passenger EVs sold in Chinese market and produced by domestic EV makers. Circles represent event study coefficients from ordinary least squares estimation. Standard errors clustered at the firm level to account for within-firm correlation. All coefficients are relative to the year 2019, one year before Tesla's product delivery in Chinese market, denoted by the vertical dashed line.

# 3 The Model

To characterize and quantitatively evaluate the global impact of China's EV industry policy, we develop a continuous-time industrial equilibrium model with two countries, Home and Foreign, and two technology lanes, GV and EV.[9] The key feature of the model is the coexisitence of two dimensions of competition: EV-GV technology competition and within technology Home-Foreign competition.

Consumers in each country consume two substitutable final goods, GV and EV. Consumption of GVs emits more greenhouse gases (GHG) that have a negative environmental externality globally. There is a continuum of segments for GV and EV products. At any point in time, the technologically leading firms at Home and Foreign in each segment/product line engage in Bertrand competition. Vehicles can be traded internationally subject to trade costs. For each technology lane, entrants and incumbent firms make R&D decisions to improve their productivity by climbing up a quality ladder.

[9] According to China's National Bureau of Statistics, the sector's value added is less than 2% of China's GDP and its employment share is about 0.6% in 2024, so feedback to economy-wide real wages, interest rates, aggregate demand is second order. We therefore adopt a partial-equilibrium framework.

## 3.1 Vehicle Preference and Demand

The representative household in Home ($c = H$) and Foreign ($c = F$) allocates an exogenous expenditure $\boldsymbol{E}_c$ on vehicle consumption. Suppose that the vehicle market consists of vehicles made by the two alternative technologies: GV ($j = g$) and EV ($j = e$). The utility derived from vehicles at time $t$ is

$$\boldsymbol{U}_c = \left[ \xi_c^{e\,\frac{1}{\sigma}} Y_c^{e\,\frac{\sigma-1}{\sigma}} + \xi_c^{g\,\frac{1}{\sigma}} Y_c^{g\,\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $\sigma > 1$ measures the elasticity of substitution between GVs and EVs. $Y_c^j$ is the consumption of technology-j final good. $\xi_c^e$ is the demand shifter specific to EVs for each country, and we normalize $\xi_c^g = 1 - \xi_c^e$.

Vehicles of technology $j$ consist of a continuum of segments, each of which can be produced by a Home and a Foreign maker. The aggregate consumption for technology $j$ final good in country $c$ is defined as

$$\ln Y_c^j = \int_0^1 \ln \left[ \gamma_c{}^{\frac{1}{\varepsilon}} [Q_c^j(s) Y_c^j(s)]^{\frac{\varepsilon-1}{\varepsilon}} + (1-\gamma_c)^{\frac{1}{\varepsilon}} [Q_{c'}^j(s) \tilde{Y}_{c'}^j(s)]^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} ds, \tag{2}$$

where $Q_c^j(s)$ is the segment-specific quality, $\varepsilon$ is the elasticity of substitution between domestic and Foreign brands within each segment, $\gamma_c$ is the demand shifter that measures the degree of Home bias, $Y_c^j(s)$ is the quantity of vehicles consumed in country c that are produced by domestic producers, and $\tilde{Y}_{c'}^j(s)$ is the quantity produced by Foreign producers. There are two types of trade barriers for importing good $j$ in country $c$, tariff rate $Tr_c^j$ and an iceberg cost $Ic_c^j$. Let $T_c^j = (1 + Tr_c^j)\, Ic_c^j$ denote the aggregate trade barrier in country $c$. The price index for vehicle type $j$ in country $c$ is therefore

$$\ln P_c^j = \int_0^1 \ln \left[ \gamma_c (P_c^j(s)/Q_c^j(s))^{1-\varepsilon} + (1-\gamma_c)(\tilde{P}_{c'}^j(s)/Q_{c'}^j(s))^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} ds.$$

The industry price index $\boldsymbol{P}_c$ is defined as

$$\boldsymbol{P}_c = \left[ \xi_c^e ((1-\varsigma_c^e) P_c^e)^{1-\sigma} + \xi_c^g ((1-\varsigma_c^g) P_c^g)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

where $\varsigma_c^j$ is the purchase subsidy/tax for purchasing a specific type of vehicle, with $\varsigma_c^j < 0$ indicating technology-$j$ good is taxed.

## 3.2 Production and Market Structure

A final good vehicle model is produced using domestic labor, $L_c$, components common to both technologies, $MT_c$, and a composite intermediates bundle, $\Gamma_c^j$. The production function is specified as

$$Y_c^j(s) = (\Gamma_c^j)^{\alpha_1}(L_c)^{\alpha_2}(MT_c)^{1-\alpha_1-\alpha_2}, \quad \forall s \in [0,1]. \tag{3}$$

The common component bundle $MT_c$ is produced in perfect competition with domestic labor with price $P_{MT,c}$[10]. Denote price of the technology-specific composite good $P_{\Gamma,c}^j$. The marginal cost of the final good producer of technology $j$ in country $c$ is

$$MC_c^j = \frac{1}{const}(P_{\Gamma,c}^j)^{\alpha_1}(w_c)^{\alpha_2}(P_{MT,c})^{1-\alpha_1-\alpha_2} \tag{4}$$

where $const \equiv {\alpha_1}^{\alpha_1}{\alpha_2}^{\alpha_2}(1-\alpha_1-\alpha_2)^{1-\alpha_1-\alpha_2}$.

The quality of a final product is determined by the producer's position in a quality ladder with step size $\Lambda$. Let $N_c^j$ denote the position of the leading firm in technology $j$, country $c$, the corresponding quality level is $Q_H^j = \Lambda^{N_c^j}$, and the quality gap between Home and Foreign producers in a segment is $M^j \equiv N_H^j - N_F^j$. In each segment, the incumbent domestic and Foreign maker engage in Bertrand price competition. To limit the markup and capture domestic competition, we assume that a leading technology in each country can be copied by other domestic firms that can produce with a $K$-step inferior product, i.e. $1/\Lambda^K$ of the leading technology's quality, for free. As in Aghion et al. (2001), final good producers' equilibrium price and profit only depend on the technology gap. We leave the details to Appendix C.1. For later reference, denote $\Pi_c^j(M)$ the profit of country $c$'s producers in technology $j$ from the domestic market, and $\tilde{\Pi}_c^j(M)$ the profit from abroad.

**Intermediate goods** The technology-specific composite good used by the final good sector is aggregated from a continuum of technology-specific intermediate goods, where each intermediate $i$ produced by Home and Foreign producers, $y_H^j(i)$ and $y_F^j(i)$, are perfect substitutes:

$$\ln \Gamma_c^j = \int_0^1 \ln(y_c^j(i) + y_{c'}^j(i))di. \tag{5}$$

[10]Such common components include tires, vehicle body, etc. Since the technologies for producing these goods are well developed and unrelated to the key components in GVs and EVs, we leave this part as exogenous.

Each intermediate product line in a country is owned by the firm that has the leading-edge technology in that country. The production function for intermediate product line $i$ of technology $j$ in country $c$ is

$$y_c^j(i) = z_c^j(i)\, l_c(i), \quad i \in [0,1], \tag{6}$$

where $z_c^j(i)$ is the firm's productivity, which is determined by the firm's position in a ladder of step size $\lambda$, and $l_c(i)$ is the labor employed by product line $i$. Hence if the position of the leading firm in a intermediate product line of technology $j$, country $c$, is $n_c^j$, the corresponding productivity level is $z_c^j = \lambda^{n_c^j}$. The intermediate technology gap between the Home and Foreign countries is defined as $m_i^j \equiv n_H^j - n_F^j$.

Similar to final good producers, an intermediate firm can sell its goods to both domestic and Foreign downstream automakers. Accessing country $c$'s market is subject to an iceberg cost $ic_c^j$ and tariff $tr_c^j$, with the total import cost being $\tau_c^j = (1 + tr_c^j)\, ic_c^j$. Let $p_c^j(i)$ denote the equilibrium price producers in country $c$ and technology $j$ paid on intermediate good $i$, which are affected by both the technology gap and trade barriers, and are detailed in Appendix C.1.[11] The price index of the intermediate bundle that enters final good producer's problem is $\ln P_{\Gamma,c}^j = \int_0^1 \ln p_c^j(i) di$.

## 3.3 Innovation and Firm Dynamics

We start with describing final good producers' problem. Each final good producer operating in segment $s \in [0,1]$ hires researchers to conduct R&D to improve the quality of its products. When a firm successfully innovates, it advances its quality by one step on the quality ladder:

$$Q_c^j(s, t + \Delta t) = \Lambda \cdot Q_c^j(s,t).$$

Arrival of successful innovation is modeled as a Poisson process. To achieve a Poisson arrival rate $X_c^j$, the firm must employ $H_c^j$ researchers. Moreover, firms' innovations leverage external basic knowledge that complements their internal R&D (Akcigit et al., 2021). The innovation production function is specified as

$$X_c^j = \Theta^j \left[ (H_c^j)^{\beta_1} (B_c^j)^{1-\beta_1} \right]^{\frac{1}{\beta_2}}, \tag{7}$$

[11] Similar to the final good sector, we assume that a leading technology in each country can be copied by other domestic firms that can produce with a $k$-step inferior technology for free.

where $\Theta^j > 0$ is the final good R&D productivity in technology $j$, and $B_c^j$ is the stock of basic knowledge produced by universities and public research labs. The parameter $0 < \beta_1 < 1$ captures the importance of applied research relative to basic research, and $\beta_2 > 1$ captures the decreasing returns to scale of R&D activities. Therefore, the cost to achieve Poisson arrival rate $X$ is $w_c \times H_c^j(X)$, where

$$H_c^j(X) \equiv [(X/\Theta^j)^{\beta_2}(B_c^j)^{\beta_1 - 1}]^{1/\beta_1}. \tag{8}$$

To characterize the automobile industry in China, we distinguish two types of automobile producers in EV technology in the Home country: *state-owned enterprises* (SOE), and *private-owned enterprises* (POE), and for simplicity, do not distinguish SOE/POE in GV. SOEs receive transfer $R_{H,S}$ from the government to finance its R&D activities, therefore each SOE generates a flow rate of $X_{H,S}$ regardless of its current and future profit and only depends on the state's funding level. On the other hand, POEs in the Home and Foreign country conduct R&D to maximize their expected value.

**Value function.** Denote $r_c$ as the interest rate of country $c$, the technology gap in each segment $M_i^j$, and the value of an incumbent final good firm is $V_c^j(M)$. An incumbent's value in country $c$ satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\begin{aligned} r_c V_c^j(M) - \dot{V}_c^j(M) =& \Pi_c^j(M) + \tilde{\Pi}_c^j(M) - X_c^{j,ent} \cdot V_c^j(M) + \mathbf{X}_{c'}^j(M) \cdot [V_c^j(M-1) - V_c^j(M)] \\ &+ \max_{X_c^j \geq 0} \left\{ (X_c^j(M) + \Delta^j \cdot \mathbf{1}_c(M))[V_c^j(M+1) - V_c^j(M)] - (1 - \chi_c^j) w_c \cdot H(X_c^j(M)) \right\} \end{aligned} \tag{9}$$

where $X_c^{j,ent}$ is entrants innovation intensity. The term $\mathbf{X}_{c'}^j(M) \equiv X_{c'}^j(M) + \Delta^j \cdot \mathbf{1}_{c'}(M) + X_{c'}^{j,ent}$ is the aggregate innovation effort on segment $M$ in country $c'$; $\Delta^j$ is the costless diffusion rate, $\mathbf{1}_c(M)$ is an indicator function that is equal to one if the firm in segment $M$ and country $c$ is a follower, and $\chi_c^j$ is the innovation subsidy rate. The first order condition yields the optimal innovation intensity

$$X_c^{j*}(M) = \left[ \frac{\beta_1}{\beta_2} \frac{(V_c^j(M+1) - V_c^j(M))(\Theta_c^j)^{\frac{\beta_1}{\beta_1}}(B_c^j)^{\frac{1-\beta_1}{\beta_1}}}{(1 - \chi_c^j) w_c} \right]^{\frac{\beta_1}{\beta_2 - \beta_1}}. \tag{10}$$

**Entrant's problem.** We assume there exists a continuum of entrants in each country with innovation efficiency $\Theta_c^{j,ent}$. Entrants choose whether to innovate on the EV or GV tech-

nology as well as innovation intensity $X_c^{j,ent}$ to maximize the following expected value,

$$\max_{j\in\{e,g\},\, X_c^{j,ent}>0} \left\{ X_c^{j,ent} \cdot \mathbb{E}V_c^j - (1-\chi_c^j) w_c \cdot H(X_c^{j,ent}) - F^j w_c + \epsilon^j \right\}.$$

where $F^j$ is the fixed switching cost in terms of labor, and $\epsilon^j$ is an idiosyncratic shock following a Gumbel distribution. The term $\mathbb{E}V_c^j$ is the expected value from innovating in technology $j$, country $c$. Upon successful innovation, entrants who choose to innovate in technology $j$ will randomly replace a domestic incumbent operating in a product line of the same technology $j$. For the Home country, we assume all entrants are POEs. We detail final good entrants' decision in Appendix C.2.

**Evolution of technology gap distributions.** Let $\mathcal{F}_S^j(M)$ be the measure of segments with international quality gaps $M$ and with a SOE as the leading firm in Home, and $\mathcal{F}_P^j(M)$ for POEs, with $\sum_M [\mathcal{F}_S^j(M) + \mathcal{F}_P^j(M)] = 1$. For simplicity, assume $\mathcal{F}_S^g(M) = 0, \forall M$. That is, we do not distinguish SOE/POEs in GVs.

The flow equations for states $M$ in the EV technology, i.e. $j = e$, are given by[12]

$$\begin{aligned} \dot{\mathcal{F}}_S^j(M) = & \underbrace{(X_{H,S}^j(M-1) + \Delta^j \mathbf{1}_c(M-1)) \cdot \mathcal{F}_S^j(M-1)}_{\text{inflow from M-1}} + \underbrace{\mathbf{X}_F^j(M+1) \cdot \mathcal{F}_S^j(M+1)}_{\text{inflow from M+1}} \\ & - \underbrace{[\mathbf{X}_{H,S}^j(M) + \mathbf{X}_F^j(M)] \cdot \mathcal{F}_S^j(M)}_{\text{outflow}}, \end{aligned} \tag{11}$$

$$\begin{aligned} \dot{\mathcal{F}}_P^j(M) = & \underbrace{\mathbf{X}_H^j(M-1) \cdot \mathcal{F}_P^j(M-1)}_{\text{inflow from M-1}} + \underbrace{\mathbf{X}_F^j(M+1) \cdot \mathcal{F}_P^j(M+1)}_{\text{inflow from M+1}} \\ & - \underbrace{[\mathbf{X}_{H,P}^j(M) + \mathbf{X}_F^j(M)] \cdot \mathcal{F}_P^j(M)}_{\text{outflow}}. \end{aligned} \tag{12}$$

For segments with gap $M$, the inflow could be from segments with gap $(M-1)$ upon successful innovation by Home producers, or segments with gap $(M+1)$ upon successful innovation by Foreign producers, while the outflow is due to successful innovation on lines with gaps $M$ by both Home and Foreign producers. Successful innovation by Home entrants in an SOE line would turn it into a POE one. The law of motion for the GV technology is the same as that for POE EV lines in equation (12).

[12] We assume $M \in [-\bar{M}, \bar{M}]$. At the boundaries $M = \pm\bar{M}$, the terms associated with $M+1$ (for $M = \bar{M}$) and $M-1$ (for $M = -\bar{M}$) are to be removed.

**Intermediate goods dynamics.** Intermediate goods producers engage in external innovation to expand and acquire more product lines. In addition, in each product line, the Foreign leading intermediate firm decides whether to establish a joint venture (JVs) with the Home producer by paying a fixed Foreign labor cost $\kappa_{\text{JV}}$. The JV produces locally in the Home market using Foreign technology, avoiding trade costs. However, the JV, while active, also facilitates technology diffusion, raising the Home firm's effective innovation rate by a factor $1 + \delta_{JV}$. JV formation and dissolution occur each period and hence not a state variable. When JV operates, the Home firm passively suspends its own production and receives a share $\alpha_{JV}$ of the JV's profits.[13]

As the value functions and evolution of the technology gaps for intermediate goods are similar to those for final goods producers. To avoid repetition, we leave the details to Appendix C.3.

## 3.4 Model Counterparts of Industrial Policy

As documented in Section 2, the government deployed nine instruments spanning capability building, consumption, and competition. We embed each instrument in the model and summarize the model counterparts as follows.

**Capability stage policy.** Public research grants in EV technologies given to universities and national research labs enter the production of public knowledge and raise the stock of external basic knowledge as:

$$X_c^{basic}(t) = \Theta_c^{basic}(R_c^{basic}(t)/w_c(t))^{1/\beta_2}, \tag{13}$$

$$\dot{B}_c^j(t) = (X_c^{j,other}(t) + X_c^{basic}(t)) - d^{basic} \cdot B_c^j(t), \tag{14}$$

where $X_c^{basic}(t)$ is the public knowledge flow, $R_c^{basic}(t)$ is public research spending funded by the government, $X_c^{j,other}(t)$ captures flow of knowledge from other sectors, and $d^{basic}$ is the depreciation rate of public knowledge.

Engagement of SOEs is modeled as providing an exogenous EV-targeted R&D that directly increases the sectoral R&D as required by the government:

$$X_H^S = \Theta_{H,S}^e \left[(R_{H,S}/w_H)^{\beta_1}(B_H^e)^{1-\beta_1}\right]^{1/\beta_2}, \tag{15}$$

[13]For simplicity, our model excludes joint ventures in GV final or intermediate goods. Joint ventures for EV final goods are not modeled as they account for a negligible market share in China's EV sales.

where $X_H^S$ is the Poisson arrival rate of successful innovation in SOEs, $R_{H,S}$ is the amount of R&D expenditure exogenously required and funded by the government.

R&D subsidy to POEs, $\chi_c^j$, directly enters the firm's value function as in Equation (9). Lastly, policy encouraging joint ventures is modeled as reduction in the fixed cost of joint venture to Foreign firms, $\kappa_{\text{JV}}$, in the Home country.

**Consumption stage policy.** Government procurement in public fleets is modeled as an exogenous demand for domestically produced EVs:

$$R_H^{procure}(t) = P_H^e(t) \times D_H^{procure}(t), \tag{16}$$

where $R_H^{procure}(t)$ is the expenditure of public fleet procurement, and $D_H^{procure}(t)$ is the number of vehicles purchased by the government.

Consumer purchase subsidy to the private consumers, $\varsigma_c^e$, enters the consumer's problem through reducing the effective relative price of EV bundles, as in equation (C.2).

The stock of public charging infrastructure evolves as

$$\dot{Charger}_c = R_c^{charger} / Cost_c^{charger} - d^{charger} \cdot Charger_c, \tag{17}$$

where $R_c^{charger}$ is the expenditure on public charger infrastructure funded by the government, $Cost^{charger}$ is the unit cost of charger, and $d^{charger}$ is the depreciation rate of chargers.

To capture that public charging infrastructure improves the convenience of EV, we assume the EV preference term, $\xi^e$, consists of two components: one that endogenously responds to public charger density, and another that is exogenous and unexplained. We detail how to estimate the impact of charging infrastructure in the calibration section.

Finally, local content requirements (LCR) are captured as increasing the iceberg cost of importing EV-specific intermediates in the Home country, $ic_H(t)$, which raises the effective cost of Foreign intermediate goods and tilt sourcing toward domestic suppliers.

**Competition stage policy.** Market-access barriers and input-cost differences increase the effective technology gap, and equivalently, reduce the Foreign firm's actual technological lead. After Tesla's Shanghai factory began operation in 2020, the firm gained access to the Home market without trade costs and was able to produce using local labor and domestically supplied intermediate inputs. We replicate this effect as a one-time change in

Foreign producers' technology lead, so that the augmented lead offsets the trade barriers and input-cost differences. We detail the procedures in the calibration section.

### 3.5 Welfare

We evaluate the welfare consequences of EV industrial policies in a partial-equilibrium environment. For each country $c$, welfare over the horizon $[t_0, T]$ is the present value of (i) consumer surplus from the automobile composite, (ii) producer net surplus (profits net of R&D costs) in final and intermediate goods, (iii) the fiscal cost of subsidies, and (iv) the environmental externality from vehicle-related GHG emissions. Following the environmental-macro literature, we treat environmental damages as additively separable in utility[14].

$$\Psi_c(T) \equiv \int_{t_0}^{T} e^{-r(\tau - t_0)}\, \psi_c(\tau)\, d\tau, \tag{18}$$

where the instantaneous welfare flow is

$$\begin{aligned} \psi_c(t) = & \underbrace{\sum_{j \in \{e,g\}} \left[ \int_0^1 \left( \Pi_c^j(s,t) - RD_c^j(s,t) \right) ds + \int_0^1 \left( \pi_c^j(i,t) - rd_c^j(i,t) \right) di \right]}_{\text{Producer net surplus}} \\ & + \underbrace{CS_c(t)}_{\text{Consumer surplus}} - \underbrace{FC_c(t)}_{\text{Fiscal cost}} - \underbrace{\Phi_c(t)}_{\text{Environmental externality}}. \end{aligned} \tag{19}$$

The consumer surplus term $CS_c(t)$ is the compensating-variation measure implied by the household demand. The fiscal-cost term $FC_c(t)$ corresponds to total government outlays on industrial policy in period $t$.[15] Finally, $\Phi_c(t)$ maps policy-induced changes in EV/GV adoption and usage into emissions and damages using the exponential damage function. Appendix C.5 provides the exact expressions used for each component and the implementation details.

## 4 Parameterization

To quantitatively evaluate the effectiveness of China's EV industrial policy, we map the Home country to China and the Foreign country to a weighted average of the five major automobile powerhouses: the United States, Japan, Germany, South Korea, and France,

[14] This additivity assumption is standard when the objective is to value policy-induced changes in emissions using a reduced-form damage function.

[15] To avoid double counting, producer profits $\Pi$ and $\pi$ are defined net of direct subsidy transfers received by firms; all subsidy payments enter welfare exclusively through $FC_c(t)$.

as detailed in Section 2. We additionally include the Rest of the World (ROW) as an exogenous market that consumes but does not engage in innovation or production. To discipline the model parameters, we initialize the economy in 2001 and estimate parameters using the first 24 years of the model's transitional path toward the long-run stationary equilibrium, matching observed time-series data from 2001 to 2024.

We assume the economy reaches a long-term steady state in 120 years, where exogenous parameters are fixed at their long-run stable values, all industrial policies have been fully phased out, and a single vehicle technology remains economically viable.[16] Below we outline the procedures to determine the initial technology gaps as well as externally and internally calibrated parameter values.

## 4.1 Initial technology gap distributions.

We construct the initial technology gap distributions for GV and EV technologies in both the final goods and intermediate goods sectors. For the final goods sector, we infer the initial gap distributions from observed differences in vehicle quality between Chinese and Foreign brands during the early 2000s. Following the canonical auto-IO literature (Berry et al., 1995), we proxy quality using total driving range for EVs and the horsepower-to-weight ratio for GVs. For vehicles produced by joint ventures (e.g., SAIC-GM-Wuling, GAC-Toyota), we attribute the vehicle's technology to the brand owner's headquarters. Given the limited commercial availability of EVs in 2001, we externally extrapolate the observed average driving range gaps of available EV models in 2008—the first year Chinese-brand EV sales appear in our data—backward to obtain the initial EV technology gaps in 2001.

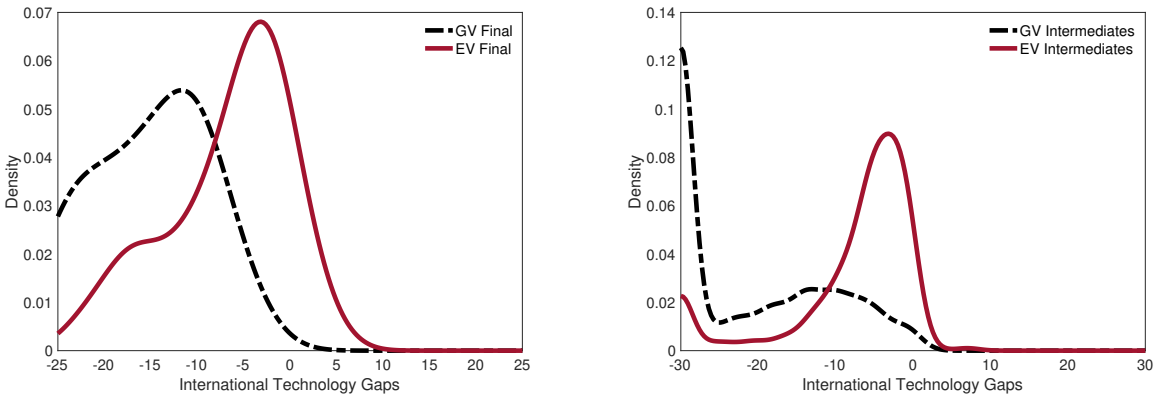
We compute the initial quality gaps as follows. First, for each segment $s$ and technology $j \in \{e, g\}$, we calculate the sales-weighted average quality, $Q_c^j(s)$, for Home and Foreign firms. The logarithmic empirical quality gap is mapped to the model's discrete state space as $\ln M^j(s) = \text{round}(\frac{\ln Q_H^j(s) - \ln Q_F^j(s)}{g_Q^j / freq^j})$, where $g_Q^j$ is the annual growth rate of aggregate sales-weighted quality, and $freq^j$ is the estimated frequency of major model redesigns. We impose an upper bound of 15 for $M$; in robustness checks, increasing this limit leaves firm values largely unchanged. Aggregating these segment-level gaps using their respective sales shares yields the empirical technology gap distribution for final goods.[17]

[16] As in Acemoglu et al. (2016), we utilize a guess-and-verify approach to determine which technology would be the surviving long-run technology.

[17] The initial fraction of SOE product lines in EV is obtained by extrapolating the SOE EV sales share in

For technology-specific intermediate goods, we follow Acemoglu et al. (2016) and estimate the initial distribution of technology gaps using cumulative patent stocks. Specifically, we construct the cumulative stock of patents filed by Chinese and Foreign entities between 1985 and 2001 for every IPC subgroup related to GV and EV components (detailed in Appendix A). We then convert patent stock differences into model gaps using the formula $m^j(i) = \text{round}(\frac{PatStock_H^j(i) - PatStock_F^j(i)}{PatFlow^j(i)/x^j})$, where $x$ is the innovation intensity in the long-run stationary equilibrium. The value of $m$ is capped at a maximum of 15.

Figure 4.1 plots the estimated initial technology gaps. Negative values indicate that China lags behind the Foreign technological frontier. The distributions for GV segments place most of their mass at substantially negative values, whereas the EV distributions are shifted rightward and concentrated around negative values closer to zero.




(a) Final Goods (b) Intermediate Goods

Figure 4.1: Initial International Technology Gaps

*Note:* This figure reports the empirical initial technology gaps distribution for GV and EV technology between China and the Foreign country (smoothed with a kernel density function). Positive values on the x-axises denote leadership of Chinese technologies and negative values denote leadership of Foreign technologies. Panel (a) plots the technology gaps distributions for final goods, where the quality gaps is measured as the difference in segment level attributes. Panel (b) plots the technology gaps distributions for intermediates, where the technology gaps is measured as the difference in patent stock across the IPC subgroups for EV and GV technologies specified in Appendix A.

## 4.2 External Parameters

**Demand system estimation.** We estimate the following empirical model using a country–year panel:

$$\ln(Sales_{c,t}^e / Sales_{c,t}^g) = (\hat{\sigma} - 1)\ \ln(P_{c,t}^e / P_{c,t}^g) + FE_c + FE_t + \varepsilon_{c,t}, \tag{20}$$

China back from 2008. We assume the initial gap distribution is identical across SOE and POE product lines.

where $FE_c$ and $FE_t$ are country and year fixed effects. To address the endogeneity of relative prices, we instrument $\ln(P_c^e/P_c^g)$ using the unit price of imported EV components. This yields an estimate of $\hat{\sigma} = 3.160$. This value is consistent with estimates of the substitution elasticity between general clean and dirty technologies (Papageorgiou et al., 2017) and slightly larger than the implied EV-GV substitution elasticity of 2.78 derived from a nested logit model of the U.S. market by Li et al. (2021).[18]

**Knowledge production function estimation.** We estimate the knowledge production technology using a firm–IPC–year panel $(f, i, t)$ of Chinese listed EV firms. We estimate the log–linear production function with firm–IPC and year fixed effects:

$$\ln(Patent_{f,i,t}) = \beta_H \ln(RD_{f,i,t}) + \beta_B \ln(PubCite_{f,i,t}) + FE_{f,i} + FE_t + \varepsilon_{f,i,t}. \tag{21}$$

Identification stems from within–firm–IPC time variation, netting out time-invariant technological capabilities ($FE_{f,i}$) and common shocks to patenting standards ($FE_t$). Mapping the estimated coefficients to the structural parameters ($\beta_H = \beta_1/\beta_2$ and $\beta_B = (1-\beta_1)/\beta_2$) yields $\hat{\beta}_1 = 0.727$ and $\hat{\beta}_2 = 2.205$. These estimates align closely with R&D cost elasticities found in the existing literature (Griliches, 1990; Hall and Ziedonis, 2001; Acemoglu et al., 2016, 2018).

**Aggregate and welfare-related parameters.** The calibration of industry-aggregate variables relies on macro data for the auto sector. The real interest rate is fixed at $r = 0.02$ in both countries. Cost shares in final-good assembly are pinned to the data: technology-specific intermediates account for $\alpha_1 = 0.55$ and production labor for $\alpha_2 = 0.2$ in both EV and GV sectors.[19] The share of JV profits accruing to Home firms is set to $\alpha_{JV} = 0.5$, reflecting national guidelines for foreign equity caps. The technology diffusion intensity associated with JVs is mapped from the DID estimate in Section 2, yielding $\delta_{JV} = 0.229$.

In our baseline partial-equilibrium setting, vehicle expenditure shares and wage rates are exogenous. We feed in the time series of total vehicle expenditure for China, Foreign, and ROW, and compute wages based on average labor compensation in motor-vehicle manufacturing from 2001 to 2024. For ROW expenditure, we aggregate the sales of vehicle brands headquartered outside China and the five core advanced economies. The price in-

[18] In Appendix Section D, we detail how the estimated preference shifter is decomposed into an endogenous component—driven by the EV stock share and public-charger density—and an exogenous residual component. This decomposition allows us to isolate the contribution of industrial policy to consumers' willingness to adopt EVs in our counterfactual exercises.

[19] Because assembly labor shares are similar across GVs and EVs, we impose a common parameter.

dex for common components is constructed from average unit export prices using corresponding HS codes. Parameter values are summarized in Table D.1. Expenditure, wages, and component prices are smoothly extrapolated to 2060 and held constant thereafter.

Finally, the environmental block follows standard literature and official climate assessments. The initial atmospheric carbon stock is set at 611 Gt, and the output elasticity of environmental damage is set to $\iota = 5.3 \times 10^{-5}$ (Golosov et al., 2014). Along the transitional path, we calibrate emissions from non-auto sectors using historical data and projections from the IPCC (IPCC, 2023), and we match our model-implied road transportation GHG emissions to estimates provided by the IEA (IEA, 2024).

**Policy parameters.** We discipline each policy instrument using direct empirical counterparts or targeted data moments. All calibrated time series within the calibration window are summarized in Table D.1, with full details provided in Appendix D.[20]

*1. Public Research Funding and Basic Knowledge Stock.* We calibrate annual public funding for basic research, $R_c^{basic}(t)$, using grant data from the "863" Program and subsequent "National Key S&T Development" Programs administered by the Ministry of Science and Technology (MoST). The basic knowledge stock, $B_c^j(t)$, enters the innovation production function for both final and intermediate goods firms. This stock is a composite of external knowledge, $\bar{X}_H^e$ (treated as exogenous knowledge spillovers from non-EV technology fields), and basic research output from public labs. We calibrate the flow of external knowledge based on the stock of patents originating outside the auto sector that cite EV technologies.

*2. R&D Requirements for SOEs.* We set the SOE innovation intensity equal to the ratio of average patent filings per firm for SOEs relative to POEs in EV final goods technologies. We then estimate an SOE-specific R&D efficiency shifter, $\Theta_{H,S}^e / \Theta_H^e$, to match the SOEs' actual R&D expenditure on EV technologies. Because financial reports do not disaggregate R&D by technology lane, we proxy the EV R&D share using the share of EV patents within total SOE patent filings. Post-calibration, both the relative innovation intensity and the efficiency shifter are held fixed at their final observed values.

*3. EV R&D Subsidies to POEs.* The R&D subsidy rate, $\chi_c(t)$, is calibrated as the annual average derived from three sources: (i) announced R&D grants to POEs under national programs (accounting for required self-funding ratios); (ii) MIIT-administered subsidy

[20]Policy series are fed into the model period by period without additional smoothing, aside from minor interpolations when an official rate is not reported at the model's frequency.

programs; and (iii) the Pretax Additional Deduction (PAD) policy, which allows a 175% super-deduction on eligible EV R&D expenses. For the Foreign country, we set the subsidy rate to the weighted average of announced EV subsidies across the five advanced economies. We assume R&D subsidies in both Home and Foreign phase out to zero by 2060.

*4. Joint Ventures in Key Components.* The joint venture (JV) policy is modeled as a variation in the fixed cost of establishing JVs, $\kappa_{\text{JV}}$. We internally calibrate this cost path to match the observed sales share of JV firms in the Chinese market. In counterfactual exercises, this fixed cost constraint is relaxed or removed. Post-calibration, the parameter remains fixed at its 2024 level.

*5. Public EV Fleet Procurement.* Public procurement is modeled as an exogenous demand shock for domestic EVs. The magnitude is determined by the ratio of total public EV sales to private EV sales (see Figure 2.5). Because observed public procurement approaches zero by the end of 2024, we extrapolate it to zero in all subsequent periods.

*6. Charging Infrastructure Investment.* The charging infrastructure policy is calibrated to match the actual charger-to-vehicle ratio in China. The unit cost of public chargers is calibrated using procurement data from the China Government Procurement System.[21] We assume the public charging capital stock depreciates at a rate of $d^{charger} = 0.118$, consistent with the average service life of EV chargers. The Foreign charger-to-EV ratio is taken exogenously from the data. Post-calibration, we project both Home and Foreign ratios to converge to a constant, identical steady-state level by 2060.

*7. Purchase Subsidies and Tax Exemptions.* The Home purchase subsidy rate, $\zeta_H^e(t)$, is sourced directly from MIIT implementation records. Foreign subsidy rates are estimated using data from the IEA Global EV Policy Tracker. The EV purchase subsidy in China was fully phased out in 2022, and the 10% tax exemption is scheduled to expire in 2025. For the Foreign country, we assume purchase subsidies gradually phase out by 2030.

*8. Local Content Requirements for EV Batteries.* The "whitelist" policy is modeled as an increase in the iceberg trade cost for EV intermediate goods entering China. We internally calibrate these costs to match the import sales shares in both the Home and Foreign markets. The resulting iceberg cost paths are displayed in Figure D.2. Tariffs for final vehicles and intermediate components are taken from the WTO World Tariff Profiles based on the HS codes reported in Table A.2.

[21] Data accessed at www.ccgp.gov.cn.

*9. Lifting Foreign Entry Restrictions.* The removal of the foreign equity cap is modeled as a one-time increase in Foreign producers' technology lead such that they can overcome trade costs and input prices differentials, denoted as $\nabla_H^j \equiv \frac{\ln T_H^j}{\ln \Lambda} + \frac{\ln(MC_F/MC_H)}{\ln \Lambda}$. The measured technology gap in segments Tesla belongs to is -1 and -2. In the 19th year in transition of the model, we reduce the gaps of EV segments that share the same gap as Tesla by $\nabla_H^j$, so that the effective technology gap, i.e. the actual gap adjusted for trade costs and input prices differentials, is equal to the actual one.

Table 4.1 summarizes all externally calibrated aggregate and welfare parameters, as well as the set of policy parameters that are externally calibrated.

Table 4.1: Externally Calibrated Parameter Values

| Parameter | Description | Value | Source |
|---|---|---|---|
| *Panel A: Aggregate parameters* | | | |
| $\sigma$ | Elasticity of subs. btwn EV & GV | 3.160 | Estimation of demand system |
| $\beta_1$ | Elasticity of public knowledge | 0.727 | R&D prod. function regression |
| $\beta_2$ | Firm's R&D cost curvature | 2.205 | R&D prod. function estimation |
| $r$ | Discount rate | 0.020 | Real interest rates |
| $\alpha_1$ | Tech-specific component share | 0.550 | Powertrain share in total cost |
| $\alpha_2$ | Labor share in final good | 0.200 | Labor compensation in total cost |
| $\alpha_{JV}$ | Profit share of joint venture | 0.500 | Average Foreign equity share |
| $\delta_{JV}$ | Tech. diffusion from joint venture | 0.229 | Tesla Shock DID coeff. |
| $\boldsymbol{E}_H, \boldsymbol{E}_F$ | Aggregate expenditure to vehicles | Table D.1 | Total sales revenue of vehicles |
| $w_H, w_F$ | Wage rates | Table D.1 | Average labor compensation |
| $P_{MT,H}, P_{MT,F}$ | Common parts price index | Table D.1 | Export unit price |
| *Panel C: Welfare parameters* | | | |
| $\phi^g$ | Units of GHG per GV | 0.053 | IEA (2024) |
| $\phi^e$ | Units of GHG per EV | 0.011 | IEA (2024) |
| $\Phi_0$ | Initial atmospheric GHG concentration | 611 | IPCC (2023) |
| $\delta_G$ | Natural decay rate of GHG | 0.0063 | IPCC (2023) |
| $\iota$ | Semi-elasticity of GHG damage | $5.3 \times 10^{-5}$ | Golosov et al. (2014) |
| *Panel B: Externally calibrated policy parameters* | | | |
| $d^{basic}$ | Knowledge depreciation rate | 0.032 | Backward citation lag |
| $Cost^{charger}$ | Unit cost of charger | 1.287 | Procurement charger price |
| $d^{charger}$ | Charger depreciation rate | 0.118 | Lifespan of EV charger |
| $R_H^{basic}(t)$ | Public R&D grants | Table D.2 | MS&T |
| $R_H^{SOE}(t)$ | SOE EV R&D outlays | Table D.2 | CAAM, Annual Reports |
| $\chi_c^e(t)$ | EV R&D subsidy rate | Table D.2 | R&D subsidy rates |
| $D_H^{pub}(t)$ | Ratio of public procurement | Table D.2 | Local procurement amount |
| $\varsigma_c^e(t)$ | EV purchase subsidy | Table D.2 | Central+local subsidy rates |
| $tr_c^e(t), tr_c^g(t)$ | Tariff rates | Table D.2 | WTO Tariff database |

*Note:* This table reports the values of parameters calibrated externally using data from 2001 to 2024.

## 4.3 Internally Calibrated Parameters

**Initial quality and prices.** The initial quality and price in the model are determined by the H-F technology gaps estimated above, the initial technology level in Foreign, and wages. First, we normalize Foreign's initial technology position to 0 for both GV final ($N_F^g(0)$, across all segments) and intermediate goods ($n_F^g(0)$, across all product lines). The initial technology level in EV intermediate goods ($n_F^e(0)$, across all product lines) is set to match the foreign EV-to-GV patent stock ratio in 2001 ($\lambda^{n_F^e(0)} = PatStock_F^e(2001)/PatStock_F^g(2001)$). The initial technology level in EV final goods ($N_F^e(0)$, across all segments) is chosen to ensure the initial model-generated GV-to-EV quality ratio in foreign market to align with the observed GV-EV drive range ratio in Foreign in 2001.[22]

Second, to account for cross-country labor efficiency difference, we assume $l_c = A_c\tilde{l}_c$, and consequently $w_c = \tilde{w}_c/A_c$, where $\tilde{l}_c$ and $l_c$ are the raw and efficiency unit of labor, $\tilde{w}_c$ is the observed wage, and $w_c$ the efficiency wage which enters into the model. The value of $A_F$ is set such that the initial Foreign GV quality-adjusted price index $\bar{P}_F^g(0) = 1$. The value of $A_H$ is chosen to ensure that the initial price ratio of the Home and Foreign GVs matches the empirical counterpart.

The remaining parameters are disciplined jointly by matching a set of targeted moments related to R&D activities, innovation, and trade. On the innovation side, we target the final goods step size $\Lambda$ to match the average growth in EV driving range, and the technology diffusion rate $\Delta$ to match pre-competition (2019) quality gaps in EV final goods.

We discipline the Home-bias parameter, $\gamma_c$, to match the observed decline in domestic brands' sales share following Tesla's entry into the Chinese market. The Home–Foreign elasticity of substitution within a segment, $\varepsilon$, governs the strength of the pro-competition effect (Aghion et al., 2001). Its value is chosen to replicate the DID estimate of the "Tesla shock" on product quality documented in Section 2. Specifically, we designate a fraction of EV segments in the model—proportional to Tesla's 2019 Chinese market share—as the "treated" group where Foreign has the largest technological lead. The remaining segments constitute the control group. We calibrate $\varepsilon$ so that the model-implied difference in productivity growth between these two groups matches the empirical DID estimate.

We identify the fixed cost of entry in EV technology, $F_e$, and the variance parameter of the i.i.d. entry shock distribution by jointly matching the EV entrant sales shares for Home

[22] The aggregate quality of technology j final good produced by producers in country $c$ is calculated as $\frac{\sum_M [Y_c^j(M)Q_c^j(M)+\tilde{Y}_c^j(M)\tilde{Q}_c^j(M)]}{\sum_M [Y_c^j(M)+\tilde{Y}_c^j(M)]}$.

and Foreign in 2019. The EV preference shifters, $\xi_c$, for Home, Foreign, and ROW are recovered internally to match observed EV stock shares and charger-to-vehicle ratios.

We are left with parameters governing innovation efficiency and iceberg costs. For both sets of parameters we made additional assumptions regarding how they change after 2025 to allow the model generate reasonable post-data predictions regarding the speed of technical change and market shares of domestic producers in Home and Foreign markets.

Parameters governing innovative efficiency in intermediate and final goods R&D ($\Theta_e, \Theta_g, \theta_e, \theta_g$) are jointly disciplined by the ratio of R&D expenditure to operating revenue for EV and GV producers between 2015 and 2024.[23] Since 2025, we assume all EV efficiency parameters grow at an annual rate of $g_\theta$ until 2060, to align the model's post-2024 technology trajectory with engineering-based forecasts for EV battery costs.[24]

Finally, the iceberg trade costs for accessing country $c$ ($K_c$ and $\kappa_c$) for the 2001-2024 period are inferred from import shares, as presented in Figure A.1. In the long-run steady state, we impose that Home (Chinese) EV final goods producers supply at most 20% of the Foreign market and at most 60% of the ROW market. We obtain the terminal trade barriers $K_\infty^{eF}$ and $K_\infty^{eR}$, and then set the post-2024 paths to converge smoothly and monotonically to these terminal values by the year 2060 and stay constant thereafter. For intermediate goods, we imposed the market-share ceilings in the Foreign market is 60% (ROW does not import intermediate goods).

**Parameter values and model fit.** The first three columns of Table 4.2 report the calibrated parameter values and their corresponding empirical targets. The calibration reveals that innovation efficiency in EV technologies is strictly higher than in GV technologies for both final and intermediate goods. This implies that—holding all else equal—directing R&D effort toward EV technologies is socially desirable. The estimated value of $g_\theta$ is $-0.058$. In a reduced-form manner, this captures the notion that "ideas are getting harder to find" as the technological frontier advances. The final three columns of Table 4.2 demonstrate that the model delivers a tight fit to the targeted empirical moments.

[23] To account for multi-product firms, we allocate a firm's total R&D expenditure to EVs and GVs proportionally based on their patent application shares in the corresponding technology domains.

[24] In counterfactual exercises, we assume that innovation efficiency in the final goods sector begins to decline at a rate of $g_\theta$ for 35 years, starting either when the global quality index reaches its 2025 baseline level, or, if that level has not yet been attained, starting in 2055. In either case, the decline lasts for 35 years. Similar assumptions are applied to innovation efficiency in the intermediate goods sector.

Table 4.2: Internally Calibrated Parameter Values

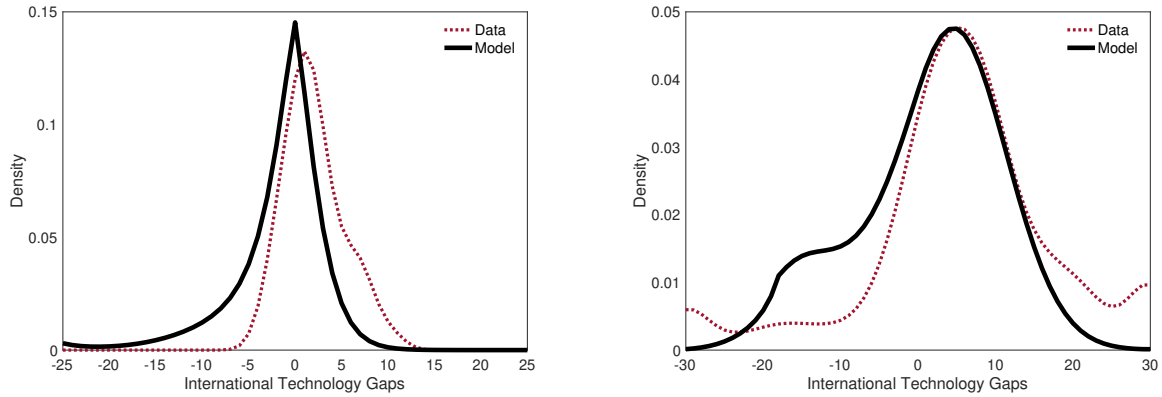
| Parameter | Description | Value | Moment | Data | Model |
|---|---|---|---|---|---|
| *Panel A: Final good sector* | | | | | |
| $\Lambda$ | Final good step size | 1.058 | Avg. EV drive range growth | 0.0515 | 0.0514 |
| $\Delta$ | Tech. diffusion rate | 0.203 | EV final mean quality gaps | -0.4242 | -0.4242 |
| $\Theta_e$ | EV POE R&D prod. | 5.847 | EV final mean R&D/revenue | 0.0683 | 0.0683 |
| $\Theta_g$ | GV R&D prod. | 1.539 | GV final mean R&D/revenue | 0.0257 | 0.0257 |
| $\gamma$ | Home preference | 0.489 | H. sales share diff. | -0.1280 | -0.1283 |
| $\varepsilon$ | EoS. btw. H & F | 4.923 | DiD coeff. of Tesla shock | 0.3972 | 0.3980 |
| $F_e$ | Fixed entry cost | 0.671 | H. EV entry rate | 0.1502 | 0.1502 |
| $\varrho$ | Shock variance | 0.802 | F. EV entry rate | 0.0582 | 0.0582 |
| $\xi^e_H(t), \xi^e_F(t)$ | EV preference shifters | Figure D.1 | Annual EV sales share | Figure 1.1 | |
| $K^e_H(t), K^e_H(t)$ | EV final good iceberg cost | Figure D.2 | Annual final import share | Figure A.1 | |
| *Panel B: Intermediate good sector* | | | | | |
| $\lambda$ | Intermediate good step size | 1.073 | Interm. price growth rate | -0.0554 | -0.0553 |
| $\delta$ | Tech. diffusion rate | 0.102 | EV interm. mean tech. gaps | 1.9980 | 1.9922 |
| $\theta_e$ | EV interm. good R&D prod. | 6.881 | EV interm. mean R&D/revenue | 0.0530 | 0.0526 |
| $\theta_g$ | GV interm. R&D prod. | 1.283 | GV interm. mean R&D/revenue | 0.0252 | 0.0252 |
| $\kappa_{\text{JV}}(t)$ | Fixed cost of joint venture | Figure D.1 | Annual JV sales share | Figure 1.1 | |
| $\kappa^e_H(t), \kappa^e_F(t)$ | EV interm. iceberg cost | Figure D.2 | Annual interm. import share | Figure A.1 | |
| *Panel C: Initial levels and common parameters* | | | | | |
| $N^e_F(0)$ | Init. F. EV final quality | 0.397 | EV & GV init. drive range ratio | 0.2579 | 0.2579 |
| $n^e_F(0)$ | Init. F. EV interm. quality | 0.438 | EV & GV init. patent stock ratio | 0.2210 | 0.2210 |
| $A_F/A_H$ | Relative labor efficiency | 2.083 | F. & H. initial GV price ratio | 1.4350 | 1.4350 |
| $g_\theta$ | R&D prod. growth | -0.058 | Battery cost drop projection | -0.3500 | -0.3511 |

*Note:* This table presents the parameters calibrated internally by matching model-generated moments to their empirical counterparts. We report the targeted empirical moment and the corresponding moment generated by the model simulation, respectively.

## 4.4 Model Validation

We conduct two sets of out-of-sample validations to further validate the parameterization of the model. First, we examine the full distribution of international technology gaps along the supply chain (upstream intermediates and downstream final assembly). Note the internal calibration targets only the mean of pre-competition stage technology gaps for EV finals and intermediates, and did not target for the distribution. Figure shows that the model replicates the empirical distributions closely. The implied densities line up with the data in both location and spread, and they capture the thicker right tail observed upstream.

Second, we validate the model using non-targeted trends in real vehicle prices, as shown in Figure 4.3. Panel (a) plots the model-generated EV price index alongside the observed average EV price in the Chinese market (deflated by CPI). The simulated path for EV price index closely aligns with the data. Next, we replicate the "Tesla shock" event study on

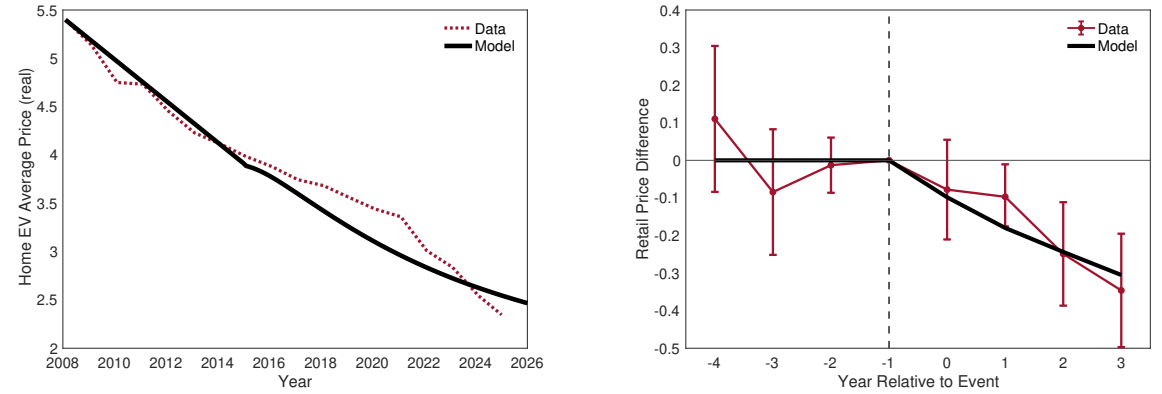



(a) EV Final Good (b) EV Intermediates

Figure 4.2: International Technology Gaps: Model vs Data

*Note:* This figure plots the model generated technology gaps distribution for GV and EV technology between China and the foreign country in comparison to the data in year 2019. The red dashed lines are the empirical distribution from vehicle attributes data and patent application data in EVs. The black solid lines show the model generate distribution of technology gaps. Both Panel (a) and (b) show the model is able to match the empirical distribution closely.

retail prices detailed in Section , which is not targeted in model estimation. We simulate the price path for treated segments directly exposed to Tesla's entry, then calculate the difference in price change between treated segments and controlled segments. As shown in Panel (b), the model matches the event-study coefficients in the post-entry years in both magnitude and persistence.




(a) Home EV Model Price (b) Tesla Shock Event Study

Figure 4.3: EV Model Prices and Event Study: Model vs Data

*Note:* This figure presents the validation exercises of the model. Panel (a) presents the model generated EV price index and the average EV price for Chinese market in data. Panel (b) shows the model replication of event study. The red line with error bars shows the coefficients and confidence interval for the event study, and the red line shows the model generated counterparts.

# 5 Policy Analysis

In this section, we first use the calibrated model to evaluate the impact of industrial policies on welfare. After that we conduct a series of counterfactual experiments to discuss general implications for industrial policies in developing economies.

## 5.1 Aggregate Impacts and Decomposition

A central objective of this paper is to quantify the effects of the 3C policy framework (detailed in Section 2) on economic outcomes. We begin by analyzing the impact on the overall development of the EV industry. We then evaluate the aggregate welfare impacts and decompose the marginal contribution of each policy instrument.

### 5.1.1 Policy Impact on the EV Industry

Table 5.1 reports the aggregate impacts of China's EV industrial policy by comparing the baseline simulated economy against a counterfactual scenario with no EV industrial policy interventions (i.e., removing public research grants, SOE R&D requirements, R&D subsidies, JV requirements, public procurement, charging infrastructure investment, purchase subsidies, tax exemptions, local content requirements, and the lifting of foreign entry restrictions). We evaluate these impacts over both the short term (2001–2025) and the long term (2001–2050).

Panel A shows that the policy interventions plays an important role in driving the domestic EV industry development. It boosts the EV domestic market share to 88.99% by 2050, more than triple the 28.64% projected in the absence of industrial policy. This rapid adoption is underpinned by accelerated innovation, evidenced by consistently higher domestic quality growth (5.01% versus 3.07% in the long run). The resulting rapid technological catch-up also allows domestic firms to capture larger global market shares in both the final good EV and EV-specific component sectors. Moreover, Panel B reveals that the policy-induced growth in the Chinese market generate positive spillovers in global EV industry. It results in higher EV penetration rates and faster quality growth for both the Foreign and Rest-of-the-World (ROW) markets compared to the no-policy counterfactual.

Figures E.1 to E.2 illustrate the dynamic policy impacts on quality and market share over different time horizons. Figure E.1 reveals that the dynamic gains from accelerating EV quality growth and intermediate productivity are sizable. The policy interventions drive a steeper decline in quality-adjusted EV prices across all markets, stimulating adoption

Table 5.1: Short- and Long-term Impacts of Industrial Policy

| | 2001–2025 Horizon | | 2001–2050 Horizon | |
|---|---|---|---|---|
| | Baseline | No Policy | Baseline | No Policy |
| *Panel A: Domestic impacts* | | | | |
| Home EV Quality Average Growth Rate | 6.25% | 3.78% | 5.01% | 3.07% |
| Home EV Market Share in Auto Sales | 46.10% | 8.80% | 88.90% | 28.60% |
| Home Brand Global EV Market Share | 62.30% | 34.90% | 69.70% | 36.90% |
| Home EV Intm. Global Market Share | 68.00% | 37.20% | 72.90% | 39.80% |
| *Panel B: Global impacts* | | | | |
| Foreign EV Quality Annual Growth Rate | 3.98% | 2.65% | 3.69% | 1.93% |
| Foreign EV Market Share in Auto Sales | 16.20% | 8.60% | 52.90% | 17.60% |
| ROW EV Market Share in Auto Sales | 11.30% | 7.60% | 76.30% | 27.50% |

*Note:* This table summarizes the impacts of China's EV industrial policy relative to a counterfactual scenario with no industrial policy interventions (i.e., removing public research grants, SOE R&D requirements, R&D subsidies, JV requirements, public procurement, charging infrastructure investment, purchase subsidies, tax exemptions, local content requirements, and the lifting of foreign entry restrictions). The "Average Growth Rate" metrics represent the annualized average over the respective horizon. All "Market Share" metrics represent the terminal value at the end of the specified horizon (i.e., the values in the year 2025 or 2050).

through enhanced affordability. Figure E.2 shows that industrial policies significantly increased EV adoption in both domestic and Foreign markets.

### 5.1.2 Fiscal Cost of Industrial Policy

We next evaluate the magnitude and trajectory of the fiscal costs associated with China's EV industrial policy. Table 5.2 reports the model-generated fiscal outlays. The model's accounting indicates that China's EV-related policy expenditures were substantial—totaling approximately USD 208.94 billion over 2001–2024—with spending heavily concentrated in purchase subsidies and private R&D support.

As a share of total EV industry revenue, policy expenditure peaked at 51.91% during the 2011–2015 period, before declining to 28.18% in 2016–2020 and 11.64% in 2021–2024, yielding an overall average of 17.46%. This downward trajectory demonstrates that fiscal intensity diminished as EV technologies matured and domestic producers achieved self-sustaining competitiveness.

For comparison, the Center for Strategic and International Studies (CSIS) estimates that the share of Chinese government support in total EV sales revenue fell from 42.4% in the 2009–2017 period to 11.4% in 2023, averaging 18.8% (Kennedy, 2018, 2024).[25] Both the

[25]According to CSIS calculations, cumulative Chinese government support totaled USD 230.9 billion, comprising R&D programs, government procurement, consumer purchase rebates, tax exemptions, and

magnitude and the downward trajectory implied by our model align closely with their independent estimates, confirming that our model-generated fiscal costs are empirically plausible.

Table 5.2: Estimated EV Policy Fiscal Spending and Comparison

| Policy Instrument | 2001–2010 | 2011–2015 | 2016–2020 | 2021–2024 | Total |
|---|---|---|---|---|---|
| Public Research Grants | 0.42 | 0.30 | 0.76 | 0.43 | 1.91 |
| SOEs R&D Expenditure | 3.70 | 4.57 | 3.22 | 5.01 | 16.50 |
| Private R&D Subsidy | 0.98 | 3.07 | 14.48 | 25.19 | 43.72 |
| Government Procurement | 1.10 | 2.34 | 5.87 | 1.65 | 10.96 |
| Subsidy + Tax Exemption | 0.01 | 11.61 | 52.95 | 66.65 | 131.21 |
| Charging Infrastructure | 0.01 | 0.23 | 1.67 | 2.73 | 4.64 |
| Total | 6.22 | 22.12 | 78.95 | 101.66 | 208.94 |
| Share of EV Revenue | 8314.67% | 51.91% | 28.18% | 11.64% | 17.46% |

*Note:* This table reports the model-generated estimates of the fiscal costs of China's EV industrial policies, alongside their share of total EV industry revenue in China. Fiscal costs are converted to billions of constant USD using annual average exchange rates.

### 5.1.3 Welfare Impact of Industrial Policy

Figure 5.1 and Table 5.3 summarize the impacts of China's EV industrial policy on domestic and global welfare, decomposing the total effect into consumer surplus, producer surplus, fiscal costs, and environmental damages.

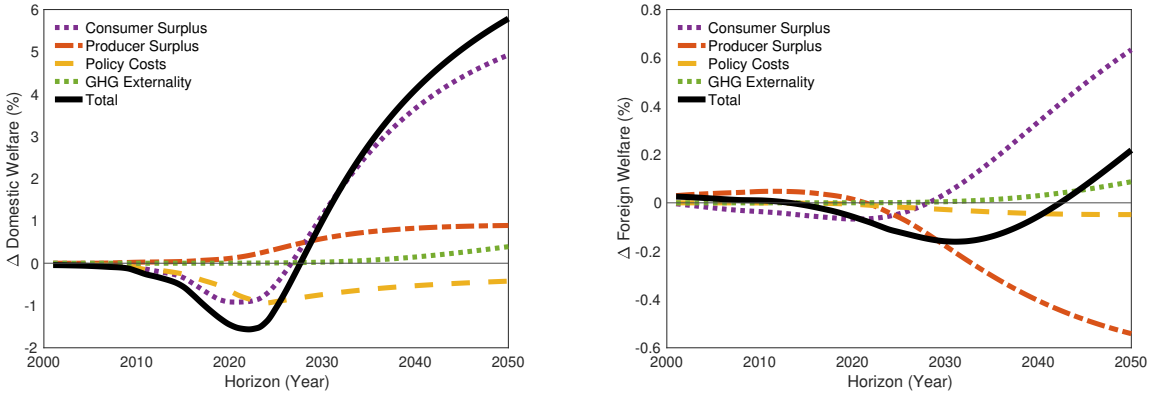
In the short run (through 2025), the discounted domestic welfare impact of the industrial policy is negative (-1.66%). While producer surplus is positive (+0.59%) as domestic EV firms expand and intermediate producers gain competitiveness, these gains are offset by substantial fiscal costs (+1.84% of consumption equivalent). Furthermore, consumer surplus declines slightly in the short run because the average quality of early-stage EVs remains below that of mature GVs, and the accumulated environmental benefits from reduced emissions are still negligible. Figure E.3 presents the flow of these welfare components over the 2001–2050 horizon, while Figure E.4 presents the sensitivity of welfare impacts under alternative future policy paths of Foreign country.

Over time, the domestic welfare impact turns strictly positive, yielding a substantial long-run gain of +5.23% by 2050. These long-term gains are overwhelmingly driven by a surge in consumer surplus (+4.23%) due to lower quality-adjusted prices, alongside higher producer surplus (+1.60%) from commanding global EV market shares. Additionally, cumulative environmental benefits materialize as a reduction in environmental externalitys

infrastructure funding.

(-0.32%). In the long run, these benefits dwarf the amortized fiscal costs of the policies.

For the Foreign country, the welfare dynamics contrast with the domestic experience: small initial gains in producer surplus eventually give way to moderate long-run welfare losses (-0.45% by 2050). On the positive side, Foreign consumers benefit substantially from lower quality-adjusted vehicle prices (+0.36%), and Foreign damages fall (-0.07%) due to accelerated global EV adoption. However, these consumer and environmental gains are outweighed by severe long-run declines in Foreign producer surplus (-0.80%) as Chinese firms intensify global competition and capture market share (as shown in Figure E.2). In the Rest of the World (ROW), which only consumes but does not produce vehicles, welfare unambiguously increases (+1.29%) due to gains in consumer surplus and lower environmental damages.




(a) Domestic Welfare

(b) Foreign & ROW Welfare

Figure 5.1: Welfare Impacts of Industrial Policy Over Different Horizons

*Note:* This figure shows the change in domestic welfare and global welfare relative to a counterfactual scenario without industrial policy (i.e., removing public research grants, SOE R&D requirements, R&D subsidies, JV requirements, public procurement, charging infrastructure investment, purchase subsidies, tax exemptions, local content requirements, and the lifting of foreign entry restrictions) over different time horizon from 2001 to 2050. Panel (a) shows the impact for Home country and Panel (b) shows the impact for the Foreign country. The black solid line shows the total welfare changes from implementing industrial policy. Above zero means positive welfare impacts and below zero means negative welfare impacts. We decomposite the welfare to consumer surplus (purple dashed line), producer surplus (orange dashed line), policy fiscal costs (red dashed line) and environmental externalities (green dashed line).

### 5.1.4 Decomposition of Policy Contributions

We next decompose the total welfare gains by sequentially switching off the three policy stages (Capability, Consumption, and Competition) to isolate the marginal contribution of each over the transition horizon. The results are shown in Figure 5.2

In the first 25 years, the marginal welfare contributions of all three stages appear negative. The Consumption stage drives the highest short-run welfare loss, as the fiscal burden

Table 5.3: Short- and Long-term Welfare Impacts of Industrial Policies

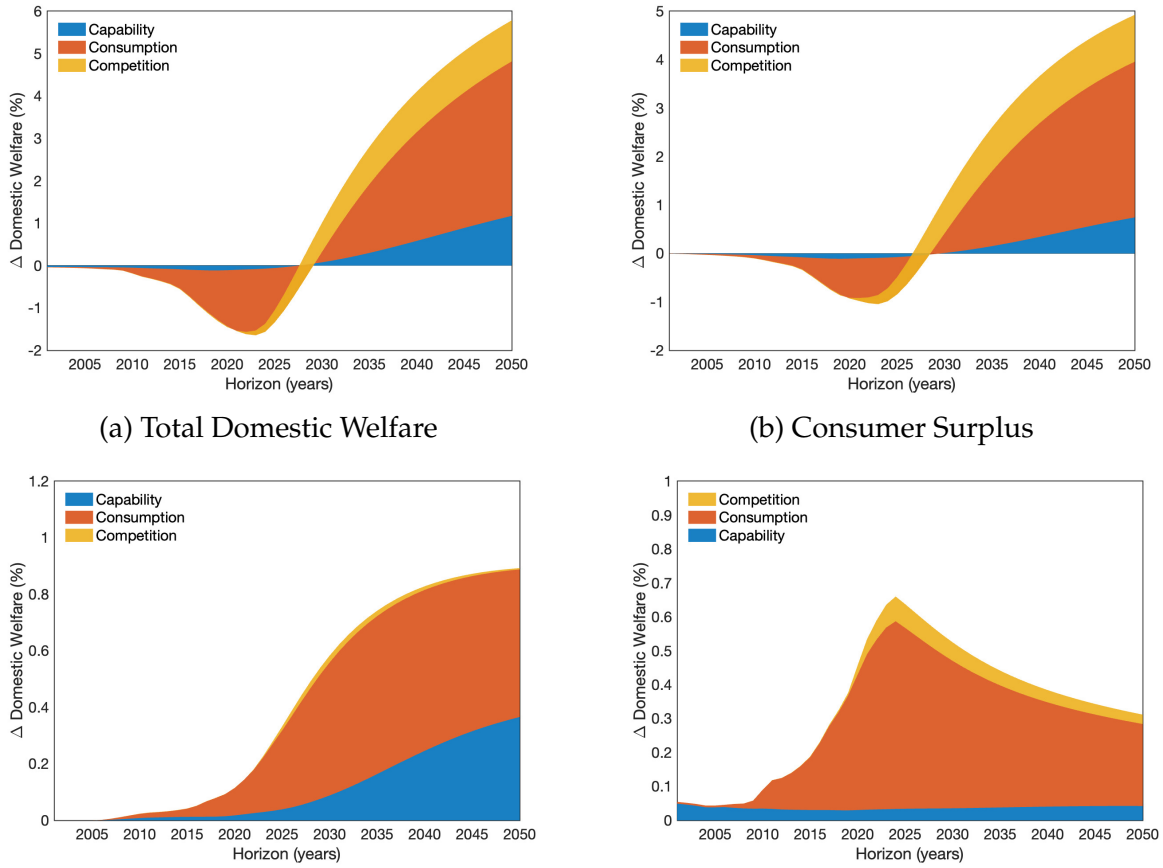
| | 2001–2025 Horizon | 2001–2050 Horizon |
|---|---|---|
| *Panel A: Domestic welfare impacts* | | |
| Δ Domestic Welfare | -1.37% | +5.52% |
| (+) Δ Consumer Surplus | -0.41% | +4.23% |
| (+) Δ Producer Surplus | +0.28% | +0.89% |
| (-) Δ Total Subsidy Costs | +1.24% | +0.84% |
| (-) Δ Environmental Damage | -0.01% | -0.34% |
| *Panel B: Global welfare impacts* | | |
| Δ Foreign Welfare | -0.11% | +0.16% |
| (+) Δ Consumer Surplus | -0.05% | +0.66% |
| (+) Δ Producer Surplus | -0.04% | -0.52% |
| (-) Δ Total Subsidy Costs | +0.02% | +0.05% |
| (-) Δ Environmental Damage | -0.001% | -0.07% |
| Δ ROW Welfare | -0.09% | +1.29% |
| (+) Δ Consumer Surplus | -0.10% | +0.89% |
| (-) Δ Environmental Damage | -0.01% | -0.40% |

*Note:* This table decomposes the relative welfare impacts of China's EV industrial policy compared to a counterfactual scenario without industrial policy (i.e., removing public research grants, SOE R&D requirements, R&D subsidies, JV requirements, public procurement, charging infrastructure investment, purchase subsidies, tax exemptions, local content requirements, and the lifting of foreign entry restrictions). All values are expressed as a percentage of baseline consumption equivalence. The $(+)$ and $(-)$ labels denote how each component enters the total welfare calculation, thus a negative value for Δ Total Subsidy Costs and Δ Environmental Damage indicates an increase in total welfare.

of purchase subsidies and infrastructure scales directly with expanding EV market size. Over a longer horizon, however, the Capability stage emerges as the backbone of the welfare gains. Upstream R&D improvements persistently reduce costs and accelerate quality growth for downstream EV producers. Consumption stage policies also generate massive long-run positive contributions by expanding the market size, which in turn incentivizes further private R&D and shifts consumer preferences toward EVs through network effects (charging infrastructure). Finally, Competition stage policies build upon the foundation of the first two stages, amplifying welfare gains by accelerating innovation, compressing markups, and reallocating market share to the most productive firms.

Figure 5.3 plots the marginal contributions to domestic welfare for specific instruments within the Capability and Consumption stages.[26] Panel (a) shows the decomposition for the Capability stage. Early on, contributions are negative because capability spending is heavily front-loaded, while quality has not yet improved enough to stimulate widespread

[26]Detailed decomposition results are provided in Appendix E.




(a) Total Domestic Welfare

(b) Consumer Surplus

(c) Producer Surplus

(d) Policy Cost

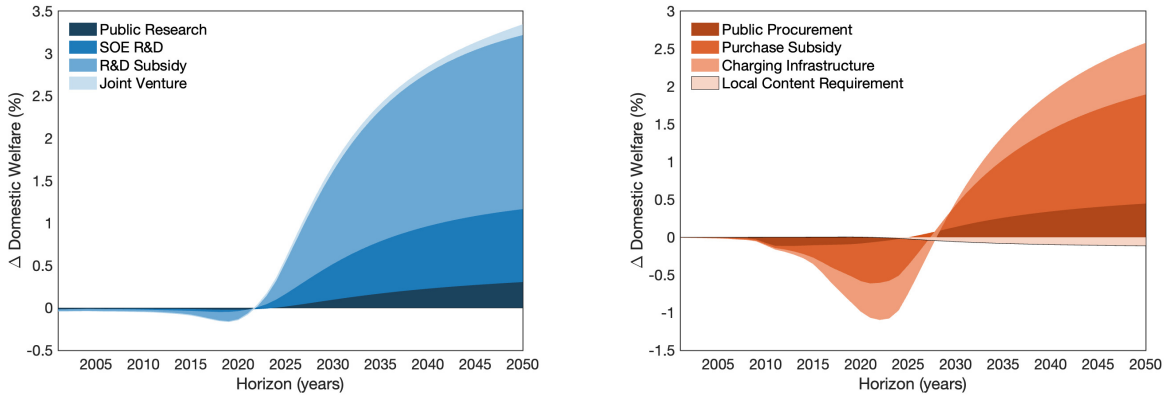
Figure 5.2: Welfare Decomposition Over Different Horizons

*Note:* This figure shows the decomposition of welfare change relative to the counterfactual scenario with no China EV industrial policy intervention. We remove the three stages sequentially from the last stage to the first stage to obtain the marginal contribution of each stage's policies. Panel (a) shows the decomposition of composition to total welfare impacts of the three stages, Capacity (blue), Consumption (orange), and Competition (yellow). Panel (b), (c) and (d) shows the decomposition of consumer surplus, producer surplus, and policy fiscal costs, respectively.

adoption. However, at roughly the 30-year horizon, the welfare payoffs scale rapidly. R&D subsidies deliver the largest long-run gains by directly raising private innovation intensity. Public research provides a persistent knowledge base that permanently improves the efficiency of private R&D. SOE R&D requirements successfully shrink technology gaps during the early years when private innovation incentives are weak, creating intertemporal spillovers that eventually crowd in private R&D. Joint Ventures in components accelerate early technology diffusion; while their aggregate effect is relatively small, it remains persistently positive.

Panel (b) of Figure 5.3 performs the same exercise for the Consumption stage. Public procurement plays a modest but crucial bridging role early on, helping jump-start demand when private EV markets are nascent. Purchase subsidies are initially the least

cost-effective instrument; they reduce domestic welfare in the short run because they force consumers to adopt EVs while the quality gap with GVs is still large. However, their contribution turns highly positive over the long horizon as they pull forward the scale required to lower battery costs. Charging infrastructure directly increases consumer utility, mitigates range anxiety, and accelerates EV adoption; its welfare contribution rises steadily and monotonically over time. In stark contrast, Local Content Requirements (the "whitelist") are persistently welfare-reducing. By restricting access to efficient foreign inputs, LCRs reduce both consumer surplus and downstream producer surplus, slow the expansion of the EV market, and ultimately dampen innovation incentives along the supply chain.




(a) Capability Stage

(b) Consumption Stage

Figure 5.3: Welfare Decomposition of Policy Stages Over Different Horizons

*Note:* This figure shows the decomposition of welfare change relative to the counterfactual scenario without each capacity stage policies (i.e. public research grants, SOE R&D requirements, R&D subsidy, joint venture requirement) and consumption stage policy (i.e. public procurement, charging infrastructure investment, purchase subsidy and tax exemption, local content requirement, Foreign leader entry). We remove the policies sequentially from the last policy to the first policy to obtain the marginal contribution of each policy instrument.

Table 5.4 presents a cost-benefit analysis of the individual policy instruments over the long run (2001–2050). On the capability side, public research grants, private R&D subsidies, and SOEs R&D mandates all generate large aggregate welfare benefits. Because these policies raise innovation arrival rates and permanently lower effective marginal costs, the induced decline in quality-adjusted prices creates massive, long-lasting gains in consumer surplus. Consequently, their benefit-to-cost ratios are relatively high (15.11 for public research grants and 5.87 for POE R&D subsidies).

Consumption stage policies also exhibit strong cost-effectiveness in the long run. Charging infrastructure yields a benefit-to-cost ratio of 4.61, while public fleet procurement and purchase incentives deliver ratios of 6.03 and 3.12, respectively. Lastly, Competition stage

policy stands out as one of the most efficient intervention (ratio of 12.46); it required virtually no direct fiscal outlay but generated massive consumer surplus through heightened competition and accelerated incumbent innovation.

Table 5.4: Long-term Benefit and Cost of Policies

| | Total Welfare Benefit (1) | Total Fiscal Cost (2) | Benefit/Cost Ratio (3) |
|---|---|---|---|
| Purchase Incentives | +1.99% | +0.96% | 2.07 |
| R&D Subsidy to EVs | +1.93% | +0.44% | 4.38 |
| Charging Infrastructure | +1.02% | +0.41% | 2.48 |
| Allow Foreign Entry | +0.97% | +0.18% | 5.39 |
| SOE R&D Requirement | +0.92% | +0.24% | 3.83 |
| Public Fleet Procurement | +0.45% | +0.19% | 2.36 |
| Public Research Grants | +0.40% | +0.07% | 5.71 |
| Joint Venture Requirement | +0.17% | +0.03% | 6.16 |
| Local Content Requirement | -0.11% | -0.06% | – |

*Note:* Values in the first two columns are reported relative to total vehicle consumption. "Total Welfare Benefit" represents the discounted total domestic welfare gain generated when each specific policy is implemented. "Total Fiscal Cost" represents the change in discounted aggregate industrial policy expenditure relative to a counterfactual scenario where that specific policy is absent.

## 5.2 Implications for Policy Design

In the following section, we explore the mechanisms underpinning the effectiveness of China's EV industrial policy. Our analysis highlights three key insights. First, policy effectiveness hinges on opportunity costs, which in our context are shaped by China's initial competitiveness in GV technology. Second, the sequencing of policies is crucial; we demonstrate the economic rationale behind the progression from Capability to Consumption to Competition. Third, effective policy intervention must be timely and sustained, yet ultimately phase out once market forces are sufficiently mature.

### 5.2.1 Opportunity Cost and Policy Effectiveness

A shift toward EVs necessarily entails the displacement of established GV technologies. Higher incumbent GV rents increase the cannibalization cost of an EV transition. China starts substantially behind the foreign frontier in GV technologies but faces a much smaller gap in EV technologies. This implies a low opportunity cost of "switching lanes": reallocating innovation effort away from GVs sacrifices relatively little incumbent rent. If China had started as a GV leader, the same EV policy bundle would produce far smaller net welfare gains. To quantify this mechanism, we construct two counterfactual scenarios

where China is initially "Neck-and-Neck" in GV, or "Ahead" in GV where the initial GV intermediate and final technology gaps are reversed, while holding the initial EV gaps fixed at their baseline levels technologies. Figure E.5 presents the counterfactual initial GV gap distributions.[27]

The results are shown in Table 5.5. The long-run domestic welfare impact of the EV policy bundle drops dramatically from +5.52% in the baseline to +2.97% and +1.69% in the "Neck-and-Neck" and "Ahead" counterfactuals. Focusing on the latter, consumer surplus gains shrink from +4.23% to +1.95%, as policy-induced EV adoption is less effective when preserving GV production remains attractive. Producer surplus gains are nearly eliminated (from +0.89% to +0.17%), reflecting that the policy now reallocates profits across technologies rather than creating new rents by catching up in an emerging sector. Environmental benefits are also severely muted, with the reduction in environmental damages falling from -0.32% to -0.21%.

These results suggest that China's early disadvantage in mature GV technologies significantly reduced the opportunity costs of directing innovation toward EVs, thereby amplifying the overall effectiveness of its EV industrial policy.

Table 5.5: Long-term Impact on Domestic Welfare with Different Initial GV Gaps

| | Baseline | Neck-and-Neck | Ahead |
|---|---|---|---|
| | (1) | (2) | (3) |
| Δ Total Welfare | +5.52% | +2.97% | +1.69% |
| (+) Δ Consumer Surplus | +4.23% | +3.00% | +1.95% |
| (+) Δ Producer Surplus | +0.89% | +0.29% | +0.17% |
| (-) Δ Total Subsidy Costs | +0.84% | +0.51% | +0.65% |
| (-) Δ Environmental Damage | -0.34% | -0.18% | -0.21% |

*Note:* This table summarizes the long-term domestic welfare impacts of China's EV industrial policy under the baseline scenario versus two counterfactual scenarios. In the counterfactuals, the initial GV technology gap distribution in both final and intermediate goods is shifted such that China is either neck-and-neck or leading in GV technologies (while EV initial gaps remain at baseline levels). We recalibrate the parameters of initial quality to match the same set of moments as baseline. The $(+)$ and $(-)$ labels denote how each component enters the welfare calculation.

### 5.2.2 Policy Sequencing

China's EV industrial policies have progressed through three distinct stages: Capability, Consumption, and Competition. In this subsection, we demonstrate the importance

[27] For the counterfactual exercise in initial technology gaps, we recalibrate the initial quality level parameters and relative labor efficiency to match the same moments as in the baseline calibration. The resulting initial quality adjusted price path is presented in Appendix E.2.2.

of policy sequencing. Specifically, we show that the effectiveness of later-stage policies builds critically upon the successful implementation of the preceding phases.

Figure 5.4 summarizes the domestic welfare gains from implementing different combinations of policy stages. For each bundle, the red bar shows the welfare impact when the included stages are implemented jointly, and the stacked bars report the welfare impacts of the corresponding stages when evaluated in isolation (i.e., turning on one stage at a time relative to the same no-policy benchmark). Therefore, differences between the red bar and the sum of the stacked components reflect dynamic complementarity (or substitutability) across stages.

The effectiveness of the Consumption-stage policies is significantly enhanced when they build upon the prior implementation of the Capability stage. Their impact is considerably greater than in a scenario where the Capability-stage instruments are absent. Two main forces, each corresponding to one of the two dimensions of competition–EV-GV technology competition and within-technology international competition–in the model, underline this result.

First, Capability-stage policies reduce the quality-adjusted price of EVs relative to GVs by lowering R&D costs. Since GV and EV are substitutable goods, a given intensity of EV price subsidies generates a larger increase in EV consumption when the EV-GV price gap is relatively small. Second, within the EV segments, both Home and Foreign producers compete. A domestic EV consumption subsidy may benefit either Home or Foreign firms, depending on the prevailing technology gap. Home EV producers initially lag behind Foreign ones, though the gap is narrower than in the GV sector. Capability-stage policies help close this gap, thereby reducing the fiscal "leakage" of subsidies to foreign producers—leakage that would otherwise amplify foreign leads and dampen domestic innovation incentives.

Figure 5.4 further demonstrates that the welfare benefits of the Competition stage are substantially larger in the presence of the prior Capability and Consumption stages, compared to a scenario where these earlier policies were not implemented. The underlying mechanism relates to the second dimension of competition in our model—within-technology competition between Home and Foreign firms.

Following Aghion et al. (2001), the step-by-step innovation framework implies that when domestic producers are technologically close to the foreign frontier, removing trade barriers generates an escape-competition effect: home firms innovate more intensively to sur-

vive and compete. However, when the technology gap is large, domestic firms have little prospect of catching up with foreign leaders, and foreign entry instead dampens their innovation incentives.[28] In our context, the Capability and Consumption stages serve precisely to narrow the technology gap by strengthening domestic firms' technological capabilities. By doing so, they amplify the pro-competitive effects of introducing foreign competition in a later stage, thereby enhancing overall welfare gains.

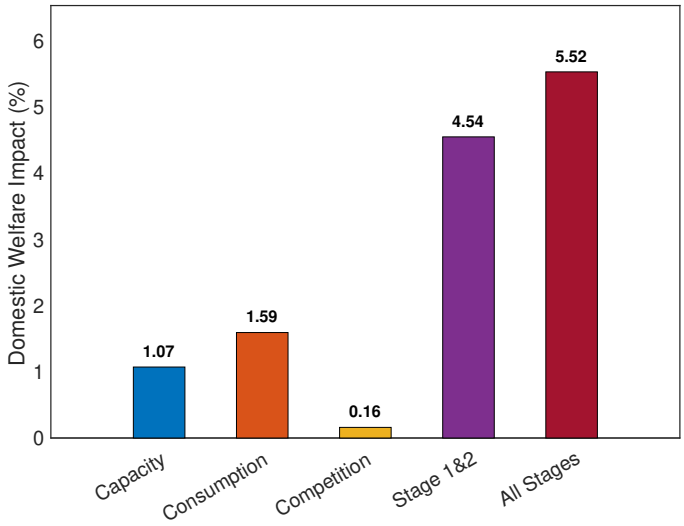



Figure 5.4: Dynamic Complementarity Across Policy Stages

*Note:* This figure reports the long-run change in domestic welfare (in percent relative to the no-policy counterfactual) under alternative bundles of industrial policies. "Stage 1" corresponds to Capability stage policies, "Stage 2" to Consumption stage policies, and "Stage 3" to Competition stage policies. The red bars report the joint welfare impact when policies are bundled across stages. The stacked bars indicate the contributions of individual stages.

**Optimal policy timing** The preceding analysis fixes the starting time of each policy stage. Next, we explore the importance of policy timing by shifting the start date of each stage, while keeping intensity and other policies same as the baseline.[29] Panel (a) of Figure 5.5 shows the results for shifting the starting time of Consumption and Consumption stage policies while holding the starting time of the Capability stage policy at year 2001. Over a 50-year horizon, the welfare response is hump-shaped and peaks when the Consumption stage policy starts in 2011, and Competition stage policy starts in 2018.

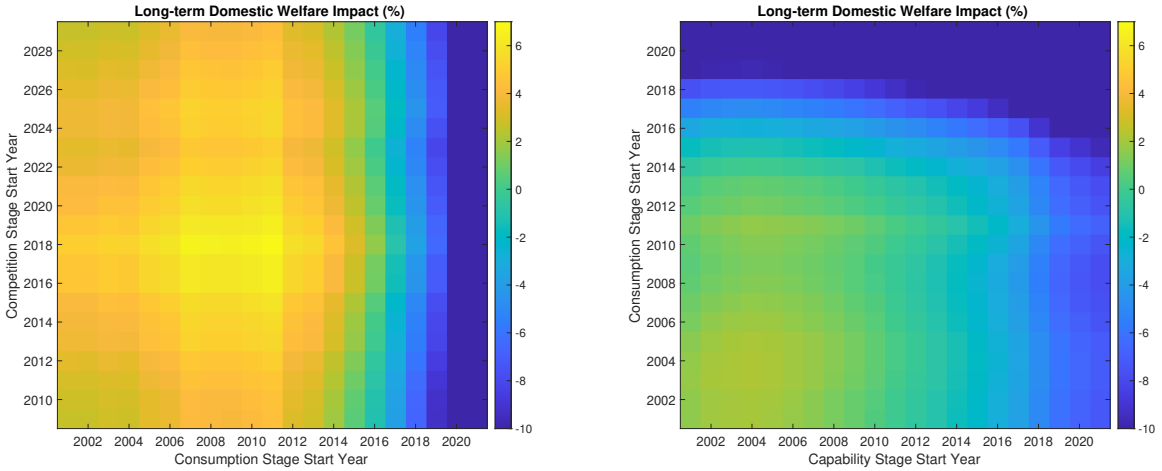
Panel (b) of Figure 5.5 shifts the start of the Capability stage and Consumption stage while fixing the Competition stage at the year 2001. The results further show that under

[28] Aghion et al. (2006), using UK microdata, show that the effect of foreign entry on domestic innovation is conditional on the technology gap: it discourages innovation when domestic firms are far from the frontier, but stimulates innovation through the escape-competition effect when they are near it.

[29] We conduct the optimal timing for individual policy stage to show the robustness of the results, as shown in Appendix E.

all alternative sequences, the welfare impact from the industrial policy would be lower than the baseline sequence of policy stages (i.e., Capacity→Consumption→Competition).

The mechanisms are analogue to what we have discussed above. Intuitively, subsidizing consumption too early when EV relative price is high is not effective, while subsidizing too late would forgo the benefit of intervention under the cumulative nature of technologies. Furthermore, introducing competition too early discourages domestic producers' innovation incentives at a time when the international technology gap is still large; while delaying foreign entry too late overprotects domestic incumbents, dampens competitive pressure when it would be most beneficial, and ultimately lowers long-run welfare. Optimal policy sequencing strikes a balance between these forces.




(a) Holding Capacity Fixed at 2001 (b) Holding Competition Fixed at 2001

Figure 5.5: Domestic Welfare Impact Over Different Policy Sequence

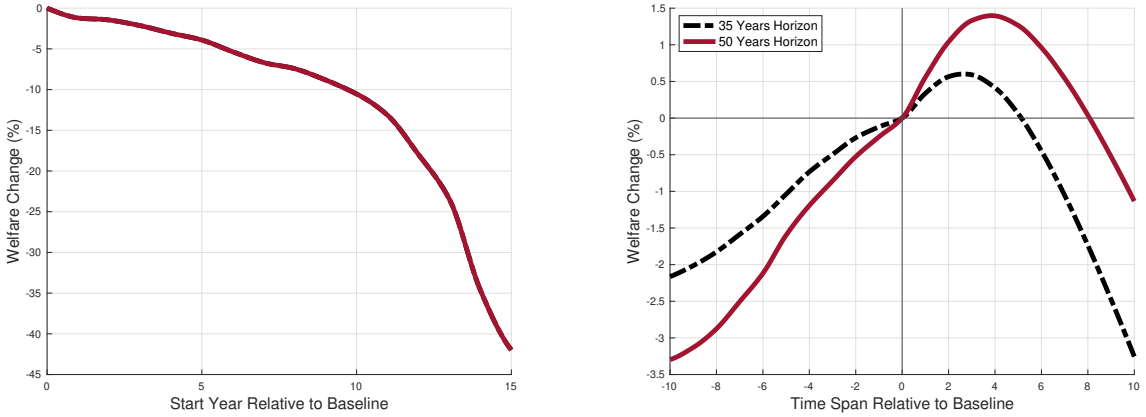
*Note:* This figure shows the domestic welfare change in counterfactual scenarios relative to the no-policy scenario. In Panel (a), we move the Consumption and Competition stage policies from 10 years earlier to 10 years later while holding the timing of the Capacity stage policy fixed as the baseline. Similarly in Panel (b), we move the Capacity and Consumption stage policies from 10 years earlier to 10 years later while fixing the timing of Competition stage policy at year 2001.

### 5.2.3 Timely Intervention, Sustainable Support, and Eventual Phase-out

Next, we analyze how the timing of policy implementation—both its start and its end—shapes aggregate effectiveness. Panel (a) of Figure 5.6 presents counterfactual exercises that shift the start date of all policies, while holding the policy span fixed. Total welfare declines monotonically as the policy start year is delayed. Consistent with Acemoglu et al. (2012, 2016), delaying policy intervention is costly due to the cumulative nature of technological progress.

Panel (b) of Figure 5.6 varies the end date of consumer purchase subsidies while keeping

start dates at baseline for both 50-year and 35-year horizons. The resulting welfare profile exhibits a clear hump shape. Subsidies must sustain long enough to enable mass EV adoption, but should be phased out once EVs become cost-competitive with GVs. In our exercise, welfare is maximized when purchase subsidies are extended by four years.




(a) Delay All Policies

(b) Extend All Policies

Figure 5.6: Domestic Welfare Impact Over Different Policy Timing

*Note:* This figure presents the long-term welfare changes in counterfactual scenarios relative to baseline China EV industrial policy timing. Panel (a) shows the result for delaying all policy stages from 0 to 15 years while fixing the time span. Panel (b) shows the result of delaying phase-out time for EV industrial policies from 0 to 15 years later.

# 6 Conclusion

This paper examines the role of industrial policies in fostering the development of China's EV sector over the past two decades. We take a holistic approach and characterize China's EV policy framework as the *3C stages*: *Capability, Consumption, and Competition*. The first *Capability* stage (2001–2008) focused on enhancing domestic firms' technological capabilities through R&D subsidies directed at universities, SOEs, and private firms. The second *Consumption* stage (2009–2019) aimed to stimulate domestic demand via public procurement, the buildup of charging infrastructure, and purchase subsidies for private consumers. The third *Competition* stage (2020–present) introduced foreign leaders (e.g., Tesla) into the domestic market and progressively phased out subsidies.

To analyze the impact of these policies, we develop a quantitative model of directed technical change featuring a tradable supply chain. The model endogenizes innovation decisions in both upstream and downstream sectors, captures international competition, and incorporates key policy instruments used in practice. Calibrated to rich micro and macro evidence, we evaluate the dynamic effects of China's EV industrial policies over differ-

ent time horizons. Our results show that although fiscal costs dominate in the short run (2001–2025), the policy package generates significant positive welfare gains over the long run (2001–2050).

Our analysis yields a set of mechanism-based lessons for policy design. First, opportunity cost matters for policy effectiveness: China's initial lag in GV technology implied a lower opportunity cost of transitioning to EVs. Second, policy sequencing is crucial. The effectiveness of later-stage policies builds upon the successful implementation of the preceding phases. Finally, policy intervention should start timely, sustain long enough for firms to become viable, but ultimately exit once market forces take hold.

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# Appendix A Data, Measurement and Variable Construction

To investigate the automobile industry at the most granular level, we assemble a multi-layer dataset covering the EV/GV market and supply chain for China, advanced economies, and rest of the world (ROW) annually from 2001 to 2024. Monetary values are deflated to 2010 prices using CPI where appropriate and converted to USD with the annual average exchange rate for cross-country comparisons. We identify firms and vehicle models with name-matching to ensure entities are consistently tracked across sources. We resolve aliases and collapse trims to a model by sales-weighted averaging of attributes. We classify firms as upstream (components) or downstream (vehicles) based on primary industry codes and manual checks for multi-activity firms.

## A.1 Vehicle Sales, Price, and Attributes

Since EV and GV are frequently classified under the same category, even at highly disaggregated industry levels (e.g., NAICS 6-digit codes), tracking the evolution of their prices directly using industry-level data from the national statistical bureaus or manufacturer associations is challenging. To address this limitation, we collected detailed product-level data on EV and GV.

Our product-level vehicle sales data in global market is from Marklines database, covering over 95% of light-duty EVs and GVs sold in the aforementioned markets. For each vehicle model, we observe sales quantity, launch dates, retail prices, segment, battery capacity/fuel efficiency, official driving range, engine horsepower, weight and size, etc.

We gathered price data for electric car and gasoline car models sold in the Chinese, US, European, Korean and Japanese markets. Our focus is on light-duty vehicles (LDVs) due to their significance in the global vehicle trade, as well as the availability of comprehensive product-level data. Second, we obtained the sales of different vehicle models in each market of interest from industry reports and market research firms, allowing for us to merge with the price of each vehicle product across different regions. then we match the price with product-level subsidy. Finally, we supplemented the data with additional information on vehicle attributes, and aggregate sales data for GV and EV in each market. Combing these data sources, we are able to construct the dataset for sales quantity and sales-weighted average prices of EV and GV for each market.

Specifically, our analysis utilizes the global sales and price data to construct the average prices EV relative price in each market. We collect from national automobile manu-

facturers' associations and automotive online platforms, including *Autohome* for China, *Kelly Blue Book* for the US, *ev-database.org* for Europe, *Autocom* for Japan and South Korea. This dataset includes the manufacturer's suggested retail price (MSRP) and detailed model-level attributes for each vehicle models.[30] We use the real vehicle prices that is inflation-adjusted for each country according to the World Bank CPI data from the World Development Indicators (WDI) database, expressed in constant US dollars. Price variations for the same model across regions reflect differences in firms' production costs and trade barriers[31].

For the EV intermediate goods, we obtain the key supplier information from NEV yearbook, which contains model-level supplier information for EV battery cells and packs, electric motors, and battery management systems.

## A.2 Patent and R&D

To measure the innovation of Chinese and Foreign manufacturers on the EV and GV technologies, we rely on global patent data and count patents based on their application or filing date.[32]. Patents data offer three key advantages for our analysis of technology progress. First, they provide a highly granular measurement of technological advancements, allowing us to differentiate innovations within the automotive industry by specific technologies—something not easily achieved with R&D expenditure and employment data, even at the firm level. Second, the data on R&D expenditures and labor as well as capital inputs are often not disclosed by small and medium-sized enterprises for privately held firms in China and in other countries. Third, the automotive sector is highly innovation-intensive, with patents serving as an effective tool for protecting against imitation. These factors make patents a reliable proxy for gauging innovative activity in the automotive industry.

Our approach follows four key steps. First, we classify each invention patent as either belonging to the EV or GV technology field based on its primary IPC (International Patent Classification) code[33]. We rely on the technology document to identify critical technolo-

[30]MSRP is the price that customer pays for the acquisition of the vehicle only, including legally required acquisition taxes, including Value-Added Tax and registration taxes, etc., but excluding tax incentives such as the consumer tax credits.

[31]For instance, in 2023, a Volkswagen ID.3 in China is sold at half its price that is sold in Europe.

[32]Using application dates is standard in empirical innovation research as they more accurately reflect the timing of R&D activities than grant dates.

[33]The CNIPA uses IPC for patent classification. We further supplement for CPCs when processing US and European patent data.

gies in areas such as powertrains, drive control systems, and other components that differentiate EVs from GVs. These technologies are then mapped to specific IPC subgroups, which serve as proxies for distinct product lines. Our classification of these IPC codes is summarized in Table A.1, which contains over 250 subgroups for each vehicle type.

Second, we assign a country of ownership to each patent by analyzing the patent assignee and inventor information. The country of the patent assignee's firm is typically used to determine the patent's ownership. If the firm is a subsidiary of a multinational company or a joint venture, which is common in the Chinese auto industry, as documented by Li et al. (2021), we split the patent's ownership evenly between the two countries involved. In cases where the assignee information is missing, we use the inventor's country to determine ownership. To adjust for patent quality, we use citations as an indicator, as higher citations for a patent typically signify superior innovation quality and are associated with faster productivity growth (Acemoglu and Akcigit, 2012). We then aggregate the total number of patents held by Chinese or foreign entities (focused on the five countries of interest) for each type of vehicles in each IPC subgroups in the year 2000 to 2023. The number is then weighted by the average number of forward citations received by the patents. For robustness check, we also use the new application of invention patents within the 5-year range for each year to ensure that the technology level is accurately reflected in our measurement.

One of the significant challenges in analyzing international patent data is the issue of multi-filing, where the same invention may be filed in multiple countries, leading to double-counting. Additionally, different aspects of the same invention may result in multiple patent filings. To avoid this, we use the patent family ID system from the ORBIS Intellectual Property database. This system identifies all patents that belong to a single invention, grouping them under a unique family ID, thereby preventing the double-counting of inventions across different countries.

Moreover, considering that more than half of the companies included in our study operate as multi-product entities that produces both GVs and EVs (similar in the intermediate good firms), it presents a challenge to distinctly attribute R&D expenditures solely to GVs or EVs at the individual firm level. In order to evaluate the R&D expenses devoted to EVs, we adopt the proportion of EV sales from each company as an indicator of the corresponding share of R&D expenditure allocated to EV technology within these firms. Subsequently, we determine the aggregate R&D spending on EV technology by compiling all firm-level R&D investment data sourced from annual reports of publicly listed

Table A.1: Patent Classification of Gasoline and Electric Vehicle Technology

| IPC Codes | Technology Field Descriptions |
|---|---|
| *Panel B: GV Technologies* | |
| B60K5 | Arrangements in internal-combustion or jet-propulsion units |
| B60K6 | Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion |
| B60K13 | Arrangement in connection with combustion air intake or gas exhaust of propulsion units |
| B60K15 | Arrangement in connection with fuel supply of combustion engines Mounting or construction of fuel tanks |
| B60S5/02 | Supplying fuel to vehicles |
| *Panel B: GV Intermediates Technologies* | |
| F02B1-F02B77 | Combustion engines in general using liquid fuel |
| F02D1-F02D37 | Controlling combustion engines on injection and valve-operating cycle |
| F02F1-F02F11 | Cylinders, pistons, or casings for combustion engines |
| F02M1-F02M71 | Supplying combustion engine with liquid fuel |
| F02N05-F02N19 | Starting combustion engine with power-operated apparatus or other means |
| F02P1-F02P23 | Ignition of internal-combustion engines |
| F16C1-F16C13 | Flexible transmission shafts and other elements of crankshaft mechanisms |
| F16C17-F16C39 | Bearing of transmission shafts in connection with engine |
| *Panel C: EV Technologies* | |
| B60K1 | Arrangement or mounting of electrical propulsion units in vehicle |
| B60K6-B60K7 | Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion |
| B60L1-B60L7 | Special equipments or arrangement of electrically-propelled vehicle |
| B60L15 | Methods, circuits or devices for controlling the propulsion of electrically-propelled vehicle |
| B60L50-B60L58 | Electric propulsion with power supplied within the vehicle |
| B60W10 | Conjoint control of vehicle sub-units of different type or different function |
| B60W20-B60W60 | Control systems specially adapted for hybrid vehicles |
| *Panel D: EV Intermediates Technologies* | |
| H01M4 | Electrodes of battery cells |
| H01M8-H01M16 | Battery cells of secondary, fuel cells and hybrid cells |
| H01M50 | Constructional details or processes of manufacture of the battery parts |
| H02J7 | Circuit arrangements for charging or depolarizing batteries or for supplying loads from batteries |
| H02K1-H02K15 | Components and manufacture of electric motors and generators |
| H02K17-H02K55 | Rotating machines, motors and generators to surge output power |
| H02M1-H02M11 | Details and types of apparatus for conversion of electric power |
| H02P1-H02P9 | Arrangements for regulating or controlling the speed of electric motors, generators, or dynamo-electric converters |
| H02P21-H02P29 | Arrangements or methods for regulating or controlling AC/DC motors |

*Note:* This table lists the classification of EV and GV technology based on the IPC codes in WIPO.

companies, in conjunction with data from the China Association of Automobile Manufacturers (CAAM), the National Bureau of Statistics (NBS) industrial enterprise census, and the ORBIS database.

## A.3 Import and Export

For the import and export of GV, EV and vehicle parts, we use the UN ComTrade database that reports the detailed import/export quantity as well as CIF and FOB prices and total value for each country at product-level (6-digit HS code). We first classify the products within the 4-digit HS code for vehicles (#8703) to EV and GV as in Table A.2. We comprise the data of China's import and export to the five markets of the foreign country and to the rest of the world.

For the intermediate goods trade, aligning with our categorization of product lines based on the technology fields unique to GV and EV, we concentrate on intermediate goods that are specifically used in GV and EV. We utilizes the technologies as classified in Table A.1, and Table A.2 provides a detailed classification of GV and EV using the 6-digit HS codes. Figure **??** presents the import shares for China and the foreign country.

## A.4 Industrial Aggregate

Throughout the paper, we envision the foreign country as an advanced country in automobile industry (a weighted combination of five major players in the international vehicle market). For the vehicle price and sales part, we use the share of their automobile market size (total sales quantity) in each year as the weight of each country, as shown in Panel A of Table A.3. For the technology part, we obtained the annual revenue of major auto companies from listed firm annual reports, and use the relative share of the total revenue of auto companies with headquarter located in the country as the weight for each year, as shown in Panel B of Table A.3.

## A.5 Industrial Policy

**R&D Grants and Subsidy** The Chinese government has allocated research grants under the "863" project since the 10th Five-Year Plan (FYP), to support R&D and technological innovation in key electric vehicle (EV) components. From the 11th to the 14th FYP, the central government further committed billions of RMB in research funding to advance core EV technologies. The entities receiving the R&D grants include public research in-

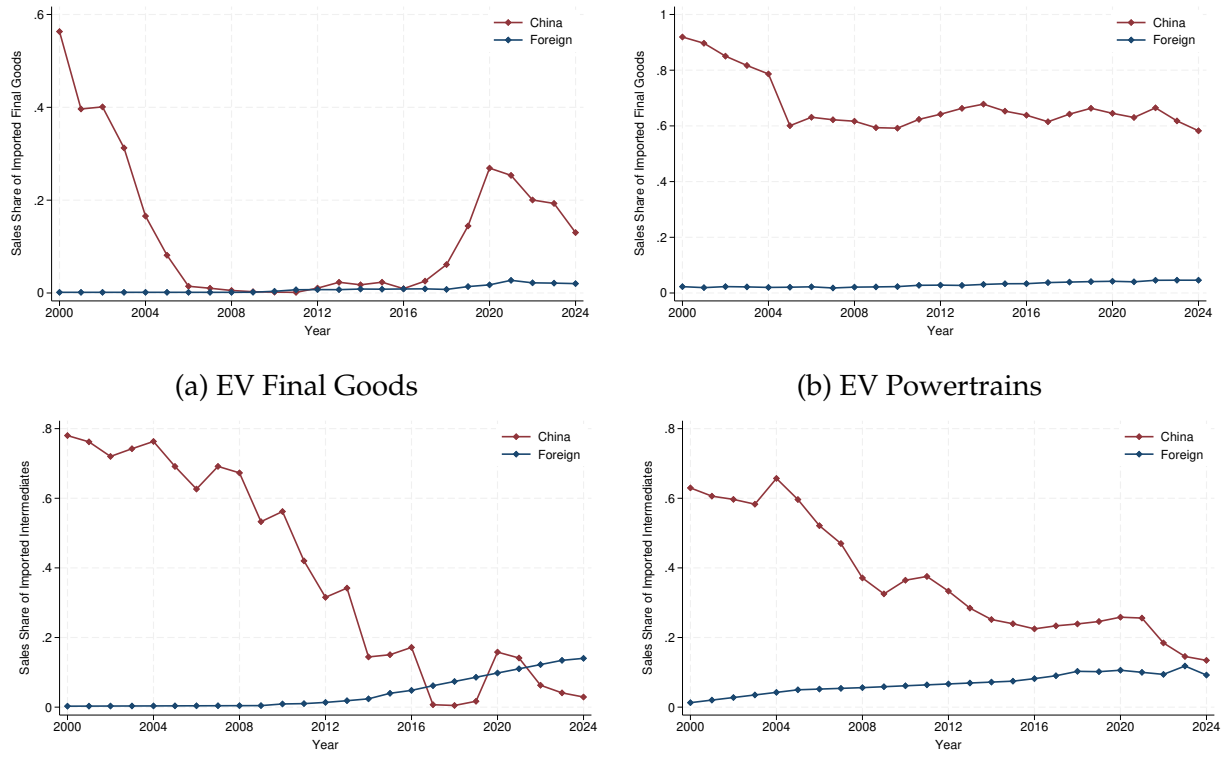
Table A.2: Vehicle Product Classification with HS Code

| 6-digit HS code | Covered Products |
|---|---|
| *Panel A: GV Final Good* | |
| 870321 | Internal combustion engine vehicles, cylinder capacity $<$ 1000cc |
| 870322 | Internal combustion engine vehicles, cylinder capacity 1000cc-1500cc |
| 870323 | Internal combustion engine vehicles, cylinder capacity 1500cc-3000cc |
| 870324 | Internal combustion engine vehicles, cylinder capacity $>$ 3000cc |
| 870331 | Internal combustion engine vehicles (diesel), cylinder capacity $<$ 1500cc |
| 870332 | Internal combustion engine vehicles (diesel), cylinder capacity 1500cc-2500cc |
| 870333 | Internal combustion engine vehicles (diesel), cylinder capacity $>$ 2500cc |
| 870340 | Hybrid gasoline vehicles incapable of being charged |
| 870350 | Hybrid diesel vehicles incapable of being charged |
| *Panel B: EV Final Good* | |
| 870360 | Plug-in hybrid gasoline vehicles, capable of being charged |
| 870370 | Plug-in hybrid diesel vehicles, capable of being charged |
| 870380 | Battery electric vehicles |
| *Panel C: GV Intermediates* | |
| 840732, 840733, 840734 | Internal combustion reciprocating piston engines |
| 840790 | Other reciprocating internal combustion piston engines |
| 840820 | Compression-ignition internal combustion piston engines |
| 840991, 840999 | Internal combustion piston engine parts |
| 841330, 841331 | Air intake filters for internal combustion engines |
| 842123 | Oil filters for internal combustion engine |
| 851110-851190 | Ignition and starting equipments |
| *Panel D: EV Intermediates* | |
| 850132, 850152, 850162 | Electric motors, output 750W–75kW |
| 850133, 850153, 850164 | Electric motors, output 750W–75kW |
| 850300, 850440, 850511 | Electric motor parts and components |
| 850710 | Lead-acid starter battery |
| 850750 | NiMH battery pack |
| 850760 | Li-Ion battery pack |
| 850790 | Battery modules, cells, and components |
| 260200, 260400, 260500 | Raw metal ores and concentrates |
| 282520, 282520, 283691 | Raw Lithium materials |

*Note:* This table shows the classification for each type of vehicle and components based on 6-digit HS code.

Table A.3: Country Weight for Price and Sales, and Patents (%)

| | *Panel A: Weight for Market* | | | | | *Panel B: Weight for Technology* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | US | GE | JP | KR | FR | JP | GE | US | FR | KR |
| 2000 | 56.41 | 11.95 | 18.88 | 4.54 | 8.22 | 35.23 | 29.44 | 15.7 | 10.6 | 9.03 |
| 2001 | 55.83 | 11.99 | 18.87 | 4.64 | 8.68 | 34.84 | 29.67 | 15.88 | 10.44 | 9.17 |
| 2002 | 55.48 | 12.08 | 18.75 | 5.25 | 8.44 | 35.23 | 29.44 | 15.70 | 10.60 | 9.03 |
| 2003 | 56.04 | 12.20 | 19.25 | 4.35 | 8.16 | 34.84 | 29.67 | 15.88 | 10.44 | 9.17 |
| 2004 | 56.95 | 12.03 | 19.27 | 3.60 | 8.15 | 36.19 | 29.36 | 17.45 | 10.85 | 6.16 |
| 2005 | 56.91 | 11.79 | 19.09 | 3.74 | 8.48 | 36.98 | 29.19 | 16.79 | 10.47 | 6.57 |
| 2006 | 56.30 | 12.46 | 18.95 | 3.89 | 8.40 | 38.34 | 30.97 | 14.32 | 9.80 | 6.57 |
| 2007 | 56.36 | 11.92 | 18.33 | 4.38 | 9.00 | 37.70 | 30.79 | 15.02 | 10.01 | 6.48 |
| 2008 | 52.18 | 13.24 | 19.65 | 4.82 | 10.11 | 36.50 | 28.03 | 20.36 | 9.13 | 5.98 |
| 2009 | 48.23 | 14.28 | 19.66 | 6.24 | 11.60 | 33.82 | 28.12 | 21.58 | 9.86 | 6.62 |
| 2010 | 48.75 | 13.25 | 20.52 | 6.26 | 11.22 | 38.35 | 26.28 | 17.95 | 9.19 | 8.23 |
| 2011 | 52.09 | 14.02 | 16.82 | 6.34 | 10.73 | 34.92 | 28.98 | 18.09 | 8.66 | 9.36 |
| 2012 | 53.94 | 12.38 | 19.59 | 5.59 | 8.51 | 34.80 | 30.23 | 18.61 | 9.26 | 7.09 |
| 2013 | 56.19 | 11.52 | 19.02 | 5.46 | 7.81 | 35.35 | 31.23 | 18.14 | 7.87 | 7.41 |
| 2014 | 56.83 | 11.33 | 18.77 | 5.61 | 7.46 | 36.34 | 30.86 | 17.97 | 7.5 | 7.33 |
| 2015 | 58.30 | 11.56 | 16.49 | 5.99 | 7.66 | 33.43 | 33.06 | 18.11 | 7.58 | 7.82 |
| 2016 | 57.92 | 12.02 | 16.11 | 5.91 | 8.03 | 34.19 | 31.86 | 19.06 | 7.00 | 7.90 |
| 2017 | 56.66 | 12.30 | 16.90 | 5.91 | 8.23 | 35.12 | 31.03 | 19.21 | 7.03 | 7.62 |
| 2018 | 56.63 | 12.23 | 16.87 | 5.85 | 8.42 | 33.55 | 32.36 | 18.26 | 8.13 | 7.71 |
| 2019 | 55.96 | 12.85 | 16.62 | 5.74 | 8.82 | 33.13 | 34.61 | 16.54 | 8.35 | 7.38 |
| 2020 | 55.63 | 12.21 | 17.19 | 7.12 | 7.85 | 33.79 | 33.50 | 16.52 | 8.24 | 7.95 |
| 2021 | 57.69 | 11.13 | 16.66 | 6.49 | 8.02 | 34.08 | 35.59 | 14.21 | 7.56 | 8.56 |
| 2022 | 56.91 | 11.85 | 16.80 | 6.73 | 7.70 | 33.79 | 33.50 | 16.52 | 8.24 | 7.95 |
| 2023 | 57.28 | 11.46 | 17.10 | 6.26 | 7.90 | 34.08 | 35.59 | 14.21 | 7.56 | 8.56 |
| 2024 | 58.90 | 11.51 | 15.94 | 5.89 | 7.77 | 34.29 | 35.13 | 16.29 | 7.67 | 6.61 |




(a) EV Final Goods

(b) EV Powertrains

(c) GV Final Goods

(d) GV Powertrains

Figure A.1: Import Share for Final Goods and Intermediates in EV and GV

*Note*: This figure shows the import share of EV and GVs and their technology-specific intermediate goods in Home and Foreign country.

stitutions and State-Owned Enterprises (SOEs) as well as Privately-Owned Enterprises (POEs). Among these, SOEs like FAW Group, SAIC Motor, and Cherry Automobile are included, as well as POEs such as Zhejiang Geely, BYD, and Ningbo Yunsheng, etc. Notably, around 80% of these subsidized firms are SOEs. Besides, there is a requirement for local governments and recipient institutions to provide matching funds at a specified ratio (specified in the released program document). Our data for R&D subsidy first draws from official documents from the Ministry of Science and Technology of China, detailing each project and its respective grant amount.

**Purchase Incentives** Table A.4 outlines the consumer subsidies provided by the Chinese central government from 2013 to 2022. For Battery EVs, subsidies were tiered by drive range, with requirements increasing from a minimum of 80 km in 2013 to 150 km by 2022, while the subsidy amount was gradually reduced. The subsidies initially cover only a few

pilot cities, later expanded to 88 cities by 2014 and reached national scale by 2016.[34] We collected the subsidy to each EV model by manufacturer from the disclosure of detailed firm- and product- level subsidy under the national level subsidy program. Additional subsidies from local governments often matched central funds, we obtained the province-level government policies from their official websites. The Leveraging the product-level vehicle model price data in Chinese market obtained from *Autohome*, we then calculate the average subsidy rate for each year weighted by the vehicle sales. Combined, central and local subsidies initially accounted for nearly 30% of the EV purchase price, as shown in Figure 2.4.

Table A.4: Amount of National Purchase Subsidy per EV by Drive Range (2013-2023)

| Drive Range | Phase I | | | Phase II | | | Phase III | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (km) | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
| $80 \leq R < 100$ | 3.5 | 3.325 | 3.15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $100 \leq R < 150$ | 3.5 | 3.325 | 3.15 | 2.5 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| $150 \leq R < 200$ | 5 | 4.75 | 4.5 | 4.5 | 3.6 | 1.5 | 0 | 0 | 0 | 0 | 0 |
| $200 \leq R < 250$ | 5 | 4.75 | 4.5 | 4.5 | 3.6 | 2.4 | 0 | 0 | 0 | 0 | 0 |
| $250 \leq R < 300$ | 6 | 5.7 | 5.4 | 5.5 | 4.4 | 3.4 | 1.8 | 0 | 0 | 0 | 0 |
| $300 \leq R < 400$ | 6 | 5.7 | 5.4 | 5.5 | 4.4 | 4.5 | 1.8 | 1.62 | 1.3 | 0.91 | 0 |
| $R \geq 400$ | 6 | 5.7 | 5.4 | 5.5 | 4.4 | 5 | 2.5 | 2.25 | 1.8 | 1.26 | 0 |

*Note:* This table lists the amount of purchase subsidy per EV in China from 2013 to 2023 in 10,000 RMB released by Ministry of Industry and Information Technology. Local governments also provide subsidies for EV purchases, and we have accounted for these subsidies in our estimation of policy intensity.

**Tariff and Non-tariff Barriers** We obtained the tariff for EV and GVs at 6-digit HS code level from the WTO World Tariff Profiles database. For the foreign country, we use the market sales as the weight as in the price and sales part.

For other non-tariff barriers, before 2020, only domestically produced vehicles or those from joint ventures with Chinese partners installed with domestically produced batteries were qualified for subsidies, excluding imported EV. This requirement was removed when the Chinese government abolished the joint-venture rule for the auto industry in 2018 and subsequently eliminated the regulation concerning white-listed batteries in 2021. Reflecting this policy shift, Tesla China received 2.1 billion RMB (equivalent to 325 million USD) in EV subsidies in 2020, the highest amount granted to any automaker in the country.

[34] Ministry of Finance of the People's Republic of China (2013). Notice on continuing new energy vehicle promotion.

**Foreign Industrial Policies** Since the beginning of 2010s, the government of countries worldwide has been adopting and continuously updating a wide range of policies to boost the EV industry and promote the EV adoption (see Table A.5).

Table A.5: Major EV Policies by Foreign Governments Since 2011

| Country | R&D Subsidy | Purchase Incentive | Infrastructure |
|---|---|---|---|
| United States | USD 268 million for battery, fuel cell, vehicle systems and infrastructure R&D | Up to USD 7,500 tax credit (phase out after 200,000 vehicles for each qualified manufacturers) | Tax credit of 30% of the cost of EVSE installation, USD 360 million for demonstration projects |
| Germany | Financial support granted for R&D for electric drivetrains and battery research | Exemption from road taxes between EUR 100-300 per year | Four regions nominated as showcase regions for BEVs and PHEVs |
| Japan | Major projects focus on EV infrastructure R&D | Subsidize 50% of the price gap between EV and corresponding GV | Subsidize 50% price of EVSE (up to YEN 1.5 million) |
| France | EUR 140 million budget with focus on vehicle R&D | EUR 450 million in rebates to consumers buying EV (90% from taxing GV) | EUR 50 million to cover 50% of EVSE cost |
| South Korea | KRW 7 trillion for R&D tax incentives and grants for EV technology | Up to KRW 6.8 million consumers EV subsidy that favor domestic producers | 20% of sales quota for automakers, and export loans and guarantees |

Source: IEA (2018).

# Appendix B Additional Empirical Results

## B.1 Joint Venture Technology Diffusion

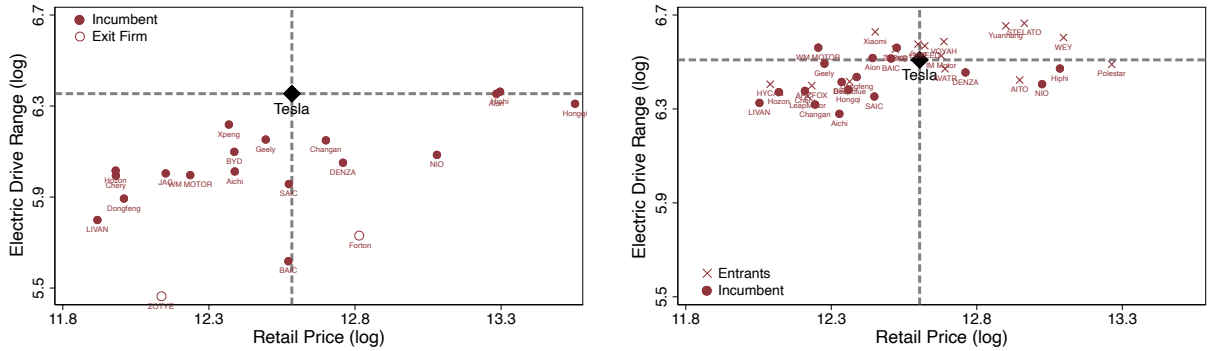
To examine the direct technology diffusion from forming EV-component related joint ventures with leading Foreign firms, we utilized the variation in component technology fields (grouped by IPCs) and compare the patenting of a treated group with at least one early invention patent filing by the joint venture or its foreign parent firms, to a control group of IPCs who did not have such patent filings before. A key concern is selection bias at the IPC level: Foreign firms don't randomly pick technology fields, but choose IPC groups with strong local capabilities or high market returns. To address this issue, we only include IPC groups with no foreign patent filings before 2000, and treat the IPC groups with first joint venture patent filings in CNIPA before 2009 (start of consumption stage) as the treated group. Our estimated result is as follows:

$$\ln Patent_{it} = \underset{(0.023)}{0.216^{***}} \times (Treated_i \times Post_t) + \underset{(0.076)}{0.473^{***}} \times \ln PatentStock_{i,t-1} + \eta_i + \lambda_t + \epsilon_{it},$$

As we show in the event study results in Figure 2.3, such treated technologies does not establish pre-treatment trends. We take this result as our parameter for additional technology diffusion from joint ventures.

## B.2 Tesla Shock

**Pro-competition effect at firm-level.** Figure B.1 provides descriptive evidence on the "pro-competition effect" associated with Tesla's entry in China by focusing on the set of Chinese brands operating in the same segments as Tesla's Model 3 and Model Y (passenger BEV models in segment C and SUV-C). In 2019 (panel a), Tesla sits at the highest relative quality/price position of the segment, while most incumbent domestic brands are clustered below Tesla in driving range and/or priced higher than Tesla's products. By 2024 (panel b), the position of Chinese firms shifts markedly. First, the mass of Chinese brands moves upward in driving range and becomes more tightly concentrated around Tesla's range level. Second, the set of domestic entrants (green circles) after Tesla's entry appears near Tesla's segment location, suggesting entry of competitive firms in respond to Tesla's presence. Taken together, this figure illustrates that Tesla's entry intensified competition within directly exposed segments, and domestic producers responded by upgrading product quality and lower their prices.




(a) 2019 (b) 2024

Figure B.1: Change in Average Segment Driving Range and Retail Price

*Note:* This figure plots the average logarithm of driving range and retail price in the same segment with Tesla's Model 3 and Model Y (BEV Sedan C class and SUV C class). The red diamond represents Tesla, blue circles represent the incumbent Chinese brand EV makers, and the green circles denote the domestic entrants after Tesla's entry Chinese market. The average logarithm of retail price and drive range of Tesla models is denoted by the dashed line.

**Robustness of event study.** Figure B.2 reports a set of robustness checks for the event-study estimates of the impact of Tesla's entry on domestic firms' EV product quality (measured by log electric driving range). Across specifications, the post-entry responses to alternative sample selections and levels of aggregation are consistent with our baseline.

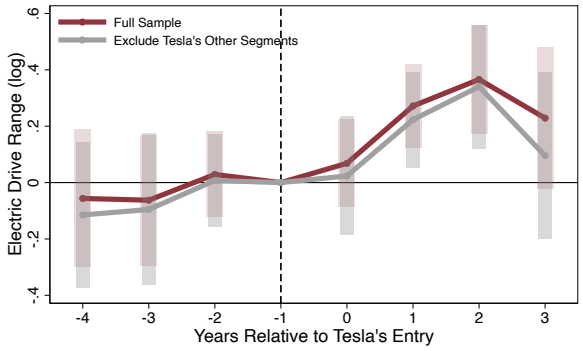
First, a possible endogeneity concern with the baseline design is that Tesla did not enter the Chinese market with its full range of products, but instead introduced only its lower-end models. Panel (a) therefore excludes Tesla's other segments from the control group. The estimated post-entry increase in range remains positive and similar in magnitude to the full-sample benchmark. A second concern is that mixing BEV and non-BEV segments could introduce differential underlying trends that are unrelated to Tesla's entry. Panel (b) restricts the analysis to BEV segments only. The results remain qualitatively unchanged. This indicates that the baseline findings are not driven by compositional changes across powertrain categories.

Our baseline panel is constructed at the maker-segment level, which can attenuate responses if firms adjust by changing the mix of models rather than improving a representative model's attributes. Panel (c) re-estimates the event study at the model level and compares it to the maker-segment estimates. The two results both show similar post-entry rise in driving range. This suggests that the results are not driven by aggregation.

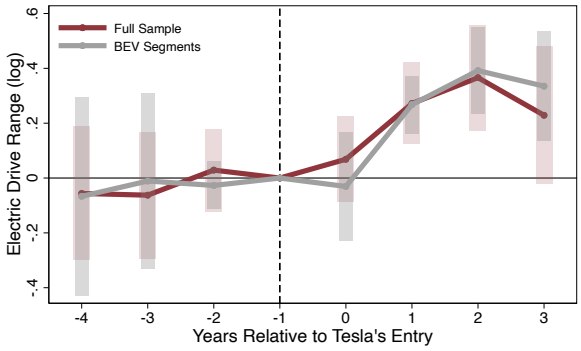
Finally, we tighten the comparison group to segments that are closest to those Tesla targeted (e.g., in terms of pre-entry price or other segment characteristics), which addresses the concern that distant segments may follow different technology or demand dynam-

ics and therefore dilute the counterfactual trend. Panel (d) shows that focusing on more comparable segments preserves the qualitative pattern and, if anything, yields a slightly more pronounced post-entry response. This reinforces the interpretation that the post-entry improvements are concentrated among segments most exposed to Tesla's competitive pressure.

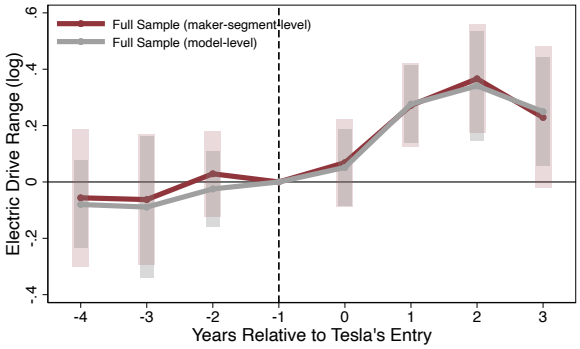
Taken together, these checks support the robustness of the event-study evidence: (i) we do not detect meaningful differential pre-trends, and (ii) the post-entry increase in EV range persists when we (a) remove potentially contaminated controls, (b) restrict to BEV segments, (c) move to model-level outcomes, and (d) further restrict the control group to more comparable segments. The magnitude and timing of the response are stable across specifications, consistent with Tesla's entry increasing competitive pressure and inducing domestic producers to accelerate quality improvements in EV technology.



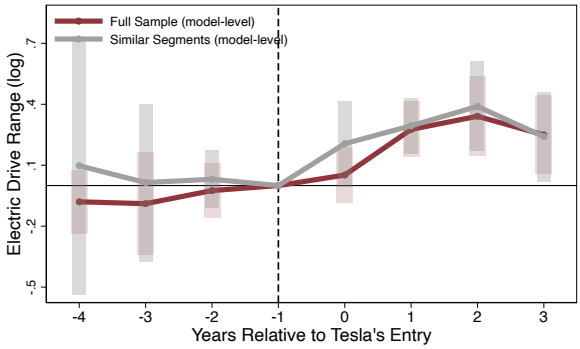

(a) Exclude Tesla's Other Segments




(b) Only Include BEV Segments




(c) Model-level Estimation




(d) Model-level with Similar Segments

Figure B.2: Tesla Shock Event Study Robustness Checks

*Note:* This figure plots the results of Tesla' entry event study with alternative control group and aggregation level compared with baseline results. Panel (a) excludes Tesla's other segments from the control group. Panel (b) restricts the control group to BEV segments. Panel (c) re-estimates the event study at the model level. Panel (d) re-estimates at model-level and only includes segments with similar average price.

**Estimation results.** We specify the regression model as Equation (B.1). The DID estimation results are reported in Table B.1. Across all specifications, the positive impact of the treatment on EV quality (driving range) remains statistically robust. Column (1)-(4) report the baseline regression results with different fixed effects. Column (5)-(7) report the regression results with alternative control groups. In particular, Column (5) excludes Tesla's other non-treated segments to address potential endogeniety in segment-level growth, which remains statistically significant at the 1% level. Column (6) restricts the sample to only Battery Electric Vehicle (BEV) segments. Finally, Column (7) constructs a control group based on segments with similar average retail prices. Despite the reduced sample size, the estimated coefficient remains relatively stable, suggesting that the main effect is not driven by unobserved heterogeneity between segment characteristics.

$$\ln Range_{f,s,t} = \beta_1 \times (Treated_s \times Post_t) + \beta_2 \ln Battery_{f,s,t} + \mathbf{FE}_f + \mathbf{FE}_s + \mathbf{FE}_t + \epsilon_{f,s,t}. \quad \text{(B.1)}$$

Table B.1: DID Regression Results

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treated × Post | 0.305*** | 0.479*** | 0.239*** | 0.397*** | 0.327*** | 0.322*** | 0.276*** |
| | (0.047) | (0.127) | (0.049) | (0.090) | (0.095) | (0.071) | (0.098) |
| Log(Battery) | 0.799*** | 0.845*** | 0.755*** | 0.791*** | 0.820*** | 0.788*** | 0.815*** |
| | (0.057) | (0.054) | (0.064) | (0.063) | (0.059) | (0.083) | (0.067) |
| Constant | 2.767*** | 2.581*** | 2.938*** | 2.789*** | 2.684*** | 2.795*** | 2.702*** |
| | (0.223) | (0.214) | (0.238) | (0.233) | (0.217) | (0.320) | (0.251) |
| Maker FE | No | No | Yes | Yes | Yes | Yes | Yes |
| Segment FE | No | Yes | No | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,428 | 1,428 | 1,394 | 1,394 | 1,310 | 1,125 | 770 |
| R-squared | 0.579 | 0.637 | 0.683 | 0.708 | 0.705 | 0.907 | 0.714 |

*Note:* Standard errors in parentheses, clustered by maker. Column (1)-(4) report the baseline regression results with different fixed effects. Column (5) reports the result excluding Tesla's other segments. Column (6) reports the result with only BEV segments. Column (7) reports the result with segments that have similar average retail price.
*** p<0.01, ** p<0.05, * p<0.1

# Appendix C Model Details and Proofs

## C.1 Equilibrium Production and Prices

**Final good producers.** Household's CES utility implies total demand for technology-$j$ good is

$$D_c^j = \xi_c^j \left( \frac{(1-\varsigma_c^j) P_c^j}{\boldsymbol{P}_c} \right)^{-\sigma} \frac{\boldsymbol{E}_c}{\boldsymbol{P}_c}. \tag{C.2}$$

For a final good firm of technology $j$ operating on segment $s$ in country $c$, the pricing problem is

$$\begin{aligned} &\max_{P_c^j(s)} P_c^j(s) Y_c^j(s) - MC_c^j(s) Y_c^j(s) \\ \text{s.t. } Y_c^j(s) = D(P_c^j(s)) \equiv &\underbrace{\xi_c \left( \frac{P_H^j(s)/Q_H^j(s)}{\bar{P}_H^j} \right)^{-\varepsilon}}_{\text{segment specific demand}} \underbrace{\left[ \left( \frac{(1-\varsigma_c^j)\bar{P}_H^j}{\boldsymbol{P}_H} \right)^{-\sigma} \frac{\boldsymbol{E}_H}{\boldsymbol{P}_H} \right]}_{\text{total demand of vehicle } j} \end{aligned}$$

It follows that $P_c^j(s) = \frac{\partial Y_c^j(s)/\partial P_c^j(s)}{\partial Y_c^j(s)/\partial P_c^j(s) + Y_c^j(s)/P_c^j(s)} MC_c^j(s)$, with $MC_c^j(s)$ the marginal cost. Denote $E_c^j(s) \equiv -\frac{\partial Y_c^j(s)/\partial P_c^j(s)}{Y_c^j(s)/P_c^j(s)}$ the price elasticity of demand for domestic firm on technology $e$ in country $c$:

$$\begin{aligned} E_c^j(s) &= (\sigma-1)(1-\bar{S}_c^j) \times S_c^j(s) + \varepsilon[1-(1-1/\varepsilon)S_c^j(s)] \\ &= \varepsilon - [(\varepsilon-1) - (\sigma-1)(1-\bar{S}_c^j)] S_c^j(s) \end{aligned}$$

where $\bar{S}_c^j$ is the expenditure share on EV in country $c$, and $S_c^j(s)$ is the domestic market share for the segment $s$ that depend only on the relative prices. As $\varepsilon > \sigma$, $E_c^j(s)$ is a decreasing function of $S_c^j(s)$. Further, $E_c^j(s)$ decreases with $\bar{S}_c^j$. Hence a firm's market power increases with its own share in segment sales, as well as the overall share of technology $j$ vehicles in total vehicle sales.

To limit the markup of the firms, we assume that there is a competitive fringe in each segment that can mimic the leader with productivity being $K$ steps behind. Therefore, the leader would set the price as

$$P_c^j(s) = \mathcal{M}_c^j(s) \cdot MC_c^j, \qquad \mathcal{M}_c^j(s) \equiv \min \left\{ \frac{E_c^j(s)}{E_c^j(s)-1}, \Lambda^K \right\} \tag{C.3}$$

Similarly, when the final good brand is exporting to the oversea market, its optimization problem yields the optimal pricing rule:

$$\widetilde{P}_c^j(s) = \widetilde{\mathcal{M}}_c^j(s) \cdot \widetilde{MC}_c^j, \qquad \widetilde{\mathcal{M}}_c^j(s) \equiv \min\left\{ \frac{\widetilde{E}_c^j(s)}{\widetilde{E}_c^j(s) - 1}, \Lambda^K \right\} \tag{C.4}$$

where $\widetilde{E}_c^j(s) = \epsilon - [(\epsilon - 1) - (\sigma - 1)(1 - \bar{S}_{c'}^j)]\widetilde{S}_c^j(s)$ is the demand elasticity for domestic producer in the foreign market, $\widetilde{MC}_c^j(s)$ is the marginal cost including the trade costs, and $\bar{S}_{c'}^j$ and $\widetilde{S}_c^j(s)$ are the expenditure share on technology $e$ and domestic market share in the foreign market, respectively.

The (before subsidy) price index for technology $j$, $P_H^j$ in Home country is defined as

$$\ln P_H^j \equiv \int_0^1 \ln\left[\gamma_H (P_H^j(s)/Q_H^j(s))^{1-\varepsilon} + (1-\gamma_H)(\widetilde{P}_F^j(s)/Q_F^j(s))^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} ds.$$

Taking the input prices and purchase subsidies as given, the market share is given by

$$\bar{S}_H^j = \frac{\xi_H^j((1-\varsigma_H^j)P_H^j)^{1-\sigma}}{\xi_H^j((1-\varsigma_H^j)P_H^j)^{1-\sigma} + \xi_H^{-j}((1-\varsigma_H^{-j})P_H^{-j})^{1-\sigma}} = \left[1 + \frac{\xi_H^{-j}}{\xi_H^j}\left(\frac{(1-\varsigma_H^{-j})P_H^{-j}}{(1-\varsigma_H^j)P_H^j}\right)^{1-\sigma}\right]^{-1}, \tag{C.5}$$

where $-j$ denotes the other technology. The segment-level market share only depends on the relative productivity (measured by technology gap $M^j(s)$) between Home and Foreign counterpart in the segment:

$$\begin{aligned} S_H^j(M^j(s)) &= \frac{\gamma_H (P_H^j(s)/Q_H^j(s))^{1-\varepsilon}}{\gamma_H (P_H^j(s)/Q_H^j(s))^{1-\varepsilon} + (1-\gamma_H)(\widetilde{P}_F^j(s)/Q_F^j(s))^{1-\varepsilon}} \\ &= \left[1 + \frac{1-\gamma_H}{\gamma_H}\left(\frac{Q_H^j(s)}{Q_F^j(s}\right)^{1-\varepsilon}\left(\frac{\widetilde{P}_F^j(s)}{P_H^j(s)}\right)^{1-\varepsilon}\right]^{-1} \\ &= \left[1 + \frac{1-\gamma_H}{\gamma_H}\left(\frac{\widetilde{\mathcal{M}}_F^j(s)\cdot\widetilde{MC}_F^j}{\mathcal{M}_H^j(s)\cdot MC_H^j}\right)^{1-\varepsilon}\left(\Lambda^{M^j(s)}\right)^{1-\varepsilon}\right]^{-1} \end{aligned} \tag{C.6}$$

The market shares in Foreign market and rest of the world can be derived analogously. As derived above, the markups $\mathcal{M}_c^j$ and $\widetilde{\mathcal{M}}_c^j$ are a function of the market shares $S_c^j$ and $\bar{S}_c^j$. Hence market shares, markups and profits can be solved as a function of the quality gaps.

**Intermediate good producers.** In each intermediate product line, there is a Home and a foreign producer engage in Bertrand price competition. Since domestic and Foreign goods are perfect substitutes, in equilibrium only the intermediate goods producer with the lowest marginal cost of production, adjusted for trade barriers, finds it profitable to produce. To account for the trade policy and relative wages, we characterize the effective technology gaps and define the import cost gaps for the technology $j$ in country $c$ as $\nu_c^j \equiv \frac{\ln \tau_c^j}{\ln \lambda}$, the relative wage gaps between the two countries as $\omega \equiv \frac{\ln(w_H/w_F)}{\ln \lambda}$. As in Akcigit et al. (2025), foreign intermediate producers would export to the Home market if

$$m \leq m_F^{j*} \equiv \arg\max_m \{m \leq \omega - \nu_H^j\}.$$

This cutoff depends on both the trade costs and the relative wages between the two countries. Similarly, Home intermediate firms would export to Foreign markets if

$$m \geq m_H^{j*} \equiv \arg\min_m \{m \geq \omega + \nu_F^j\}.$$

Table C.1 presents the equilibrium price and markups for domestic intermediate good producers

Table C.1: Price and Markup for Intermediates Producers

| | $m < m_H^{j*}$ | $m_H^{j*} \leq m \leq m_F^{j*}$ | $m > m_F^{j*}$ |
|---|---|---|---|
| $p_H^j$ | – | $\min\{\tau_H^j w_F/z_F^j,\ \lambda^k w_H/z_H^j\}$ | $\min\{\tau_H^j w_F/z_F^j,\ \lambda^k w_H/z_H^j\}$ |
| $\widetilde{p}_H^j$ | – | – | $\min\{w_F/z_F^j,\ \tau_F^j \lambda^k w_H/z_H^j\}$ |
| $p_F^j$ | $\min\{\tau_F^j w_H/z_H^j,\ \lambda^k w_F/z_F^j\}$ | $\min\{\tau_F^j w_H/z_H^j,\ \lambda^k w_F/z_F^j\}$ | – |
| $\widetilde{p}_F^j$ | $\min\{w_H/z_H^j,\ \tau_H^j \lambda^k w_F/z_F^j\}$ | – | – |
| $\eta_H^j$ | – | $\min\{m - \omega + \nu_H^j,\ k\}$ | $\min\{m - \omega + \nu_H^j,\ k\}$ |
| $\widetilde{\eta}_H^j$ | – | – | $\min\{m - \omega - \nu_F^j,\ k\}$ |
| $\eta_F^j$ | $\min\{\omega - m + \nu_F^j,\ k\}$ | $\min\{\omega - m + \nu_F^j,\ k\}$ | – |
| $\widetilde{\eta}_F^j$ | $\min\{\omega - m - \nu_H^j,\ k\}$ | – | – |

The associated profit is

$$\pi_H^j(m) = \begin{cases} 0 & \text{if } m < m_H^{j*} \\ (1-1/\lambda^{\eta_H^j(m)})P_{M,H}^j M_H^j & \text{if } m_H^{j*} \le m \le m_F^{j*} \\ (1-1/\lambda^{\eta_H^j(m)})P_{M,H}^j M_H^j + (1-1/\lambda^{\tilde{\eta}_H^j(m)})P_{M,F}^j M_F^j & \text{if } m > m_F^{j*} \end{cases}$$
$$\pi_F^j(m) = \begin{cases} (1-1/\lambda^{\eta_F^j(m)})P_{M,F}^j M_F^j + (1-1/\lambda^{\tilde{\eta}_F^j(m)})P_{M,H}^j M_H^j & \text{if } m < m_H^{j*} \\ (1-1/\lambda^{\eta_F^j(m)})P_{M,F}^j M_F^j & \text{if } m_H^{j*} \le m \le m_F^{j*} \\ 0 & \text{if } m > m_F^{j*} \end{cases} \tag{C.7}$$

## C.2 Entrants' Problem in the Final Good Sector

Assume the value $\epsilon^j$ follows an *i.i.d.* Gumbel distribution with mean 0 and shape parameter *var*. The optimal R&D intensity and the expected return from a successful external innovation on technology $j$ in country $c$ is

$$X_c^{j*} = \left[\frac{\beta_1}{\beta_2}\frac{\mathbb{E}V_c^j(\Theta_c^j)^{\frac{\beta_1}{\beta_1}}(B_c^j)^{\frac{1-\beta_1}{\beta_1}}}{(1-\chi_c^j)w_c}\right]^{\frac{\beta_1}{\beta_2-\beta_1}}, \qquad V_c^{j*} = \frac{\beta_2-\beta_1}{\beta_2}\mathbb{E}V_c^j X_c^{j*}. \tag{C.8}$$

Normalize $F^g = 0$. Equation (3.3) can be rewritten as

$$\max\left\{V_c^{e*} - F^e w_c + \epsilon^e,\ V^{g*} + \epsilon^g\right\}$$

The probability that an entrant in country $c$ chooses to innovate on EV is

$$Pr\left[V_c^{g*} + \epsilon^g \le V_c^{e*} - F^e w_c + \epsilon^e\right],$$

which is equivalent to

$$\begin{aligned} &\int Pr\left[\epsilon^g \le \Delta V_c - F^e w_c + \epsilon\right] \cdot Pr\left[\epsilon^e = \epsilon\right] d\epsilon \\ &= \int \exp\left(-\exp\left(-\frac{\epsilon + \Delta V_c - F^e w_c}{var}\right)\right)\frac{1}{var}\exp\left(-\exp\left(-\frac{\epsilon}{var}\right)\right)\exp\left(-\frac{\epsilon}{var}\right) d\epsilon \\ &= \int \frac{1}{var}\exp\left(-\frac{\epsilon}{var}\right)\exp\left\{-\exp\left(-\frac{\epsilon}{var}\right)\left(1+\exp\left(-\frac{\Delta V_c - F^e w_c}{var}\right)\right)\right\} d\epsilon \end{aligned}$$

where $\Delta V_c \equiv V_c^{e*} - V_c^{g*}$. Define $\tilde{\epsilon} \equiv \exp\left(-\frac{\epsilon}{var}\right)$, then $d\tilde{\epsilon} = -\frac{1}{var}\exp\left(-\frac{\epsilon}{var}\right) d\epsilon$, the

fraction of entrants choosing to innovate on EV is given by

$$\int e^{-\left(1+\exp\left(-\frac{\Delta V_c - F^e w_c}{var}\right)\right)\tilde{\epsilon}} d\tilde{\epsilon} = \frac{1}{1+\exp\left(-\frac{\Delta V_c - F^e w_c}{var}\right)}.$$

## C.3 Intermediates Values and Dynamics

**Innovation** In both countries, an intermediate firm is defined as a collection of intermediate product lines in which it has leading-edge technology, as in Klette and Kortum (2004) and its R&D is directed to either EV or GV technology. Denote $\tilde{n}_f$ the number of leading product lines firm $f$ owns. A successful innovation randomly lands on a product line, replaces the current leading firm and improves its productivity by $\lambda$.

The number of innovations within a time interval $\Delta t$ that an innovating firm can achieve follow a Poisson process, the rate of which depends on the firm's knowledge base measured by $\tilde{n}_f$, total researchers hired $\boldsymbol{h}_f^j$, and basic knowledge $B_c^j$:

$$\mathbf{x}_{c,f}^j = \theta^j \, \tilde{n}_f^{1-\frac{\beta_1}{\beta_2}} \left[ (\mathbf{h}_f^j)^{\beta_1} (\tilde{n}_f \, B_c^j)^{1-\beta_1} \right]^{\frac{1}{\beta_2}}, \tag{C.9}$$

where $\theta^j$ is the intermediate good R&D efficiency, and the elasticities are defined similar to the final good innovations. Define the firm's per-line R&D intensity as $x_c^j \equiv \mathbf{x}_{c,f}^j / \tilde{n}_f$.

**Firm values** In each product line, the joint venture decision is made by the foreign leader and passively accepted by the Home firm. Denote

$$J(m^j(i)) = \begin{cases} 1 & \text{if a joint venture is active on line } i \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases}$$

Joint ventures do not compete directly with the Home or foreign parent firms in the Home market, but their market power is constrained by potential imitators. The profits for the lagging Home firm and leading Foreign firm that forms a joint venture are

$$\pi_{H,JV}^j = \alpha_{JV}(1 - 1/\lambda^k) P_{M,H}^j M_H^j, \quad \pi_{F,JV}^j = (1 - 1/\lambda^k)[(1 - \alpha_{JV}) P_{M,H}^j M_H^j + P_{M,F}^j M_F^j]. \tag{C.10}$$

For an intermediate firm $f$ with $\tilde{n}_f$ leading-edge product lines of vehicle type $j$, denote $\boldsymbol{m}_f \equiv \{m_i^j\}_{i \in k_f}$ the set of international technology gap on each owned product line. Denote $v_c^j(\boldsymbol{m}_f)$ the value of an incumbent firm. The value function for Foreign firms satis-

fies:

$$r_F v_F^j(\boldsymbol{m}_f) - \dot{v}_F^j(\boldsymbol{m}_f) = \underbrace{\max_{x_F^j} \left\{ \tilde{n}_f \times \mathbb{E}\left[ (x_F^j + \delta^j \mathbf{1}_F(m^j(i')) [v_F^j(\boldsymbol{m}_f \cup \{m^j(i') - 1\}) - v_F^j(\boldsymbol{m}_f)] \right] - \tilde{n}_f (1 - \chi_F^j) h(x_F^j) w_F \right\}}_{\text{Change of value from successful innovation}}$$

$$+ \sum_{i \in k_f^j} \left\{ \begin{array}{c} \max \left[ \underbrace{\pi_F^j(m_i^j) + [\mathbf{x}_H^j + \delta^j \mathbf{1}_H(m_i^j)] \cdot [v_F^j(\boldsymbol{m}_f \backslash \{m_i^j\} \cup \{m_i^j + 1\}) - v_F^j(\boldsymbol{m}_f)]}_{\text{value from NOT forming a joint venture}}, \right. \\ \left. \underbrace{\pi_{F,\text{JV}}^j + [(1 + \delta_{JV}) \mathbf{x}_H^j + \delta^j \mathbf{1}_H(m_i^j)] \cdot \left[ v_F^j(\boldsymbol{m}_f \backslash \{m_i^j\} \cup \{m_i^j + 1\}) - v_F^j(\boldsymbol{m}_f) \right] - \kappa_{\text{JV}} - inf \cdot \mathbf{1}_F(m_i^j)}_{\text{value from forming a joint venture}} \right] \\ + \underbrace{(\mathbf{x}_F^j + \delta^j \mathbf{1}_F(m_i^j)) \cdot \left[ v_F^j(\boldsymbol{m}_f \backslash \{m_i^j\} - v_F^j(\boldsymbol{m}_f) \right]}_{\text{change of value from foreign innovation}} \end{array} \right\}$$

where $\mathbf{x}_c^j \equiv x_c^j + x_c^{j,ent}$ is the aggregate innovation intensity of intermediate firms in technology $j$ country $c$, $\delta^j$ is the costless technology diffusion rate, $\mathbf{1}_c(m_i^j)$ is an indicator function that equals to 1 if country $c$ is a technology follower in a product line of gap $m_i^j$, and $\gamma$ is the additional technology diffusion associated with joint ventures. The value inf is a very large value so that Foreign firms choose to form joint ventures only if they lead technologically in a product line.[35]

As in Klette and Kortum (2004), the value function takes an additive form. At a single product line level, the per product line value is defined as

$$\begin{aligned} r_F v_F^j(m) - \dot{v}_F^j(m) &= \max_{x_F^j \geq 0} \left\{ \bar{v}_F^j(x_F^j) - (1 - \chi_c^j) h(x_F^j) w_c \right\} - (\mathbf{x}_F^j + \delta^j \mathbf{1}_F(m)) v_F^j(m) \\ &+ \max \left\{ \begin{array}{c} \pi_F^j(m) + (\mathbf{x}_H^j + \delta^j \mathbf{1}_H(m)) \cdot \left[ v_F^j(m+1) - v_F^j(m) \right], \\ \pi_{F,\text{JV}}^j + ((1 + \delta_{JV}) \mathbf{x}_H^j + \delta^j \mathbf{1}_H(m)) \cdot \left[ v_F^j(m+1) - v_F^j(m) \right] - \kappa_{JV} - \inf \cdot \mathbf{1}_F(m) \end{array} \right\}. \end{aligned} \tag{C.11}$$

where $\bar{v}_F^j(x_F^j) \equiv \sum_{m'} (x_F^j + \delta^j \mathbf{1}_F(m')) v_F^j(m' - 1) \cdot \mu^j(m')$ is the expected value per-line, with $\mu^j(m)$ denoting the fraction of lines with the technology gap $m$.

[35] Numerically, we simply assume joint venture is an option for Foreign firms only if it leads technologically in a product line

An incumbent's value in the Home country satisfies the following HJB equation:

$$r_H v_H^j(\boldsymbol{m}_f) - \dot{v}_H^j(\boldsymbol{m}_f) = \underbrace{\sum_{i\in n_f}\left[(1-J(m_i^j))\pi_H^j(m_i^j) + J(m_i^j)\cdot\pi_{H,\text{JV}}^j\right]}_{\text{flow profits}} + \max_{x_H^j}\Big\{-\tilde{n}_f(1-\chi_H^j)h(x_H^j)w_c$$
$$+ \underbrace{\tilde{n}_f\mathbb{E}\left[(x_H^j(1+J(m^j(i')\cdot\gamma)+\delta^j\mathbf{1}_H(m^j(i'))\cdot[v_H^j(\boldsymbol{m}_f\cup\{m^j(i')+1\})] - v_H^j(\boldsymbol{m}_f)\right]\Big\}}_{\text{Change of value from successful innovation}}$$
$$+\sum_{i\in\tilde{n}_f}\left\{\begin{array}{c}\underbrace{(x_H^j(1+J(m_i^j)\cdot\delta_{JV})+\delta^j\mathbf{1}_H(m_i^j))\cdot\left[v_H^j(\boldsymbol{m}_f\backslash\{m_i^j\}) - v_H^j(\boldsymbol{m}_f)\right]}_{\text{Change of value from other Home firms' innovation}}\\ +\underbrace{(x_F^j+\delta^j\mathbf{1}_F(m_i^j))\cdot\left[v_H^j(\boldsymbol{m}_f\backslash\{m_i^j\}\cup\{m_i^j-1\}) - v_H^j(\boldsymbol{m}_f)\right]}_{\text{Change of value from Foreign firms' innovation}}\end{array}\right\}$$

with the per-line value satisfying

$$r_H v_H^j(m) - \dot{v}_H^j(m) = (1-J(m_i^j))\pi_H^j(m) + J(m_i^j)\cdot\pi_{H,\text{JV}} + \max_{x_H^j\geq 0}\left\{\bar{v}_H^j(x_H^j) - (1-\chi_H^j)h(x_H^j)w_c\right\}$$
$$-(\mathbf{x}_H^j(1+J(m_i^j)\cdot\delta_{JV})+\delta^j\mathbf{1}_H(m))\cdot v_H^j(m) + (\mathbf{x}_F^j+\delta^j\mathbf{1}_F(m))\cdot\left[v_H^j(m-1) - v_H^j(m)\right]. \tag{C.12}$$

where $\bar{v}_H^j(x_H^j) \equiv \sum_{m'}[x_F^j(1+J(m')\cdot\delta_{JV})+\delta^j\mathbf{1}_H(m')]v_H^j(m'+1)\cdot\mu^j(m')$ is the expected per-line value at Home. Therefore the optimal innovation intensity is given by

$$x_c^{j*} = \left[\frac{\beta_1}{\beta_2}\frac{\bar{v}_c^j(\theta_c^j)^{\frac{\beta_1}{\beta_1}}(B_c^j)^{\frac{1-\beta_1}{\beta_1}}}{(1-\chi_c^j)w_c}\right]^{\frac{\beta_1}{\beta_2-\beta_1}}. \tag{C.13}$$

**Entry** For each technology $j$, there exists a unit mass of potential entrants to the intermediate good sector, which has access to the same innovation technology as incumbents. Entrants innovate to maximize the expected profit

$$\max_{x_H^j}\left\{\bar{v}_c^j(x_c^{j,ent}) - (1-\chi_c^j)h(x_c^{j,ent})\,w_c\right\}.$$

The value functions for GV intermediate good producers are the same, except that there are no joint venture decisions. Conditional on entry, the entrants' optimal value of $x_c^{j,ent}$ is the same as Equation (C.13).

**Technology Gap Evolution** The technology gap distribution in intermediate product lines, $\mu^j(m)$, evolves as follows:

$$\dot{\mu}^j(m) = \underbrace{(\mathbf{x}_H^j(1+J(m-1)\delta_{JV}) + \delta^j \mathbf{1}_H(m-1)) \cdot \mu^j(m-1)}_{\text{inflow by H innovation}} + \underbrace{(\mathbf{x}_F^j + \delta^j \mathbf{1}_F(m+1)) \cdot \mu^j(m+1)}_{\text{inflow by F innov.}} - \underbrace{[\mathbf{x}_H^j(1+\delta_{JV}\sum_{m'} J(m')\mu^j(m')) + \mathbf{x}_F^j + \delta^j(1-\mu^j(0))] \cdot \mu^j(m)}_{\text{outflow}} \tag{C.14}$$

Intuitively, inflows into the state $m$ will occur from $m+1$ with successful foreign innovations and from $m-1$ when domestic innovations succeed. Outflows from the technology gap $m$ are driven by both domestic and Foreign innovations.

## C.4 Aggregate Index and Industrial Growth

We define the industrial equilibrium of this model as follows.

**Definition 1.** *Fix a country $c$ and an initial time $t_0$. Let the aggregate state be*

$$\mathcal{S}_c(t) \equiv \Big(\{\mathcal{F}_{S,c}^j(t), \mathcal{F}_{P,c}^j(t), \mu_c^j(t)\}_{j\in\{e,g\}},\ B_c(t),\ \boldsymbol{G}_c(t)\Big),$$

*where $\mathcal{F}_{S,c}^j$ and $\mathcal{F}_{P,c}^j$ are the distributions of SOE and POE final-good gaps, $\mu_c^j$ is the intermediate-good gap distribution, $B_c$ is basic knowledge stock, and $\boldsymbol{G}_c(t)$ is the policy vector. Take as given an exogenous path for aggregate objects $\{w_c(t), r_c(t), E_c(t), P_{MT,c}(t)\}_{t\geq t_0}$, an* industry Markov–perfect equilibrium *(MPE) is a collection of:*

1. *Markov policy functions for each firm type map the current state into innovation decisions such that actions depend on time only through $\mathcal{S}_c(t)$ according to Equation (10) and (C.13).*

2. *Continuation values $\{V_{S,c}^j(M,t), V_{P,c}^j(M,t), v_c^j(m,t)\}$ that solve the corresponding HJB equations (9) and (C.12) given the equilibrium pricing rules, demand, and the law of motion for the states.*

3. *Segment-level prices and price indices $\{p_c^j(M,t), P_c^j(t), \boldsymbol{P}_c(t), P_{\Gamma,c}^j(t)\}_{j\in\{e,g\}}$ and quantities consistent with: (i) household demand and aggregation following (1) and the relevant price-index, and (ii) the firm's pricing rule implied by international gaps and policy wedges.*

4. *Given innovation intensities and transition rates, the distributions evolve according to the Kolmogorov forward equations described in Equation (11), (12) and (C.14);*

5. *For each $t \geq t_0$, final- and intermediate-good markets clear in each country subject to trade costs and policy wedges, and all accounting identities for revenues, profits, and expenditures hold.*

The long-run stationary equilibrium is characterized by the following proposition.

**Proposition 1.** *Under model assumptions, there exists a unique long-run stationary equilibrium with the following properties: (i) wage, interest rate and policy variables are constant, and there are no SOEs or joint ventures; (ii) one of the technology $j \in \{e, g\}$ dominates and the other technology asymptotically diminishes in both final good and intermediates; (iii) the distributions of quality/technology gaps for final and intermediate goods of the surviving technology are stationary, $\dot{\mathcal{F}}^j(M) = 0$, $\dot{\mu}^j(m) = 0$; (iv) the equilibrium growth rates of output in Home and are the same and a constant.*

*Proof.* We begin with the intermediate good sector. The price index of intermediates of vehicle type $j$ in Home country is given by

$$\begin{aligned}\ln P^j_{\Gamma,H} &= \int_0^1 \ln \min\{\frac{w_H}{z^j_H}, \lambda^k \tau_H \frac{w_F}{z^j_F}\} \cdot \mathbb{I}_{m^j_i \leq \hat{m}^j_H} \, di + \int_0^1 \ln \min\{\lambda^k \frac{w_H}{z^j_H}, \tau_H \frac{w_F}{z^j_F}\} \cdot \mathbb{I}_{m^j_i > \hat{m}^j_H} \, di \\ &= \ln\left(\frac{w_H}{Z^j_H}\right) + mk^j_H \cdot \ln \lambda,\end{aligned}$$

where we define the technology index in the intermediates as $\ln Z^j_c = \int_0^1 \ln z^j_c(i) \, di$, and the equilibrium markups as $mk^j_H \equiv \sum_{m^j \leq \hat{m}^j_H} \min\{m^j - \omega + \nu^j_H + k, 0\} \cdot \mu^j(m^j) + \sum_{m^j > \hat{m}^j_H} \eta^j_H(m^j)\mu^j(m^j)$. Similarly, the price index for Foreign intermediates is given by

$$\begin{aligned}\ln P^j_{M,F} &= \int_0^1 \ln \min\{\lambda^k \frac{w_F}{z^j_F}, \tau_F \frac{w_H}{z^j_H}\} \cdot \mathbb{I}_{m^j_i \leq \hat{m}^j_F} \, di + \int_0^1 \ln \min\{\frac{w_F}{z^j_F}, \lambda^k \tau_F \frac{w_H}{z^j_H}\} \cdot \mathbb{I}_{m^j_i > \hat{m}^j_F} di \\ &= \ln\left(\frac{w_F}{Z^j_F}\right) + mk^j_F \cdot \ln \lambda,\end{aligned}$$

where the technology index is defined as above and the equilibrium markup is $mk^j_F \equiv \sum_{m^j \leq \hat{m}^j_F} \eta^j_F(m^j)\mu^j(m^j) + \sum_{m^j > \hat{m}^j_F} \min\{\omega + \nu^j_F + k - m^j, 0\} \cdot \mu^j(m^j)$.

From the aggregate technology index, we can derive

$$\ln Z^j_H = \int_0^1 \left[\ln\left(\frac{z^j_H(i)}{z^j_F(i)}\right) + \ln z^j_F(i)\right] di = \ln Z^j_F + \ln \lambda \int_0^1 m^j_i \, di.$$

Hence, under the stationary distribution of technology gaps, $Z_H^j$ and $Z_F^j$ will grow at the same rate. Note

$$\ln Z_H^j = \sum_{m>0} \ln z_H^j(m)\mu^j(m) + \ln z^j(0)\mu^j(0) + \sum_{m<0} \ln z_F^j(m)\mu^j(m) + \sum_{m<0} \ln(\frac{z_H^j(m)}{z_F^j(m)})\mu^j(m)$$
$$\sum_{m>0} \ln z_H^j(m)\mu^j(m) + \ln z^j(0)\mu^j(0) + \sum_{m<0} \ln z_F^j(m)\mu^j(m) + \sum_{m<0} m \ln\lambda \cdot \mu^j(m)$$

where $z^j(0) \equiv z_H^j(0) = z_F^j(0)$. The growth rate of $Z_H^j$ is

$$g_Z^j = \left[\sum_{m^j \geq 0} \mathbf{x}_H^j \mu^j(m^j) + \sum_{m^j \leq 0} \mathbf{x}_F^j \mu^j(m^j)\right] \ln\lambda.$$

It follows that both technology indices in Home and Foreign grow at the same rate, $g_Z^j$, in a stationary equilibrium.

For vehicles, the price index for technology $j$ in Home is defined as $\ln P_H^j \equiv \int_0^1 \ln P_H^j(s)ds$, where

$$\begin{aligned} P_H^j(s) &\equiv \left[\gamma_H (P_H^j(s)/Q_H^j(s))^{1-\varepsilon} + (1-\gamma_H)(\widetilde{P}_F^j(s)/Q_F^j(s))^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \\ &= \frac{P_H^j(s)}{Q_H^j(s)}\left[\gamma_H + (1-\gamma_H)\left(\frac{\widetilde{P}_F^j(s)/P_H^j(s)}{Q_F^j(s)/Q_H^j(s)}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}} \\ &= \frac{\mathcal{M}_H^j(s)\cdot MC_H^j}{Q_H^j(s)}\left[\gamma_H + (1-\gamma_H)\left(\frac{(\widetilde{\mathcal{M}}_F^j(s)\cdot \widetilde{M}C_F^j)/(\mathcal{M}_H^j(s)\cdot MC_H^j)}{Q_F^j(s)/Q_H^j(s)}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}} \end{aligned}$$

As the markups $\mathcal{M}_H^j(s), \widetilde{\mathcal{M}}_F^j(s)$ are functions of the quality gap $M$, we denote $P_H^j(M)$ the price in a segment with gap $M$ and have

$$P_H^j(M) = \frac{MC_H^j}{Q_H^j(s)} f_H^j(M), \quad f_H^j(M) \equiv [\gamma_H(\mathcal{M}_H^j(M))^{1-\varepsilon} + (1-\gamma_H)(\frac{\widetilde{M}C_F^j}{MC_H^j}\Lambda^M \widetilde{\mathcal{M}}_F^j(M))^{1-\varepsilon}]^{\frac{1}{1-\varepsilon}}$$

Since successful innovation in the final good sector raise its quality in segment s by $\Lambda$, changes in $\ln P_H^j(s)$ from a successful Home innovation (by either incumbent or entrant) in a line with gap $M$ is

$$\Xi_H^j(M) = -\ln\Lambda + \ln f_H^j(M+1) - \ln f_H^j(M),$$

and changes in $\ln P_H^j(s)$ from a successful foreign innovation (by either incumbent or

entrant) in a line with gap $M$ is $\Xi_F^j(M) = \ln f_H^j(M-1) - \ln f_H^j(M)$. Note that $\Xi_H^j(M) + \Xi_F^j(M) = -\ln \Lambda$.

The growth rate of the price in segment-M, $P_H^j(M)$, is

$$\frac{d \ln P_H^j(M)}{dt} = \alpha \frac{d \ln P_{\Gamma,H}^j}{dt} + \mathbf{X}_H^j(M)\, \Xi_H^j(M) + \mathbf{X}_F^j(M)\, \Xi_F^j(M),$$

which implies the growth rate of the aggregate price index, $\ln P_H^j \equiv \sum \ln P_H^j(M) \mathcal{F}_j(M)$, is

$$g_P^j = -g_Z^j + \sum_M \mathcal{F}^j(M) \left[ \mathbf{X}_H^j(M) \Xi_H^j(M) + \mathbf{X}_F^j(M) \Xi_F^j(M) \right] + \sum_M \frac{d\, \mathcal{F}_j(M)}{dt} \ln P_H^j(M).$$

The last term is 0, and hence $g_P^j$ is constant, in a stationary equilibrium.

As $\ln Y_H^j \equiv \int_0^1 \ln Y_H^j(s) ds = \int_0^1 \ln(I_H / P_H^j(s)) ds$, the aggregate output $Y_H^j$ grows at the negative of $g_P^j$.

Last, note that $\ln P_F^j \equiv \sum_M \mathcal{F}(M) \ln P_F^j(M) = \ln P_H^j + \sum_M \mathcal{F}(M) \ln(\frac{P_F^j(M)}{P_F^j(M)})$. As the last term is a constant in a stationary equilibrium, $P_F^j$ and $P_H^j$ grow at the same rate. It follows that foreign output also grows at the negative of $g_P^j$.

□

## C.5 Welfare Calculation

This section provides an explanation of the welfare calculation in our model. The total welfare $\mathbb{W}_c$ is the discounted sum of all welfare components over time, integrating components that aggregates consumer surplus (CS), producer surplus (PS), environmental externalities from GHG, and net fiscal costs. We report monetary welfare in terms of Billion USD, as well as welfare changes as a percentage of industry revenue.

**Consumer surplus** For comparing the welfare impact of different alternative parameter settings or policies and computing the optimal policy, we evaluate the change of CS relative to the baseline model using the compensating variation (CV) method. Denote $E(U_c, \boldsymbol{P}_c) = U_c \times \boldsymbol{P}_c$ the expenditure function that represents the minimum cost required for consumers to achieve a utility level $U_c$ given the price index $\boldsymbol{P}_c$.

The compensating variation is the difference in expenditure between the policy scenario

and the baseline scenario required to maintain the original utility level: $\text{CV} = E(U^0, \boldsymbol{p}^1) - E(U^0, \boldsymbol{p}^0)$. When $\text{CV} > 0$, consumers need more money under the policy scenario to reach $U^0$ (welfare loss); when $\text{CV} < 0$, it means that consumers need less money under the policy scenario to reach $U^0$ (welfare gain). Consumer surplus change due to policy changes is directly obtained from the CV: $CS = -\text{CV} = E(U^0, \boldsymbol{p}^0) - E(U^0, \boldsymbol{p}^1)$.

**Environmental externality from vehicle use.** Now we describe how we translate vehicle consumption into greenhouse-gas (GHG) emissions, atmospheric carbon concentration, and welfare damages. To capture this environmental externality, we monetize the welfare loss associated with GV consumption by evaluating its impact on total GHG emissions and the resulting social costs from climate-related damages. Our approach follows the carbon-cycle representation widely used in quantitative climate-economy models (Weitzman, 2009; Golosov et al., 2014; Acemoglu et al., 2012, 2016).

Let $Sales_t^e$ and $Sales_t^g$ denote total sales (globally) of EV and GV in period $t$, aggregating domestic sales and exports across countries in the model. Vehicle stocks are computed by accumulating past sales net of retirements:

$$Stock_t^j = \sum_{\tau \leq t} frac_{t-\tau} \, Sales_\tau^j, \qquad j \in \{e, g\},$$

where $fract_{t-\tau} \in [0, 1]$ is the fraction of vehicles sold $(t - \tau)$ years ago that remain in operation. We map vehicle stocks into annual GHG emissions using technology-specific emission factors (in $CO_2$ per vehicle-year):

$$Emit_t^{\text{car}} = \phi_e \, Stock_t^e + \phi_g \, Stock_t^g,$$

where $\phi_g > \phi_e \geq 0$. Total global emissions are the sum of vehicle emissions and an exogenous non-vehicle component $Emit_t^{\text{other}}$:

$$Emit_t^{\text{total}} = Emit_t^{\text{car}} + Emit_t^{\text{other}}.$$

Let $\Phi_t$ denote atmospheric carbon concentration (or carbon stock), and $\bar{\Phi}_t$ the atmospheric carbon concentration without the road transportation sector.[36] Following Golosov

[36] We initialize the carbon stock at the level in 2000 as the base year.

et al. (2014), we specify that

$$\Phi_t = \int_0^t (1 - \delta_\tau^{\text{total}}) Emit_\tau^{\text{total}} \, d\tau, \tag{C.15}$$

$$\delta_t^{\text{total}} \equiv (1 - \varphi_P)(1 - \varphi_T \, e^{-\varphi \, t}), \tag{C.16}$$

$$\bar{\Phi}_t = \int_0^t (1 - \delta_\tau^{\text{other}}) Emit_\tau^{\text{total}} \, d\tau \tag{C.17}$$

where $\varphi_P \in (0,1)$ is the permanent retention rate, $\varphi > 0$ governs the decay speed of transitory carbon, and $\varphi_T > 0$ governs the contemporaneous loading of emissions into the transitory reservoir.

We translate changes in atmospheric carbon into output-equivalent damages using an exponential damage function. Let $GDP_t^W$ denote world GDP (taken as exogenous in our partial-equilibrium implementation). Damages are computed as the change in the damage factor relative to a reference path:

$$\Gamma_t^W = \left( e^{-\iota(\bar{\Phi}_t - \Phi_0)} - e^{-\iota(\Phi_t - \Phi_0)} \right) GDP_t^W, \tag{C.18}$$

where $\iota > 0$ governs curvature and $\Phi_0$ is a normalization level.[37] We analogously compute country-$c$ damages by scaling with $GDP_t^c$ when reporting domestic components.

**Net fiscal costs** The net fiscal cost is calculated as the sum of all policy spending in the EV industrial policy.

$$FC_H(t) = \sum_j \left[ \begin{array}{l} R^j_{U,H}(t) + H(X^{j,S}(t)) w_H(t) + \chi^j_H(t) w_H(t) \sum_M (H(X^j_H(M,t)) + \hat{H}(\hat{X}^j_H(M,t)) \mathcal{F}_j(M) \\ + \chi^j_H(t) w_H(t) \sum_m h(z^j_H(m,t)) \mu_j(m) + P^j_H(t) \tilde{D}^j_H(t) + R_{C,H}(t) + \varsigma^j_H(t) \left( P^j_H(t) D^j_H(t) + \widetilde{P}^j_F(t) \widetilde{D}^j_F(t) \right) \end{array} \right].$$

[37] In the counterfactual analysis, we compute $\Phi_t$ separately under each equilibrium (baseline and counterfactual), and report $\Delta\Gamma_t$ as the difference in discounted damages across equilibria.

# Appendix D Calibration Details

In this section we present the additional details for the parameter calibration in our baseline model.

## D.1 Parameter estimation algorithm.

To estimate the set of model parameters internally, we choose a vector of parameter values to minimize the objective function

$$\sum_k \omega_k \frac{|\text{model}_k(\theta) - \text{data}_k|}{0.5 \times |\text{model}_k(\theta) + \text{data}_k|}$$

where $k$ denotes the $k^{th}$ moment in the model and the data, and $\omega_k$ denotes the weight of moment $k$.

## D.2 Demand System Estimation

We recover the EV preference parameter as

$$\ln\left(\frac{\hat{\xi}^e_{c,t}}{1-\hat{\xi}^e_{c,t}}\right) = \ln\left(\frac{\bar{S}^e_{c,t}}{1-\bar{S}^e_{c,t}}\right) + (\widehat{\sigma}-1)\ln\left(\frac{\bar{P}^e_{c,t}}{\bar{P}^g_{c,t}}\right).$$

where $\hat{\sigma}$ is estimated value of the elasticity of substitution between EV and GVs. We assume that EV preferences consist of two components: one that endogenously responds to the EV stock share and public charger density, and a residual component that is exogenous and unexplained. To obtain the endogenous component, we run the following estimation,

$$\ln\left(\frac{\hat{\xi}^e_{c,t}}{1-\hat{\xi}^e_{c,t}}\right) = \underset{(0.102)}{0.721^{***}} \ln StockShare_{c,t-1} + \underset{(0.082)}{0.371^{***}} \ln ChargerRatio_{c,t-1} + \alpha_c + \lambda_t + \nu_{c,t}.$$

The endogenous component is calculated as

$$\min\{0.476 * \hat{\xi}^e_{c,t}, \frac{\exp\{0.721 * X_1 + 0.371 * X_2\}}{1 - \exp\{0.721 * X_1 + 0.371 * X_2\}}\}$$

where $X_1$ and $X_2$ denote $\ln StockShare_{c,t-1}$ and $\ln ChargerRatio_{c,t-1}$ respectively. The value of the endogenous component is capped at $0.476 * \hat{\xi}^e_{c,t}$, reflecting the fact that in

the above regression the explanatory power of the two variables, $\ln StockShare_{c,t-1}$ and $\ln ChargerRatio_{c,t-1}$, is 47.6%.

The unexplained, exogenous component is obtained as a residual—that is, the estimated preference, $\widehat{\xi}^{e}_{c,t}$, minus the endogenous component. In the counterfactual analysis, we hold this exogenous component fixed at its baseline level and recompute the endogenous component based on the implied EV stock share and charger density. This allows us to isolate the effect of industrial policy on consumers' willingness to adopt EVs.

## D.3 External Parameter Values

There are three sets of time-varying parameters in our baseline model that we calibrated from external sources.

**Aggregate Parameters** We calibrate the aggregate expenditure on Chinese and Foreign-produced vehicles in Home, foreign and the rest of the world markets $\{\boldsymbol{E}_{H,t}, \boldsymbol{E}_{F,t}, \boldsymbol{E}_{ROW,t}\}$ during the year 2001 to 2024 to the actual data collected from China Association of Automobile Manufacturers (CAAM) for Chinese markets, and sourced from National Automobile Dealers Association (NADA), Japan Automobile Manufacturers Association (JAMA), European Automobile Manufacturers Association (ACEA), and Korea Automobile Manufacturers Association (KAMA) for vehicles in the United States, Japan, Germany, France and South Korea respectively. The All prices are converted to a common currency (billion USD) using annual average exchange rates from the International Monetary Fund (IMF), and are adjusted for inflation using the Consumer Price Index (CPI). To represent the total spending on vehicles produced by these countries for the rest of the world, we utilize the total import value from China and the weighted average values from five countries at the 6-digit HS code level from the UN ComTrade database. The calibrated values are presented in Table D.1.

**Policy Parameters** We set the policy parameters for both Home and Foreign country in our baseline model based on the observed policies as presented in Section A. Table D.2 presents the values in the calibration window. On the transitional path, we set the R&D subsidy, public fleet procurement ratio and purchase subsidy policies to phase out in 2030, and all tariffs stay at the last observed period.

Now we introduce the calibration details related to the public research funding policy. Specifically, we count the total number of backward citations made by EV patents (as

Table D.1: External Calibrated Expenditure, Prices, and Policy Outlay

| Year | (1) $\boldsymbol{E}_H$ | (2) $\boldsymbol{E}_F$ | (3) $\boldsymbol{E}_{ROW}$ | (4) $w_H$ | (5) $w_F$ | (6) $P_{MT,H}$ | (7) $P_{MT,F}$ | (8) $R^U$ | (9) $R^{SOE}$ |
|---|---|---|---|---|---|---|---|---|---|
| 2001 | 0.22 | 2 | 0.94 | 1 | 14.36 | 5.72 | 3.36 | 0.06 | 0 |
| 2002 | 0.25 | 2 | 0.97 | 1.07 | 14.42 | 5.62 | 3.41 | 0.05 | 0.11 |
| 2003 | 0.28 | 2 | 1 | 1.14 | 14.47 | 5.53 | 3.47 | 0.04 | 0.15 |
| 2004 | 0.32 | 1.99 | 1.04 | 1.21 | 14.53 | 5.45 | 3.53 | 0.02 | 0.13 |
| 2005 | 0.36 | 1.99 | 1.07 | 1.29 | 14.58 | 5.36 | 3.58 | 0.02 | 0.06 |
| 2006 | 0.4 | 1.99 | 1.11 | 1.38 | 14.64 | 5.27 | 3.64 | 0.11 | 0.07 |
| 2007 | 0.46 | 1.99 | 1.15 | 1.47 | 14.69 | 5.19 | 3.7 | 0.06 | 0.14 |
| 2008 | 0.52 | 1.99 | 1.18 | 1.57 | 14.75 | 5.11 | 3.76 | 0.03 | 0.16 |
| 2009 | 0.58 | 1.98 | 1.22 | 1.67 | 14.81 | 5.03 | 3.82 | 0.02 | 0.14 |
| 2010 | 0.66 | 1.98 | 1.26 | 1.78 | 14.87 | 4.95 | 3.88 | 0.04 | 0.47 |
| 2011 | 0.75 | 1.98 | 1.31 | 1.9 | 14.92 | 4.87 | 3.95 | 0.05 | 0.35 |
| 2012 | 0.84 | 1.98 | 1.35 | 2.03 | 14.98 | 4.79 | 4.01 | 0.05 | 0.32 |
| 2013 | 0.95 | 1.98 | 1.4 | 2.16 | 15.04 | 4.71 | 4.07 | 0.05 | 0.21 |
| 2014 | 1.08 | 1.97 | 1.44 | 2.31 | 15.1 | 4.64 | 4.14 | 0.04 | 0.23 |
| 2015 | 1.22 | 1.97 | 1.49 | 2.46 | 15.15 | 4.56 | 4.21 | 0.03 | 0.2 |
| 2016 | 1.38 | 1.97 | 1.54 | 2.62 | 15.21 | 4.49 | 4.28 | 0.21 | 0.14 |
| 2017 | 1.56 | 1.97 | 1.59 | 2.8 | 15.27 | 4.42 | 4.35 | 0.23 | 0.28 |
| 2018 | 1.76 | 1.97 | 1.65 | 2.98 | 15.33 | 4.35 | 4.42 | 0.18 | 0.41 |
| 2019 | 1.99 | 1.96 | 1.7 | 3.18 | 15.39 | 4.28 | 4.49 | 0.02 | 0.44 |
| 2020 | 2.26 | 1.96 | 1.76 | 3.39 | 15.45 | 4.21 | 4.56 | 0.12 | 0.44 |
| 2021 | 2.55 | 1.96 | 1.82 | 3.62 | 15.51 | 4.15 | 4.64 | 0.18 | 0.47 |
| 2022 | 2.88 | 1.96 | 1.88 | 3.86 | 15.57 | 4.08 | 4.71 | 0.1 | 0.49 |
| 2023 | 3.26 | 1.96 | 1.94 | 4.12 | 15.63 | 4.01 | 4.79 | 0.07 | 0.54 |
| 2024 | 3.69 | 1.95 | 2 | 4.39 | 15.69 | 3.95 | 4.86 | 0.07 | 0.58 |

*Note:* This table shows the external calibrated time-variant parameter values. Columns (1)-(3) show the total vehicle expenditure parameters of the Chinese, foreign weighted average, and rest of the world markets in 2000-2035. Unit for expenditures are converted in the welfare analysis in constant billion US dollars. Columns (4)-(5) show the raw wage rates in Home and Foreign, with the first period of Home wage normalized to 1. Columns (6)-(7) show the unit price for common components in Home and Foreign.

defined in Table A.1) to all non-EV technology fields from 2001 to 2024, and pick the top 80 IPC groups as external knowledge sources (85% in total backward citations). The flow of public research entering the basic knowledge stock is calibrated using the number of EV patents filed by Chinese universities and public labs.

The initial level of the basic knowledge stock, $B_c^e(0)$, is set equal to the initial stock of external knowledge, $X_{H,0}^{e,U}$, using the initial patent stocks in these IPC groups. We then calibrate the path of external knowledge flow with the annual new patent applications in these technology fields, normalized by the initial patent stocks. The initial level of public research flow is determined by the ratio of public patent citations relative to external sources citations at year $t_0 = 2001$. Similarly, the public knowledge flow is calibrated to the new patent applications by public institutes and universities. To match the government expenditure data, we internally estimate the research efficiency of public institutes period by period. Post-calibration, we keep the public research productivity at the last period's value, assuming that public grants are gradually phased out until 2060. Then we project the trajectory of external knowledge flow starting from the last observed level so that the basic knowledge stock reaches its steady-state level. Following Rassenfosse and Jaffe (2018), we set the depreciation rate for basic knowledge to $d^{basic} = 0.11$. The resulting path for basic knowledge and public research flows is reported in Figure D.3. In the baseline scenario, we assume that the initial knowledge stock for Home and Foreign EVs is identical to avoid different implied innovation productivity of the two countries. In the counterfactual experiments, we then allow the domestic knowledge stock to evolve in response to the implemented policies. Given our focus on EV policies, we normalize the basic knowledge stock for GV technologies to 1 for both the Home and Foreign countries.

**Greenhouse Gas Externality** With the exponential damage function specified in Section 3, we calibrate the parameters to the estimation in IPCC (2023) and compares our result with Nordhaus (2017). In particular, the GHG emissions from other sectors is picked from historical data and projections in IPCC AR6 report, and China's real GDP and world aggregate real GDP is derived from the World Bank database. For the future transitional path, we assume China's GDP growth rate gradually decrease to 2% after 2050, and the world GDP growth from 2024 to 2050 is 2.4%, then slowly decrease to 2% after 50 years, which is consistent with the long run growth assumptions in the literature (e.g. Nordhaus (2014)). Table D.3 shows the parameter values from the calibration.

Table D.2: External Calibrated Policy Parameter

| Year | (1) $\chi_H^e$ | (2) $\chi_F^e$ | (3) $R^{SOE}$ | (4) $D^{Pub}$ | (5) $\varsigma_H^e$ | (6) $\varsigma_F^e$ | (7) $Tr_H$ | (8) $Tr_F$ | (9) $tr_H^{int}$ | (10) $tr_H^{int}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | 0.57 | 0 | 1.52 | 0 | 0 | 0 | 0.45 | 0.05 | 0.35 | 0.03 |
| 2002 | 0.56 | 0 | 1.57 | 0 | 0 | 0 | 0.40 | 0.05 | 0.25 | 0.03 |
| 2003 | 0.55 | 0 | 1.64 | 0 | 0 | 0 | 0.35 | 0.05 | 0.22 | 0.03 |
| 2004 | 0.52 | 0 | 1.67 | 0 | 0 | 0 | 0.31 | 0.05 | 0.19 | 0.03 |
| 2005 | 0.51 | 0 | 1.96 | 0 | 0 | 0 | 0.28 | 0.05 | 0.16 | 0.03 |
| 2006 | 0.5 | 0 | 1.85 | 0 | 0 | 0 | 0.25 | 0.05 | 0.13 | 0.03 |
| 2007 | 0.49 | 0 | 1.6 | 0 | 0 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2008 | 0.47 | 0.10 | 1.83 | 25.54 | 0 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2009 | 0.46 | 0.15 | 1.98 | 14.76 | 0 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2010 | 0.44 | 0.18 | 1.9 | 5.54 | 0 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2011 | 0.42 | 0.18 | 1.72 | 4.76 | 0 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2012 | 0.4 | 0.18 | 1.67 | 4.86 | 0.25 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2013 | 0.37 | 0.18 | 1.45 | 1.78 | 0.28 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2014 | 0.35 | 0.18 | 1.47 | 0.98 | 0.38 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2015 | 0.33 | 0.18 | 1.22 | 0.39 | 0.38 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2016 | 0.30 | 0.18 | 1.36 | 0.14 | 0.38 | 0 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2017 | 0.28 | 0.18 | 1.22 | 0.04 | 0.35 | 0.08 | 0.25 | 0.05 | 0.11 | 0.03 |
| 2018 | 0.26 | 0.18 | 1.20 | 0.02 | 0.35 | 0.08 | 0.15 | 0.05 | 0.11 | 0.03 |
| 2019 | 0.26 | 0.18 | 1.25 | 0.02 | 0.30 | 0.12 | 0.15 | 0.05 | 0.06 | 0.03 |
| 2020 | 0.26 | 0.18 | 1.15 | 0.01 | 0.21 | 0.13 | 0.15 | 0.05 | 0.06 | 0.03 |
| 2021 | 0.26 | 0.18 | 1.11 | 0.01 | 0.18 | 0.15 | 0.15 | 0.05 | 0.06 | 0.03 |
| 2022 | 0.26 | 0.18 | 1.23 | 0.01 | 0.14 | 0.16 | 0.15 | 0.05 | 0.06 | 0.03 |
| 2023 | 0.25 | 0.18 | 1.14 | 0.00 | 0.10 | 0.16 | 0.15 | 0.05 | 0.06 | 0.03 |
| 2024 | 0.24 | 0.18 | 0.91 | 0.00 | 0.10 | 0.16 | 0.15 | 0.05 | 0.06 | 0.03 |

*Note:* This table shows the policy parameters calibrated from the observed actual policy intensity. Columns (1)-(2) show the intensity of R&D subsidy to EV technology in Home and Foreign. Column (3) shows the ratio of innovation intensities for SOE verses POE in Home. Column (4) shows the ratio of public EV procurement verses private EV sales in Home. Columns (5)-(6) show the intensity of purchase subsidy of EVs in Home and Foreign. Columns (7)-(10) show the import tariff rates for final good and intermediate goods in Home and Foreign.

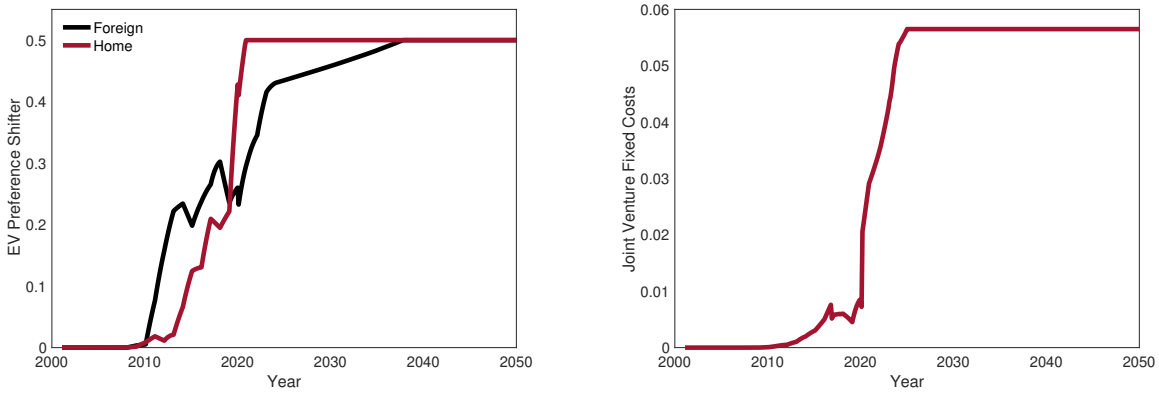
Table D.3: Environmental Externality Parameter

| *Panel A: Historical Data* | | | | *Panel B: Projection* | | | |
|---|---|---|---|---|---|---|---|
| Year | $\bar{G}$ | $\boldsymbol{Y}_{world}$ | $\boldsymbol{Y}_H$ | Year | $\bar{G}$ | $\boldsymbol{Y}_{world}$ | $\boldsymbol{Y}_H$ |
| 2000 | 37.39 | 48437.26 | 2770.11 | 2024 | 46.01 | 95587.01 | 18000.10 |
| 2001 | 36.84 | 49422.3 | 3001.02 | 2025 | 45.45 | 97881.1 | 18810.11 |
| 2002 | 38.04 | 50567.14 | 3275.12 | 2026 | 45.19 | 100230.25 | 19637.75 |
| 2003 | 38.78 | 52131.52 | 3603.88 | 2027 | 44.93 | 102635.77 | 20482.17 |
| 2004 | 40.9 | 54463.87 | 3968.37 | 2028 | 44.67 | 105099.03 | 21342.43 |
| 2005 | 42.07 | 56653.58 | 4420.54 | 2029 | 44.42 | 107621.41 | 22217.47 |
| 2006 | 43.55 | 59180.66 | 4982.88 | 2030 | 44.16 | 110204.32 | 23106.16 |
| 2007 | 43.92 | 61768.75 | 5691.99 | 2031 | 42.82 | 112849.22 | 24030.41 |
| 2008 | 43.22 | 63038.81 | 6241.30 | 2032 | 40.89 | 115557.61 | 24967.6 |
| 2009 | 43.34 | 62192.60 | 6827.90 | 2033 | 38.9 | 118330.99 | 25916.37 |
| 2010 | 45.26 | 65002.11 | 7554.11 | 2034 | 36.91 | 121170.93 | 26875.27 |
| 2011 | 46.44 | 67170.76 | 8275.59 | 2035 | 34.92 | 124079.03 | 27842.78 |
| 2012 | 47.38 | 68978.97 | 8926.36 | 2036 | 33.33 | 127056.93 | 28817.28 |
| 2013 | 48.07 | 70960.63 | 9619.60 | 2037 | 31.74 | 130106.3 | 29797.07 |
| 2014 | 49.18 | 73182.74 | 10333.93 | 2038 | 30.14 | 133228.85 | 30780.37 |
| 2015 | 48.7 | 75472.47 | 11061.57 | 2039 | 28.55 | 136426.34 | 31765.34 |
| 2016 | 48.64 | 77596.07 | 11819.15 | 2040 | 26.96 | 139700.57 | 32750.07 |
| 2017 | 48.73 | 80274.26 | 12640.25 | 2041 | 25.93 | 143053.39 | 33732.57 |
| 2018 | 48.83 | 82909.02 | 13493.44 | 2042 | 24.91 | 146486.67 | 34710.81 |
| 2019 | 49.06 | 85127.63 | 14296.37 | 2043 | 23.89 | 150002.35 | 35682.72 |
| 2020 | 50.2 | 82677.38 | 14616.41 | 2044 | 22.86 | 153602.4 | 36646.15 |
| 2021 | 48.58 | 87927.47 | 15851.28 | 2045 | 21.84 | 157288.86 | 37598.95 |
| 2022 | 47.13 | 90774.58 | 16319.00 | | | | |
| 2023 | 46.57 | 93346.69 | 17175.67 | | | | |

*Note:* This table shows the calibration of environmental externality related parameters from the IPCC and World Bank in 2000-2023. The estimation of GHG emission in sectors other than transportation is in Gigaton unit. The historical GDP of China's and world are expressed in constant 2020 billion USD.

## D.4 Internal Parameter Values

We internally back out the time-variant parameters in the model, targeting the sales share of EVs in annual vehicle sales, and the import share in final goods and intermediates from UN ComTrade Database, presented in Figure A.1. Figures D.1 and D.2 present the internally calibrated demand shifters, joint venture fixed costs and iceberg costs for each period $t$ targeting the observed sales shares.

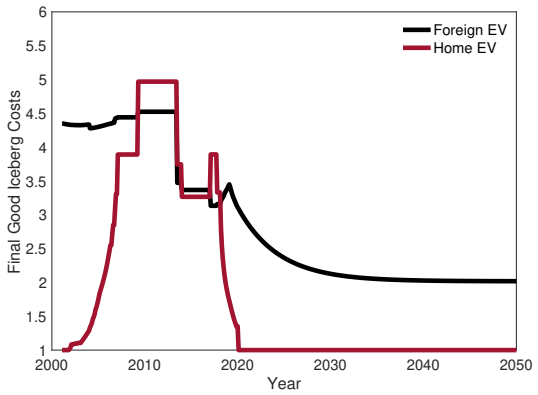



(a) EV Preference Shifter

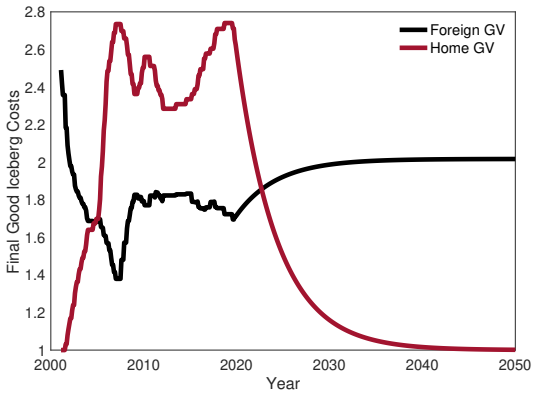
(b) Joint Venture Fixed Cost

Figure D.1: Internally Calibrated Parameter Values

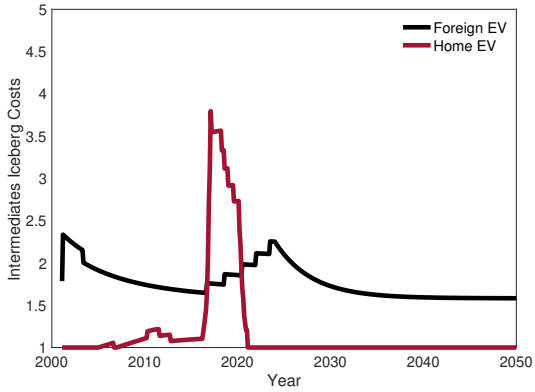
*Note:* Panel (a) shows the internally calibrated preference shifter $\{\xi^e_{H,t}, \xi^e_{F,t}\}$, and Panel (b) shows the fixed cost for joint ventures $\{\kappa_{\text{JV,t}}\}$. Panel (c) and (d) shows the iceberg costs for EV intermediate goods and final goods respectively.



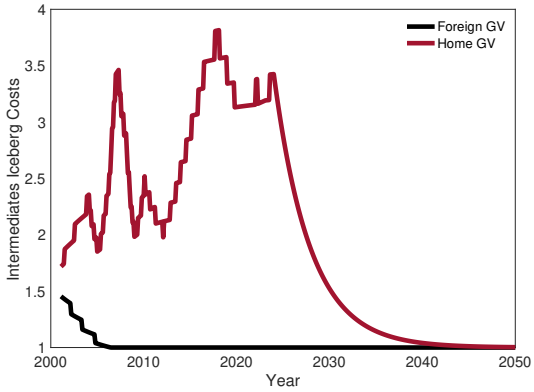

(a) EV Final Good Iceberg Costs




(b) GV Final Good Iceberg Costs




(c) EV Intermediates Iceberg Costs




(d) GV Intermediates Iceberg Costs

Figure D.2: Internally Calibrated Iceberg Costs

*Note:* Panel (a)-(b) shows the internally calibrated iceberg costs for EV final good goods. Panel (c) and (d) shows the iceberg costs for EV intermediate goods respectively.

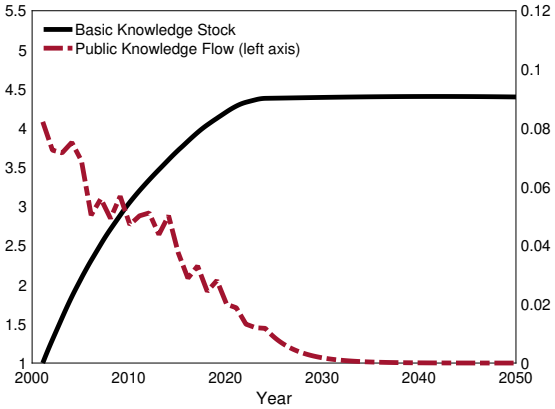



Figure D.3: Calibrated Path for Basic Knowledge Stock

*Note:* This figure shows the internally calibrated basic knowledge stock in EV technology with and without public knowledge flow.

# Appendix E Additional Quantitative Results

## E.1 Decomposition of Policy Impacts

Table E.1: Short- and Long-term Welfare Impacts of Industrial Policies

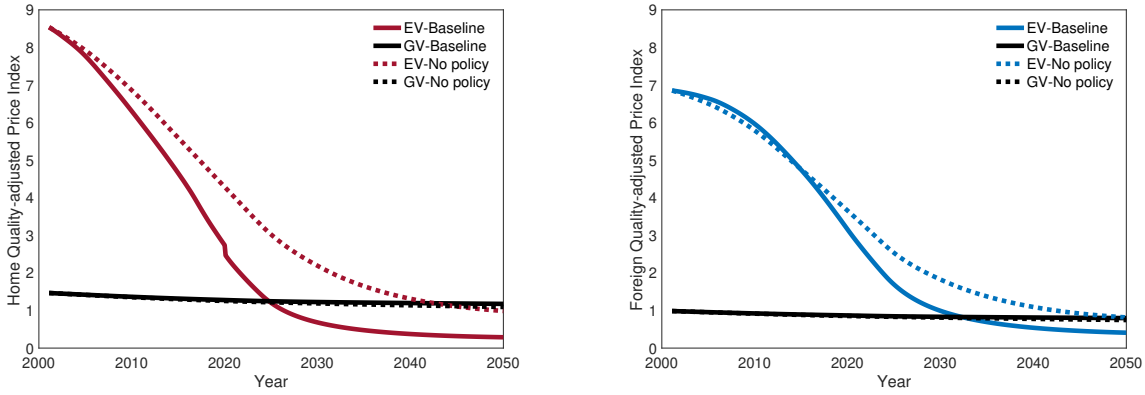
| | 2001-2025 horizon | 2001-2050 horizon |
|---|---|---|
| *Panel A: Domestic welfare impacts (B$)* | | |
| Δ Domestic Welfare | -187.81 | +1507.91 |
| — Δ Consumer Surplus | -46.84 | +1219.30 |
| — Δ Producer Surplus | +67.01 | +459.98 |
| — Δ Total Subsidy Costs | +208.57 | +262.48 |
| — Δ Environmental Damage | -0.59 | -91.14 |
| *Panel B: Global welfare impacts (B$)* | | |
| Δ Foreign Welfare | -1.88 | -254.71 |
| — Δ Consumer Surplus | -10.60 | +202.88 |
| — Δ Producer Surplus | +15.01 | -459.20 |
| — Δ Total Subsidy Costs | +6.61 | +37.65 |
| — Δ Environmental Damage | -0.34 | -39.26 |
| Δ ROW Welfare | -12.61 | +1102.5 |
| — Δ Consumer Surplus | -13.45 | +1004.3 |
| — Δ Environmental Damage | -0.84 | -98.15 |

*Note:* This table summarizes welfare impacts of China EV industrial policy relative to a counterfactual scenario without interventions. All numbers are converted to constant billion USD.

### E.1.1 Welfare Impacts of Individual Policy Instruments

To further unpack the mechanisms driving the aggregate results, Table E.2 evaluates the marginal long-term impact of each individual policy instrument. For each column, we simulate a counterfactual economy where only that specific policy is permanently removed, holding all other baseline policies constant. The table reports the net change in welfare and its components when the policy is implemented.

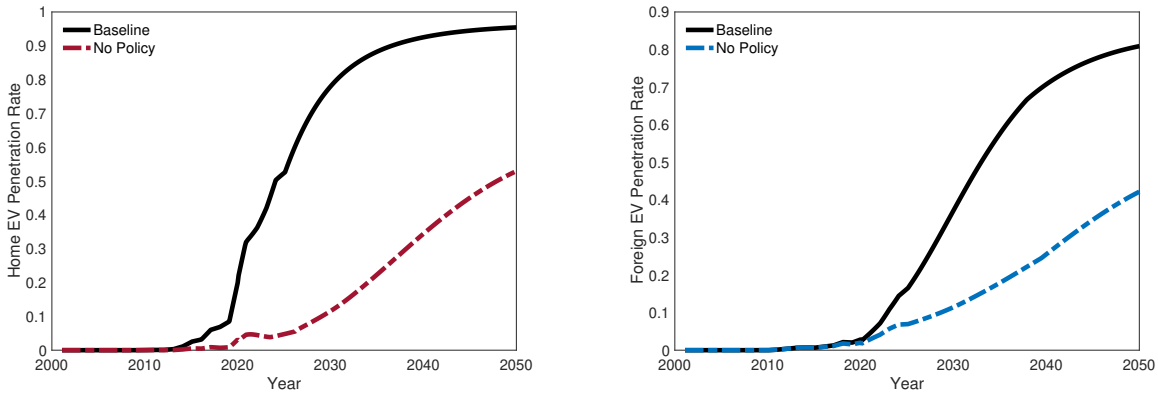
Panel A reveals that capability stage interventions generate positive long-run welfare gains primarily by accelerating innovation and structurally lowering the quality-adjusted prices faced by consumers. The most impactful capability instrument is the provision




(a) Home (b) Foreign

Figure E.1: Impacts of Industrial Policy on Quality-adjusted Price Index

*Note:* This figure shows the quality-adjusted price index in Home and Foreign country relative to a counterfactual scenario without industrial policy over different time horizon.




(a) Home EV Market Share (b) Foreign EV Market Share

Figure E.2: Impacts of Industrial Policy on EV Market Shares

*Note:* This figure shows the sales share of EVs in Home and Foreign country relative to a counterfactual scenario without industrial policy over different time horizon.

of POE R&D Subsidies, which increases total long-run domestic welfare by 2.37%. By directly alleviating the cost of innovation, this subsidy stimulates private R&D efforts, translating into large consumer surplus gains (+2.16%) and higher producer surplus (+0.36%).

Panel B highlights a stark divergence between market-expanding subsidies and market-restricting protectionism. EV purchase subsidy and government investment in charging infrastructure emerge as the dominant drivers of welfare in the Consumption stage, raising total domestic welfare by 2.11% and 1.62%, respectively. However, EV purchase subsidy is the most fiscally expensive single policy (+0.69% in subsidy costs). In contrast, the Local Content Requirement (LCR) generates a net welfare loss (-0.32%). By

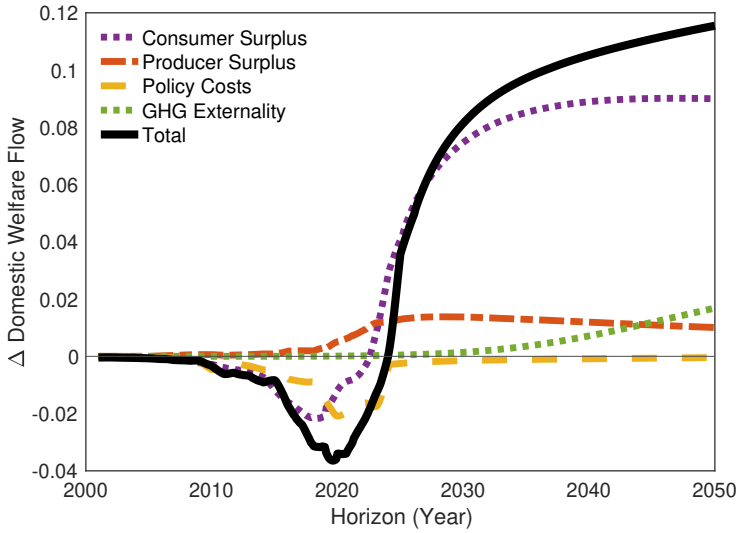



Figure E.3: Welfare Impacts of Industrial Policy Flow

*Note:* This figure shows the flow of welfare changes relative to a counterfactual scenario without industrial policy over different time horizon.

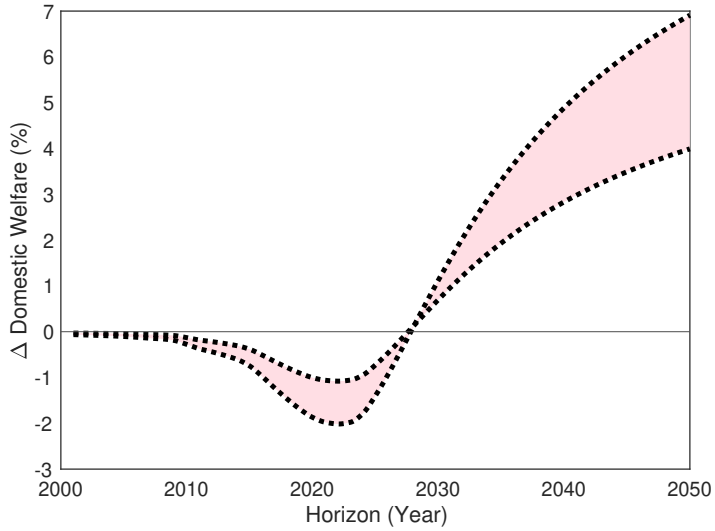



Figure E.4: Range of Welfare Impacts of Industrial Policy

*Note:* This figure shows the range of welfare changes relative to a counterfactual scenario without industrial policy over different time horizon based on different future foreign policy path. The lower dashed line indicates the scenario with the highest EV import iceberg cost of Foreign country (5% market share cap for Home producers in Foreign country), and the highest dashed line indicates the lowest (50% market share cap for Home producers in Foreign country).

raising the iceberg trade costs for foreign EV intermediate goods, the LCR forces domestic final-good producers to source from less efficient domestic battery suppliers, which raises marginal costs that are passed on to consumers (reducing consumer surplus by 0.28%) and ultimately shrinks the market size for EVs, which depresses downstream EV producer surplus (-0.10%). This result highlights that protectionist measures that distort

input sourcing could be welfare-reducing.

Table E.2: Long-term Impacts of Individual Policy Instruments

| *Panel A: Capability Stage* | | | | |
|---|---|---|---|---|
| | Public Research | SOE R&D | R&D Subsidy | Joint Ventures |
| Δ Domestic Welfare | +0.40% | +0.92% | +1.93% | +0.17% |
| (+) Δ Consumer Surplus | +0.48% | +0.81% | +2.16% | +0.17% |
| (+) Δ Producer Surplus | +0.04% | +0.31% | +0.36% | +0.08% |
| (-) Δ Total Subsidy Costs | +0.07% | +0.24% | +0.44% | +0.03% |
| (-) Δ Environmental Damage | -0.02% | -0.03% | -0.09% | -0.01% |
| *Panel B: Consumption Stage* | | | | |
| | Public Procurement | Infrastructure | Purchase Subsidy | Whitelist (LCR) |
| Δ Domestic Welfare | +0.45% | +1.02% | +1.99% | -0.11% |
| (+) Δ Consumer Surplus | +0.69% | +1.81% | +2.23% | -0.08% |
| (+) Δ Producer Surplus | +0.06% | +0.17% | +0.79% | -0.10% |
| (-) Δ Total Subsidy Costs | +0.19% | +0.41% | +0.96% | -0.06% |
| (-) Δ Environmental Damage | -0.02% | -0.06% | -0.11% | -0.01% |

*Note:* This table shows the change in total domestic welfare when each individual policy instrument is implemented, compared to a counterfactual scenario where only that specific policy is removed. The $(+)$ and $(-)$ labels denote how each component enters the welfare calculation.

## E.2 More Counterfactual Policy Analysis

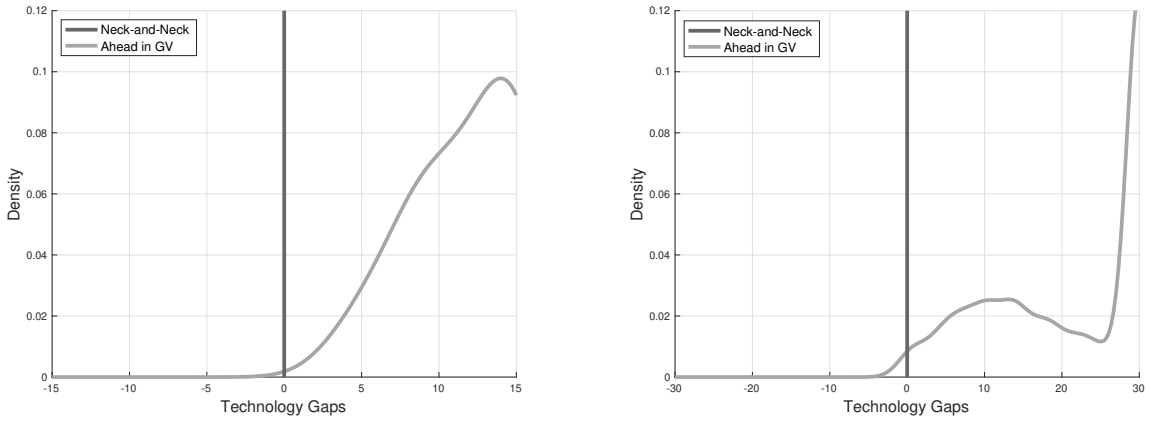
### E.2.1 Initial Technology Gap in Counterfactual Exercise

Figure E.5 presents the counterfactual initial technology gap distributions for final goods and intermediate goods in GV technology.

### E.2.2 Economic Fundamentals and the Effectiveness of Industrial Policy

Our quantitative model is solved in partial equilibrium. Wages and aggregate vehicle expenditure paths are therefore taken as exogenous inputs, disciplined by observed data in the baseline calibration. This section reports counterfactual exercises that vary these economic fundamentals to assess how much the estimated effectiveness of China's EV industrial policy depends on cross-country factor-cost differences and market-size differences.

First, we set Home and Foreign wages to be equal over the transition, while keeping all other baseline primitives and the policy path unchanged unless stated otherwise. We then compute the welfare impact of the baseline industrial policy bundle. Column (2) of Table E.3 presents the results of the counterfactual exercises. Equalizing wages increases the




(a) GV Final Good (b) GV Intermediate Good

Figure E.5: Counterfactual Initial Technology Gaps

*Note:* This figure shows the counterfactual initial technology gaps in GV technologies. Panel (a) shows the distribution for final goods and Panel (b) shows the distribution for intermediate goods.

estimated policy effect to +5.81% (baseline: +5.52%). The intuition is that, in the baseline, the wage wedge contributes to Home producers' cost advantage and therefore supports Home's competitiveness in the incumbent GV lane. This highlights that the effectiveness of industrial policy depends on the initial relative position to the frontier and equaling wages reinforce this pattern by weakening the GV profitability channel, whereas eliminating initial GV disadvantage removes the key wedge that makes lane switching socially (and privately) optimal.

We next set Home and Foreign vehicle expenditure paths to be the same over time, keeping wages and other primitives at their baseline values (unless otherwise stated). This removes cross-country differences in market size and therefore in the scale of profits and innovation incentives. Column (3) of Table E.3 present the results of the counterfactual exercises. Equalizing expenditures reduces the policy impact to +2.80%, compared to +5.52% in the baseline. The mechanism is a market-size channel: because innovation incentives depend on the expected value of being a leader, larger market size increases the payoff to cost reductions and quality improvements. In the baseline, cross-country expenditure differences imply that policy-induced improvements in Home EV competitiveness translate into larger increases in both consumer welfare, therefore stronger dynamic gains. When expenditures are equalized, this amplification is attenuated, as EV adoption occur on a smaller effective scale.

Table E.3: Long-term Impact on Domestic Welfare with Different Initial GV Gaps

| | Baseline (1) | $w_H = w_F$ (2) | $I_H = I_F$ (3) |
|---|---|---|---|
| Δ Total Welfare | +5.52% | +5.81% | +2.80% |
| (+) Δ Consumer Surplus | +4.23% | +4.90% | +2.26% |
| (+) Δ Producer Surplus | +0.89% | +0.91% | +0.63% |
| (-) Δ Total Subsidy Costs | +0.84% | +0.46% | +0.36% |
| (-) Δ Environmental Damage | -0.34% | -0.44% | -0.26% |

*Note:* This table summarizes the long-term domestic welfare impacts of China's EV industrial policy under the baseline scenario versus two counterfactual scenarios with equalized cross-country wages. Column (2) presents the counterfactual results for equalized wages, and Column (3) presents the results with equalized wages and the initial GV technology gap distribution in both final and intermediate goods is shifted such that China is neck-and-neck in GV technologies (while EV initial gaps remain at baseline levels). The $(+)$ and $(-)$ labels denote how each component enters the welfare calculation.

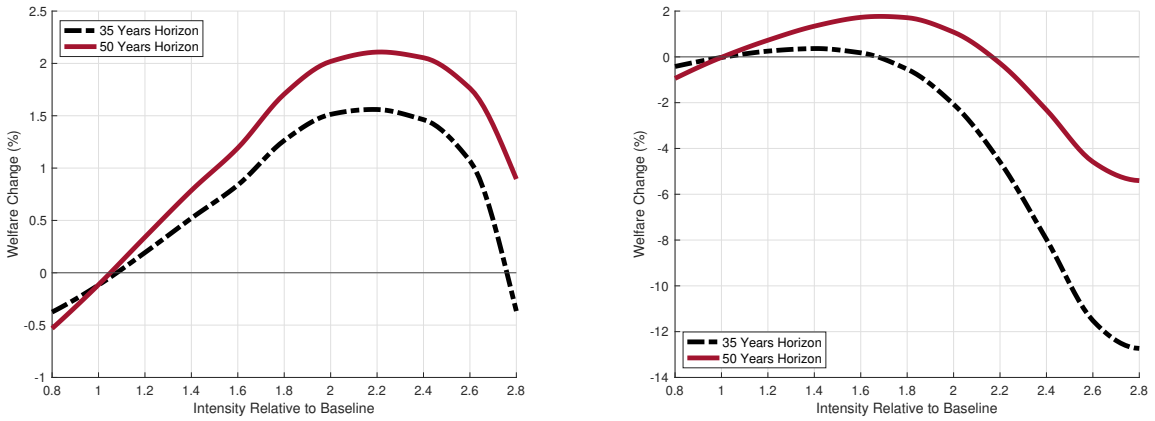
### E.2.3 Optimal Policy Intensity

Lastly, we numerically explore the optimal intensity of the industrial policies. Holding policy timing fixed, we scale the intensity of the Capability and Consumption stages from the baseline and report welfare at 25- and 50-year horizons.

Over a 25-year horizon, raising policy intensity strictly reduces welfare for both stages, especially for the Consumption stage, as fiscal costs explode while EV quality is still relatively low. However, over a 50-year horizon, welfare is hump-shaped with respect to intensity. Panel (a) of Figure E.6 shows that for Capability policy, long-run welfare rises steeply and peaks at roughly 2 times the baseline intensity, before declining as diminishing returns and factor-reallocation costs dominate. Panel (b) shows that for Consumption policy, the peak occurs earlier, at 1.8 times the baseline intensity. Furthermore, the post-peak decline is much sharper for Consumption policy, reflecting the severe misallocation wedges and massive fiscal burdens that persist at very high subsidy rates. Taken together, these counterfactual exercises suggest that, conditional on historical timing, the socially efficient approach would have utilized a moderately above-baseline intensity, with a stronger relative tilt toward Capability investments.

## E.3 Industrial Policy's Impact on Employment

Here we present the back-of-envelope calculation of China's industrial policy's impact on sectoral employments in Home and Foreign. Table E.4 shows the results for each instruments for the three development stages.




(a) Capability Stage (b) Consumption Stage

Figure E.6: Long-term Welfare Change Over Different Intensity

*Note:* This figure shows the domestic welfare change in counterfactual scenarios relative to baseline China EV industrial policy intensity. We change the intensity of Capability/Consumption stage policies from 80% to 280% of baseline level. Panel (a) shows the result for Capability stage and Panel (b) shows the result for Consumption stage.

Table E.4: Policy Impacts on Vehicle Manufacturing Employment

| | **Domestic** | | **Foreign** | | **Global** | |
|---|---|---|---|---|---|---|
| | -2025 | -2050 | -2025 | -2050 | -2025 | -2050 |
| *Panel A: Impact of Capacity Stage* | | | | | | |
| Total | +11.39 | +415.38 | -5.26 | -314.56 | +6.12 | +100.81 |
| Public Research | +2.69 | +87.53 | -1.31 | -68.51 | +1.38 | +19.02 |
| SOE R&D | +3.93 | +114.33 | -2.04 | -88.18 | +1.89 | +26.15 |
| R&D Subsidy | +10.18 | +253.69 | -4.42 | -190.60 | +5.75 | +63.09 |
| Joint Ventures | +0.53 | -0.02 | -0.23 | +0.60 | +0.29 | +0.58 |
| *Panel B: Impact of Consumption Stage* | | | | | | |
| Total | +9.96 | +463.2 | -3.43 | -339.99 | +6.53 | +123.22 |
| Public Fleet | +1.26 | +8.08 | -0.23 | -5.33 | +1.04 | +2.75 |
| Purchase Subs. | +8.01 | +117.07 | -2.71 | -83.91 | +5.30 | +33.16 |
| Infrastructure | +8.71 | +324.76 | -3.24 | -237.22 | +5.47 | +87.54 |
| Whitelist | -0.51 | -15.69 | +0.33 | +12.54 | -0.18 | -3.15 |
| *Panel C: Impact of Competition Stage* | | | | | | |
| Total | +3.55 | +26.39 | -0.33 | -9.41 | +3.22 | +16.98 |