Foreign Entry, Local Sourcing, and Domestic Welfare: Evidence from Tesla's Manufacturing in China*

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Abstract

Products from a leading foreign manufacturer can hurt domestic rivals through competition, yet its local production and sourcing can help them through spillovers that lower their production costs and fixed costs of introducing new products. I estimate a model of consumer demand, oligopoly pricing, and product introduction to study these opposing forces and their welfare effects in China's passenger vehicle market, where Tesla began producing electric vehicles (EVs) in Shanghai and sourcing their components locally in 2019. The marginal costs of rival EVs sharing Tesla's core-part suppliers fell more than those of other rival EVs. The fixed costs of introducing battery-electric models similar in size to Tesla's locally produced models also fell relative to those of smaller battery-electric models. Counterfactual analysis shows that competition from Tesla's Shanghai-built models discourages rivals from introducing new products, while these cost reductions encourage them. On net, rivals' new product offerings rise by about 32 percent relative to a market without Tesla's local production and sourcing. Domestic welfare rises, and consumers receive most of the gain. Allowing rivals to adjust their offerings raises consumers' gains by about 27 percent. Domestic producer gains accrue to EV start-ups because their models share more suppliers with Tesla and are closer to its models in size. Established Chinese automakers lose.

Keywords: foreign direct investment, supplier spillovers, product choice, electric vehicles, moment inequalities.

JEL: F23, L13, L62.

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1 Introduction

What are the effects of a leading multinational's entry on consumers and domestic industry? The entrant's products may compete closely with those of domestic firms, benefiting consumers but diverting sales from these firms. Yet domestic firms need not lose overall if the entrant's local production and component sourcing also promote their development. Many governments act on this possibility, pairing foreign entry with incentives to produce and source locally. For example, Thailand conditions support for foreign electric vehicle (EV) manufacturers on local production obligations,[1] Hungary has welcomed BYD's investment and encouraged links with domestic suppliers,[2] and Japan provides substantial subsidies to attract TSMC's semiconductor production.[3]

Whether domestic industry benefits from such policies, however, is not clear a priori. The entrant's local sourcing creates supply-side spillovers, which are changes in domestic firms' costs that work through suppliers serving both the entrant and the domestic firms. These spillovers can go either way. Economies of scale and learning at shared suppliers may lower domestic firms' input costs, while capacity constraints at those suppliers or preferential terms for the entrant may raise them (Alfaro-Ureña et al., 2022; Inderst and Valletti, 2011). The net effects on domestic firms' costs and profits are therefore empirical questions, as are their responses through prices and product offerings and the resulting welfare effects.

A substantial literature studies spillovers that travel through such supplier linkages (Rodríguez-Clare, 1996; Markusen and Venables, 1999; Javorcik, 2004; Alfaro-Ureña et al., 2022; Kee, 2015; Blalock and Gertler, 2008). Other work measures the welfare effects of foreign entry through changes in consumer prices, retail profits, and labor incomes (Atkin et al., 2018). To my knowledge, no study quantifies how competition from a foreign entrant's products and spillovers from its local sourcing jointly shape prices, product offerings, and the welfare of consumers and domestic producers.

This paper provides that quantification in the context of Tesla's move into large-scale local production and sourcing in the Chinese EV market. Tesla initially sold expensive electric models imported from the United States in modest volumes; it then built its first Gigafactory outside the United States in Shanghai and began delivering Shanghai-built cars in December

[1] See Thailand Board of Investment, "EV Board Gives the Green Light to EV 3.5 Package, Positioning Thailand as the Key Regional Hub for Electric Vehicle Manufacturing" (November 1, 2023), pp. 1–2. The package linked subsidies and tax incentives to domestic production to offset vehicle imports.

[2] See Hungarian Investment Promotion Agency, "More Than Hundred Hungarian Companies at BYD's Supplier Forum in Budapest" (October 16, 2024). The government agency organized the forum to connect BYD with Hungarian suppliers.

[3] See Japan's Ministry of Economy, Trade and Industry, *Outline of Semiconductor Revitalization Strategy in Japan* (July 2024), pp. 6–7, reporting approved subsidies of up to JPY 476 billion and JPY 732 billion for the first and second plants of TSMC's joint venture JASM, respectively.

2019.[4] The Shanghai Gigafactory is Tesla's largest global manufacturing plant by production volume and capacity, and it sources components extensively from local suppliers that also sell parts to rival automakers.

For the empirical analysis, I assemble nationwide private-car registration records for China from 2017 to 2023, matched to vehicle prices and characteristics. I supplement these with household survey data on income and car purchases. I also collect component-level supplier records for each EV model. The registration and survey data identify households' preferences for gasoline cars and EVs, and the supplier records identify which rival models share suppliers with Tesla's Shanghai plant, the basis for estimating spillovers through these supplier linkages.

Two patterns stand out. First, after Tesla began local production, rival automakers' battery-electric vehicle (BEV) offerings in Tesla's size classes (Mid and Upper-mid, where its Model 3 and Model Y mainly compete) nearly quadrupled between 2019 and 2022, while their plug-in hybrid (PHEV) offerings in those classes rose much less and their gasoline offerings changed little.[5] Second, core BEV attributes such as electric range, battery capacity, and size improved mainly through the introduction of new models, while those of continuing models barely changed. These patterns motivate modeling new product offerings, alongside prices, as a central margin of adjustment for domestic producers.

To quantify how competition from Tesla's Shanghai-built models and the supply-side spillovers from its local sourcing shape these responses, I build and estimate a structural model of household car demand, oligopolistic pricing, and new-model introductions, in which rival firms respond to both forces. Following Berry et al. (1995), I estimate a random-coefficients logit model of demand. I allow households to differ in their price sensitivity and preferences for EVs, using the household survey data to discipline this heterogeneity. Firms compete in prices, and I recover marginal costs from their pricing decisions. I then use a difference-in-differences design to estimate the marginal-cost spillover from Tesla's local component sourcing. Specifically, I compare marginal-cost changes before and after local production began between rival EV models that share suppliers with Tesla's Shanghai plant and those that do not, separately for core EV parts such as traction batteries and electric drives and for general parts such as seats and tires. This shows whether the spillover lowers

[4] Throughout, "entry" refers to Tesla's start of local production and component sourcing in Shanghai in late 2019, not its earlier entry through imports, which began in 2013.

[5] A BEV runs only on electricity. A PHEV combines a gasoline engine with a smaller battery. Among cars in the registration data for 2020–2022, the average PHEV battery was 15 kWh, about one-third of the average BEV's 49 kWh. An extended-range EV is driven only by its electric motor and uses a small gasoline engine to recharge the battery. PHEVs and extended-range EVs accounted for 24 percent of EV registrations over the same period. Because Tesla sells only BEVs, its designs and the battery and electric-drive suppliers it shares with rivals bear most directly on rivals' BEVs.

or raises rivals' marginal costs, and through which parts. I measure a rival model's exposure to Tesla's suppliers by whether it shares at least one supplier with Tesla's Shanghai plant for the same part and by how many it shares. Identification is supported by evidence that exposure was largely predetermined and that exposed and unexposed rival models followed similar cost paths before local production began.

Firms also decide whether to introduce new BEV and gasoline models, anticipating the profits they would earn under price competition. Following the literature on endogenous product offerings (Eizenberg, 2014; Wollmann, 2018; Fan and Yang, 2020), I estimate the fixed costs of introducing new models with revealed-preference moment inequalities (Pakes et al., 2015; Dickstein and Morales, 2018), together with restrictions that match the frequency of new-model introductions.[6] I allow these fixed costs to depend on product and firm characteristics and on a product's similarity to Tesla's locally produced models. Guided by the descriptive patterns, I measure this similarity by size class. The estimates show whether introducing BEVs similar to Tesla's became cheaper after Tesla began local production, relative to smaller BEVs and to gasoline models of the same sizes, which Tesla does not sell.

The demand estimates reveal substantial heterogeneity in households' price sensitivity and preferences for EVs. Higher-income households are less price sensitive and more willing to buy EVs, and the estimated substitution patterns indicate that Tesla competes more closely with rival EVs than with gasoline cars.

The supply estimates show reductions in both the marginal costs of production and the fixed costs of product introduction. After Tesla began local production, the marginal costs of rival EV models sharing core-part suppliers with its Shanghai plant fell by about 19 percent relative to those of other rival EVs. For the fixed cost of introducing new models, the estimates imply a 56 to 68 percent decline for BEVs in Tesla's size classes, or Tesla-size BEVs, relative to smaller BEVs and to gasoline models of the same sizes. These fixed-cost estimates reflect a sharp shift in rivals' new BEV offerings toward Tesla's size classes after 2019, beyond what changes in profits explain.[7]

Combining the demand and supply estimates, I use counterfactual simulations to quantify the welfare effects of Tesla's local production and sourcing. The reference is a 2020–2022 market in which Tesla continues to import but does not produce or source locally. I separate two effects. The competition effect adds Tesla's Shanghai-built models while holding rivals' costs fixed. The supply-side spillover effect is the additional effect of lowering rivals' marginal costs and fixed costs of introducing new models by their estimated reductions. I compute

[6] As in Crawford et al. (2018) and Luo (2024), I take a revealed-preference approach with a parametric disturbance, which gives the probability of each product introduction decision.

[7] Computed profits come from the estimated demand and pricing model and account for changes in demand, marginal costs, subsidies, and the products on sale, including Tesla's.

each effect in two cases. With offerings fixed, rivals keep their observed products and adjust only prices.[8] In full equilibrium, rivals also choose which products to offer, and both cost reductions can change their offerings.

Tesla's local production and sourcing benefit consumers and, in aggregate, domestic producers. In full equilibrium and at the upper-end estimate of a 68 percent decline in fixed costs, domestic welfare rises by RMB 170.2 billion per year over 2020–2022: consumer surplus rises by RMB 160.6 billion, and domestic producers' profits, net of the fixed costs of introducing new models, rise by RMB 9.6 billion.[9] The producer gain is unevenly distributed. Net profits rise by RMB 24.7 billion for EV start-ups but fall by RMB 10.7 billion for established Chinese automakers, whose variable profits fall and spending on new models rises; joint ventures (JVs) and other foreign automakers producing in China also lose. Start-ups gain for two reasons: more of their EV sales come from models that share core-part suppliers with Tesla and therefore had lower marginal costs, and a larger share of their BEV sales is in Tesla's size classes, where introducing new models became cheaper.

Supply-side spillovers account for about 70 percent of the domestic welfare gain, and competition from Tesla's Shanghai-built models for the rest. The two forces also push rivals' product offerings in opposite directions. Competition from Tesla's models alone reduces rivals' new product offerings by 1.4 per year, whereas the spillovers more than offset this drop, resulting in a net increase of 14.2 per year, or 32 percent, mostly in Tesla-size BEVs.

Rivals' product responses shift the domestic welfare gain from producers to consumers. With offerings fixed, consumer surplus rises by RMB 126.6 billion and domestic producers' net profits by RMB 46.0 billion. In full equilibrium, consumer surplus rises by RMB 160.6 billion, about 27 percent more, while domestic producers' net profits rise by only RMB 9.6 billion. Producers gain less because the additional models are costly to introduce and compete with one another and with Tesla. Domestic welfare changes little, from RMB 172.7 billion to 170.2 billion.[10]

The results above attribute the full 68 percent decline in fixed costs to Tesla's local pro-

[8]Lower marginal costs then change rivals' prices and variable profits, and lower fixed costs only reduce the cost of introducing their observed products. Section 7 gives the details.

[9]Domestic welfare includes the profits of firms producing in China other than Tesla, including joint ventures and foreign-owned producers. It excludes the profits of Tesla and importers, as well as government spending and revenue. Each year's changes in consumer surplus and variable profits are valued over 15 quarters, the median sales life of an EV model. Appendix I.3 states the time horizons and accounting methods.

[10]How competition and supply-side spillovers balance depends on market conditions, such as demand, rivals' product mix, and rivals' exposure to Tesla's suppliers. When Tesla's locally produced line-up is moved two years earlier, to 2018–2020, a period when the Chinese EV market was much smaller, domestic welfare still rises, but competition outweighs the marginal-cost spillover and rivals introduce fewer new products. Section 7.2 summarizes this exercise, and Appendix K reports it in full.

duction and sourcing and thus give the upper end of the effects on offerings and welfare. At the lower-end estimate of a 56 percent decline, the results barely change: rivals' new product offerings rise by 13.8 per year and domestic welfare by RMB 168.5 billion. Even if Tesla caused none of the fixed-cost decline, offerings rise by 6.3 per year and domestic welfare by RMB 143.4 billion, about 84 percent of the main estimate. In each case, supply-side spillovers account for about two-thirds of the welfare gain and more than offset competition's effect on offerings, and rivals' product-offering responses again shift the gain toward consumers.

This study contributes to three strands of literature. The first studies how multinational production affects host-country firms and industrial development. Foreign entry can upgrade local suppliers (Rodríguez-Clare, 1996; Markusen and Venables, 1999; Javorcik, 2004; Alfaro-Ureña et al., 2022), and these benefits can extend to other domestic firms through shared suppliers (Blalock and Gertler, 2008; Kee, 2015). At the same time, stronger competition can hurt domestic firms (Aitken and Harrison, 1999; Atkin et al., 2018). In Chinese autos, Bai et al. (2025) document know-how spillovers from JVs to affiliated domestic partners. I add to this literature in two ways. First, I provide evidence on the shared-supplier channel, using marginal costs recovered from the pricing model to estimate how exposure to the entrant's suppliers affects rivals' production costs. Second, I estimate spillovers that reduce the fixed costs of introducing new products similar to the entrant's.

The second literature studies how competition and technology shape firms' product offerings and welfare. Product choices respond to upstream innovation and changes in market structure (Eizenberg, 2014; Wollmann, 2018; Fan and Yang, 2020, 2025), and new products are an important source of consumer gains (Petrin, 2002). Supply relationships also affect variety: Crawford et al. (2018) show how vertical integration changes which television channels distributors carry and the resulting welfare effects. Chatterjee et al. (2026) study how foreign competition affects product offerings through spillovers across complementary markets. I study how a single entrant shapes rivals' offerings through two opposing forces within the same market: competition from its products and spillovers that lower rivals' production costs and the cost of introducing new models. Comparing fixed with endogenous product offerings then shows how product adjustment changes the welfare effects of entry.

The third literature evaluates automobile and EV policies. Studies examine trade restrictions and multinational production (Goldberg, 1995; Berry et al., 1999; Head and Mayer, 2019). Other work evaluates fuel economy standards and how firms adjust vehicle attributes in response (Klier and Linn, 2012; Leard et al., 2023), as well as purchase subsidies, charging infrastructure, and EV attributes (Springel, 2021; Remmy, 2026; Barwick et al., 2024; Wang and Xing, 2024). Recent work also studies battery learning, domestic-content incentives,

and changes in global product offerings (Barwick et al., 2025; Allcott et al., 2024; Sabal, 2026). I complement this work by quantifying the welfare effects of a foreign entrant's local production and sourcing in China's EV market, incorporating the less-studied response of rivals' new product introductions. The results inform policies that attract foreign producers and encourage local sourcing: their effects extend beyond the entrant to domestic rivals and consumers, through both competition and supply-side spillovers.

The rest of the paper is organized as follows. Section 2 describes the institutional setting and the data. Section 3 documents the growth of the EV market, Tesla's position, rivals' shared suppliers, and changes in rivals' product offerings. Section 4 presents the model, Section 5 explains estimation and identification, and Section 6 reports the estimates. Section 7 quantifies the welfare effects of Tesla's local production and decomposes them by channel, and Section 8 concludes.

2 Institutional Setting and Data

2.1 From joint ventures to Tesla's wholly owned Shanghai plant

Following the Chinese economic reform in 1978, foreign carmakers could produce vehicles in China only through JVs with a Chinese partner, and could own at most 50 percent of the venture. The policy was designed to bring in foreign technology and capital, and the ownership cap was meant to protect the domestic industry from hold-up by foreign carmakers. In 1983, American Motors Corporation (AMC, later acquired by Chrysler) and Beijing Automobile Works (now part of BAIC Group) agreed to form Beijing Jeep Corporation, China's first automotive joint venture. Over the following two decades, many foreign carmakers formed JVs with Chinese partners, including Volkswagen with Shanghai Automotive Industry Corporation (SAIC) and First Automobile Works (FAW), Ford with Changan Automobile, General Motors with SAIC, and Toyota with Guangzhou Automobile Industry Group (GAC).

With China's admission to the World Trade Organization in 2001, lower tariffs, and a growing middle class, the car market grew rapidly. In January 2007, China surpassed Japan to become the world's second-largest vehicle market, after the United States, and in 2009 it became the largest, a title it has held ever since. Yet foreign carmakers still dominated domestic car sales, and Chinese automakers' exports remained small.

Given foreign carmakers' advantage in conventional vehicles, the Chinese government began promoting new-energy vehicles (NEVs) in the early 2010s to advance independent innovation and build a new competitive advantage. In the policy documents, an NEV is mainly a BEV or a PHEV, together with other electric vehicles such as extended-range EVs. From

2010, the central government provided purchase subsidies, paid as rebates through manufacturers. By 2020, cumulative subsidies exceeded RMB 150 billion, with rebates covering up to 60 percent of a vehicle's price (The Paper, 2023). Between 2013 and 2018 the subsidy was linked more tightly to electric range and battery energy density, and the payments were gradually reduced. The nationwide cash purchase subsidy was phased out from 2019 and ended on December 31, 2022. The government's stated goal was to move the EV industry from subsidy-driven to market-driven growth.

Around the same time, China also lifted the JV cap. On April 17, 2018, the National Development and Reform Commission (NDRC) announced that foreign ownership limits on automakers would be phased out over five years, in order to open the market, ease trade barriers, and promote competition and innovation. On July 28, 2018, China lifted the foreign ownership restriction on EV production. The liberalization later extended to commercial and passenger vehicles, and some JVs in conventional vehicles, such as BMW Brilliance, gained majority foreign ownership.

Tesla was the first carmaker to take advantage of this liberalization. It had entered the Chinese market in late 2013, initially selling only high-priced imports. The Model S started at RMB 734,000, about 50 percent above its U.S. price (Chinanews, 2022; CNBC, 2014). On July 10, 2018, shortly before the ownership cap was lifted, Tesla signed an agreement with the Shanghai government to build a wholly owned plant in Lingang. This was Tesla's first factory outside the United States and China's first wholly foreign-owned car plant. The Shanghai government described it as the city's largest foreign manufacturing project and pledged full support for its construction (Xinhua, 2018). Construction began on January 7, 2019, and Tesla delivered the first locally produced Model 3, a mid-size sedan, on December 30, 2019. The locally produced Model Y, a mid-size SUV, followed in 2021. In early 2021, starting prices were approximately RMB 250,000 for the Model 3, after purchase subsidies, and RMB 340,000 for the Model Y (Securities Times, 2021; Reuters, 2020). These substantially lower prices let Tesla reach a wider set of consumers and compete directly with major domestic EV makers.

2.2 Tesla's local sourcing

Tesla's Shanghai plant sources extensively from local component suppliers. Its battery suppliers included CATL and LG Energy Solution's Nanjing plant, and its electric-drive supplier was Huayu, a subsidiary of SAIC. In September 2022, Tesla vice president Grace Tao said the localization rate of the Shanghai plant's supply chain had reached 95 percent. Suppliers were concentrated in Shanghai, Suzhou, Ningbo, Nantong, and other cities in the Yangtze

River Delta. She said the rise in localization had raised production efficiency and cultivated a group of capable suppliers for the industry (Chinanews, 2022). In November 2023 she said that the localization rate of parts was above 95 percent, that Tesla had signed more than 400 local tier-1 suppliers, and that more than 60 of them had entered its global supply chain. She described Tesla's success in China, in a larger sense, as the success of China's supply chain (China Daily, 2023).

2.3 Data sources

I build a comprehensive database of new-car registrations from 2017 to 2023, vehicle characteristics and prices, model-level component suppliers, purchase policies, and household demographics. I do so by combining multiple data sources.

New-car registrations. Quantities come from compulsory insurance records covering every new private car registered in China from 2017 to 2023, by month, province, and vehicle model.[11] There were 134.3 million registrations in all. I aggregate registrations to quarters to measure product-level quantities in each provincial market. The registration histories also identify when individual models first appear and when they cease to be sold.

Vehicle characteristics and prices. I collect vehicle characteristics and manufacturer's suggested retail prices (MSRPs, or guide prices) from Autohome.cn, a major public source of car attributes in China. For each trim, I collect the MSRP, size, segment, electric range, battery capacity, fuel consumption, horsepower, curb weight, and wheelbase. Autohome assigns each model to a segment that combines size and body style, such as a compact SUV or a mid-size sedan. Body styles are sedans, SUVs, MPVs, and light commercial vehicles. Pooling sedans and SUVs of the same size, I group segments into four size classes: Small, Compact, Mid, and Upper-mid. I link trims to registrations by vehicle name, model year, and powertrain.

Policy. Central purchase subsidies and purchase-tax rules come from the published national schedules.[12] Local purchase subsidies are coded from provincial and city policy notices

[11] Guo and Xiao (2023) and Wang (2026) use the same records.

[12] See Ministry of Finance, Ministry of Science and Technology, Ministry of Industry and Information Technology, and National Development and Reform Commission (2016); Ministry of Finance, Ministry of Industry and Information Technology, Ministry of Science and Technology, and National Development and Reform Commission (2018, 2019, 2020b,a, 2021); Ministry of Finance and State Administration of Taxation (2016).

as a share of the central subsidy, by province, period, and powertrain, with cities weighted by their sales.

Suppliers. Component-supplier relationships come from MarkLines, which lists, for each car model, the suppliers of its main components: EV-specific components, such as traction batteries and electric drives, and general parts, such as seats and tires. Matching these suppliers with those of Tesla's Shanghai plant shows which rival models share a supplier with Tesla, and for which components. This allows me to compare the effects of sharing Tesla's suppliers across types of components.

Households. The number of family households each year comes from the National Bureau of Statistics, and province population shares from the 2020 census (National Bureau of Statistics of China, 2021). Household income and car purchases come from the China Family Panel Studies (CFPS; Xie and Hu, 2014). I use waves 2016 to 2022. The survey provides the household income distribution and information on how car purchases vary with income; the household counts determine the number of potential buyers in each market.

2.4 Products, prices, and markets

Demand products. A product in the demand model is a combination of operating entity, model, segment, powertrain, import status, and a band of electric range (for EVs) or engine displacement (for gasoline cars). The operating entity is the enterprise on the registration record. Powertrains are BEV, PHEV, extended-range EV, and gasoline. I refer to BEVs, PHEVs, and extended-range EVs together as EVs. The demand sample contains 10,002 national product-quarters, covering 269 gasoline products, 316 BEVs, and 147 PHEVs and extended-range EVs. These products account for 78 percent of total registrations. Appendix A describes how the products are built and which of them enter the sample.

Firms. A firm is the domestic group or the JV that sells the product. It sets prices and chooses which products to offer.[13] I distinguish three firm types: established Chinese automakers, such as BYD, Geely, SAIC, and Changan; EV start-ups, such as NIO, XPeng, Li Auto, and Leapmotor; and JVs and other foreign automakers producing in China, such as FAW–Volkswagen, SAIC–GM, and GAC–Toyota. Established Chinese automakers are firms with an earlier vehicle business, together with the EV brands they own, such as Geely's

[13]Each demand product has one operating entity, and each operating entity belongs to one firm. A firm can include several operating entities: 15 of the 71 firms in the demand sample do. The same model can then be more than one demand product. The imported Lexus ES, for example, is registered under two Toyota enterprise names and enters as two products, while one firm sets its price.

Zeekr and GAC's Aion. EV start-ups are new EV-focused passenger-car makers outside these established groups. Appendix A.1 gives the classification rules, and Table A1 lists the five largest firms in each group.

Prices. I use MSRPs, as is standard in this literature (Barwick et al., 2024; Grieco et al., 2024). Let P^c_{jt} be the national consumer price of product j in quarter t. It equals the MSRP minus the central purchase subsidy S_{jt} plus the vehicle purchase tax T_{jt}. The subsidy S_{jt} is the per-car central purchase subsidy for product j in quarter t under the national subsidy schedule, and it is zero for gasoline cars. The purchase tax T_{jt} is zero for BEVs, PHEVs, and extended-range EVs. For a gasoline car the statutory rate is 10 percent of the MSRP, and 7.5 percent in 2017 if the engine is at most 1.6 liters. The consumer price in province m, P_{jmt}, also subtracts the local subsidy L_{jmt}. The firm price, P^f_{jt}, adds the central subsidy back and removes the purchase tax:

$$P_{jmt} = P^c_{jt} - L_{jmt}, \qquad P^f_{jt} = P^c_{jt} + S_{jt} - T_{jt}. \tag{1}$$

I use the consumer price P_{jmt} in demand and the firm price P^f_{jt} in profits and in recovering marginal costs. I hold S_{jt}, T_{jt}, and L_{jmt} fixed when the firm changes its price. The local subsidy is zero for gasoline cars and after June 25, 2019.[14]

Markets. A market is a province in a quarter: 31 provinces and 28 quarters give 868 markets. The size of a market is one quarter of the national number of family households, split across provinces by their 2020 population shares:

$$M_{mt} = \tfrac{1}{4}\, H_{y(t)} \times \frac{\text{Pop}^{2020}_m}{\sum_{m'} \text{Pop}^{2020}_{m'}}, \tag{2}$$

where H_y rises from 445.7 million households in 2017 to 486.0 million in 2022 (482.4 million in 2023). The outside option is not buying a new car in the quarter.

Summary statistics. Table 1 summarizes the national product-quarters in the demand sample. Gasoline cars have an average MSRP of RMB 170,900. BEVs have an average MSRP of RMB 197,600, an electric range of 377 km, and a battery capacity of 50 kWh. PHEVs and extended-range EVs are more expensive on average, at RMB 321,900, and have shorter electric ranges and smaller batteries: 78 km and 16 kWh, respectively. These averages partly reflect which models are in each group. BEVs include many low-priced microcars;

[14] Among EV sales, 78 percent received a positive local subsidy in 2017, 64 percent in 2018, and 36 percent in the first half of 2019.

Table 1: Summary statistics: demand sample

	Gasoline		BEV		PHEV/EREV	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Quarterly registrations	16,395	17,264	3,250	9,768	2,689	7,993
MSRP (RMB 10,000)	17.09	10.50	19.76	16.25	32.19	26.52
Central subsidy (RMB 10,000)	0.00	0.00	1.14	1.27	0.62	0.68
Local subsidy (RMB 10,000)	–	–	0.18	0.46	0.07	0.20
Footprint (m^2)	8.38	0.63	7.60	1.58	8.92	0.56
Horsepower	158.0	44.0	169.3	140.9	167.1	100.6
Curb weight (kg)	1,470	232	1,561	465	1,907	284
Electric range (km)	–	–	376.8	142.2	78.0	41.7
Battery capacity (kWh)	–	–	50.3	22.5	16.4	8.2
Fuel consumption (L/100 km)	6.65	0.93	–	–	2.30	1.94
Product-quarters	5,578		2,991		1,433	
Distinct products	269		316		147	

Notes: One observation is a national product-quarter in the demand sample. Local subsidies are registration-weighted across provinces. EREV denotes an extended-range EV.
The demand sample contains 10,002 product-quarters and 732 distinct products.

excluding microcars and microvans raises their average MSRP to RMB 234,900. The mean for PHEVs and extended-range EVs is elevated by high-priced imported models. Among models produced in China, the average is RMB 257,900. Average central subsidies are RMB 11,400 for BEVs and RMB 6,200 for PHEVs and extended-range EVs. The corresponding local subsidies average RMB 1,800 for BEVs and RMB 700 for PHEVs and extended-range EVs.

3 Descriptive Evidence

Before presenting the model, I describe EV market shares, Tesla's competitive position, its supplier relationships with rival producers, and changes in rivals' product offerings around the start of Tesla's local production.

3.1 The EV market and Tesla's position

Figure 1 shows that EVs grew from a niche to nearly a third of the new-car market within a few years. The EV share of new private-car registrations rose from 1.6 percent in 2017 to 30.1 percent in 2023, when 5.6 million EVs were registered. Tesla began producing cars in Shanghai and sourcing components locally when EVs still accounted for a small share of new-car registrations in China.

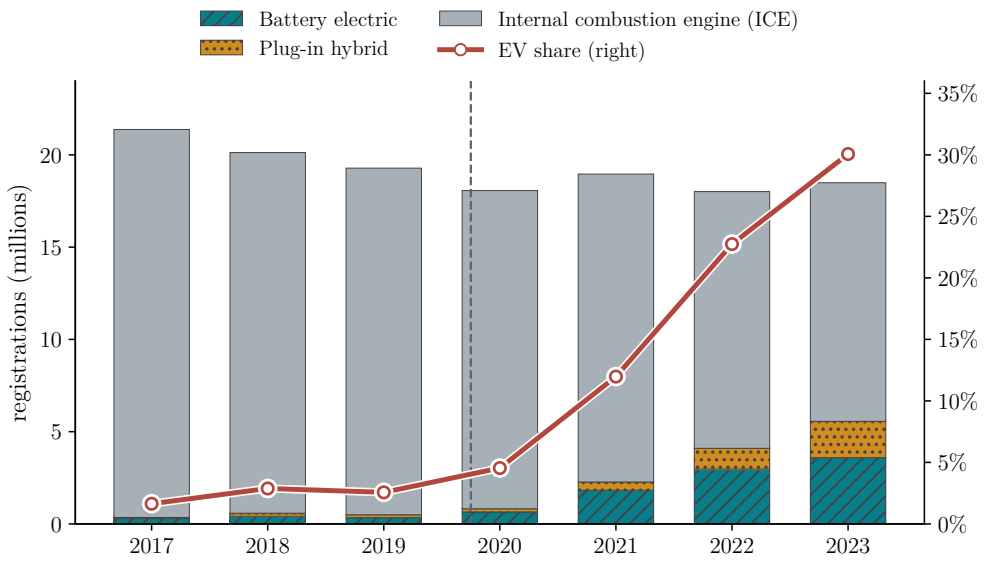


Figure 1: New private-car registrations and the EV share, 2017–2023

Notes: Bars are annual new private-car registrations by powertrain; the line is the EV share (right axis). EVs are BEVs, PHEVs, and extended-range EVs. The sample covers all 134.3 million registrations in the registration panel. The dashed line marks Tesla's first China-built deliveries (December 2019).

Figure 2 shows Tesla's position: with very few models, it competes directly with domestic EV makers in mainstream segments. It accounted for 15.4 percent of EV registrations in 2020 and about 9 percent in 2022 and 2023. In 2023 it sold two model lines, about 260,000 cars per line, four times BYD's average of about 62,000; the Model Y was China's best-selling car of any powertrain that year. Tesla's domestic rivals grew differently, by introducing many models.

3.2 Rivals' shared suppliers

Tesla's Shanghai plant shares many suppliers with rival automakers producing in China. Among the 105 rival EV models with a known battery maker, 54 share a battery or electric-drive supplier with the Shanghai plant. These models come from 24 makers, and the overlap runs primarily through CATL, which supplies 46 of them. Other shared suppliers include Huayu, LG Energy Solution's Nanjing plant, and Joyson. The overlap is relatively stable over time, with few rival models switching into or out of the group using Tesla's suppliers. It provides a channel through which Tesla's local production can affect rivals' production costs.

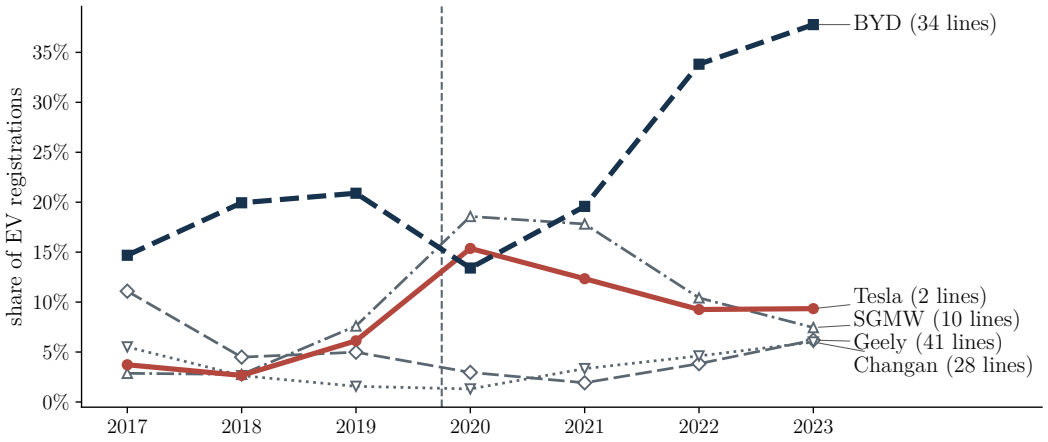


Figure 2: Shares of EV registrations: Tesla and the largest domestic EV makers
Notes: Each line is a firm's share of EV registrations. The number of model lines (model × powertrain) sold in 2023 is in parentheses. SGMW is SAIC–GM–Wuling. The dashed line marks Tesla's first China-built deliveries.

3.3 New product offerings in Tesla's size classes

After Tesla began local production, rivals shifted their new BEV offerings toward Tesla's size classes, while their gasoline offerings showed no such shift. I call the Mid and Upper-mid classes, where the Model 3 and Model Y mainly compete, *Tesla size*, and the Small and Compact classes *smaller sizes*. A model is a firm–nameplate–powertrain combination.

Figure 3 documents the shift using observed introduction rates and annual regression comparisons. Figure 3(a) focuses on the annual decision modeled in Section 4.4: whether a firm introduces a new model of a given size class and powertrain. A *potential product* is defined by the firm, size class, powertrain, and year; it is introduced if the firm brings at least one new model in that size class and powertrain to market during the year. The *new-model introduction rate* is the share of potential products introduced.[15] Pooling the years before 2020 and from 2020 onward, the Tesla-size BEV introduction rate rose from 2.7 to 8.5 percent, while the rate for smaller BEVs fell from 15.5 to 9.6 percent. By 2022, the annual Tesla-size BEV introduction rate reached 12.5 percent, exceeding the 7.5 percent rate for smaller BEVs. Gasoline introduction rates declined in both size groups, with no similar shift toward Tesla's size.

I also estimate the probability that a potential product is introduced, using Poisson pseudo-maximum likelihood. The model controls for persistent differences in firms' intro-

[15]The sample contains 2,427 potential products of 88 firms in 2018–2022. In each year in which it sells any car, a firm has a potential BEV product in each size class, and in each year in which it sells a gasoline car, it also has a potential gasoline product in each size class. Appendix F gives the construction rules.

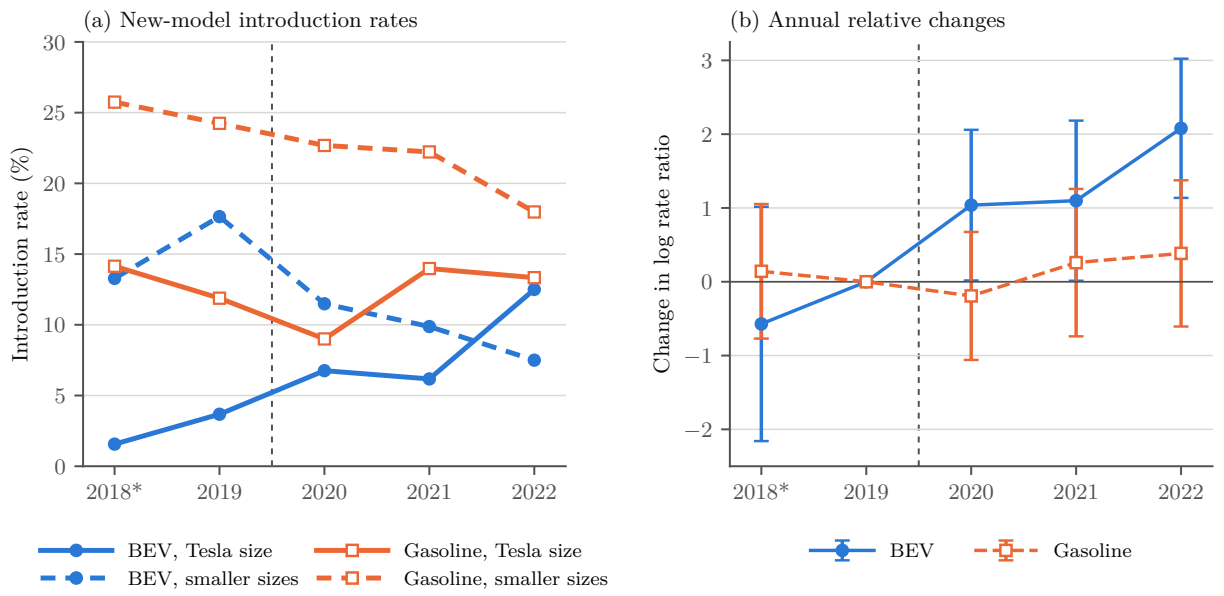


Figure 3: New-model introductions around Tesla's local production

Notes: Panel (a) is the share of potential products with at least one new model of 100 or more first-year registrations; multiple new models count once (2,427 potential products, 88 firms). Panel (b) is the change from 2019 in the log ratio of Tesla-size to smaller-model introduction rates, for BEVs and for gasoline models (1,581 potential products, 57 firms). The gap between the two series is the triple difference in Table 2. Bars are 95 percent confidence intervals, clustered by firm. Tesla size is Mid and Upper-mid. *2018 covers 2018Q2–Q4. The dashed line marks Tesla's first China-built deliveries in December 2019.

duction rates and for common changes over time:

$$\mathbb{E}[d_{fcey} \mid f, c, e, y] = \exp\left(\alpha_{fe} + \gamma_{ec} + \lambda_{ey} + \sum_{s \in \{2018,2020,2021,2022\}} \theta_{es}\, \text{Near}_c\, \mathbf{1}\{y = s\}\right). \quad (3)$$

Here d_{fcey} equals one if firm f introduces at least one new model in size class c and powertrain e during year y, and zero otherwise. The indicator Near_c identifies Tesla's size classes, and e denotes BEVs or gasoline models. Firm–powertrain fixed effects α_{fe} account for persistent differences in firms' introduction rates. Powertrain–size-class fixed effects γ_{ec} capture systematic differences across sizes, while powertrain–year fixed effects λ_{ey} absorb annual changes common to all sizes of a powertrain. Standard errors are clustered by firm.

Figure 3(b) plots the coefficients θ_{es}. Each coefficient measures how the log ratio of Tesla-size to smaller-model introduction rates changed from 2019, the reference year. A positive coefficient indicates a shift toward Tesla's size classes. The BEV coefficients are 1.0 in 2020, 1.1 in 2021, and 2.1 in 2022: relative to 2019, the ratio of Tesla-size to smaller-BEV introduction rates roughly tripled in 2020 and 2021 and rose about eightfold by 2022. Gasoline models show no statistically significant shift toward Tesla's size.

Table 2: Changes in new-model introduction rates at Tesla's size

Comparison	Estimate
BEV: Tesla size × post	1.650
	(0.395)
Gasoline: Tesla size × post	0.080
	(0.342)
Triple difference: BEV minus gasoline	1.570
	(0.476)

Notes: Poisson estimates of the post-2019 change in the Tesla-size introduction rate relative to smaller sizes, separately by powertrain. The regression includes firm × powertrain, powertrain × size class, and powertrain × year fixed effects, using 1,581 potential products of 57 firms, which include all 301 introduced potential products. Standard errors, clustered by firm, are in parentheses.

To summarize the shift in a single estimate, Table 2 replaces the annual interactions with one interaction for the pooled period 2020–2022, using the same fixed effects and 2018–2019 as the reference period. This before-and-after comparison matches the fixed-cost model in Section 5.3. For BEVs, the ratio of Tesla-size to smaller-model introduction rates increased by a factor of about 5.2, with no comparable shift for gasoline models. The difference between the two powertrains is statistically significant.

Tesla-size BEV introduction rates also rose in all three firm types: from 2.8 to 8.6 percent among established Chinese automakers, from 6.0 to 9.9 percent among EV start-ups, and from zero to 6.5 percent among JVs and other foreign automakers.

The shift in introductions changed the mix of models on sale. Among firms producing in China, excluding Tesla and the five luxury makers defined in Section 4.4, Tesla-size BEV models on sale nearly quadrupled, from 14 in 2019 to 55 in 2022, and reached 78 in 2023. Smaller BEV models rose from 92 in 2019 to 137 in 2021 and then fell to 100 in 2023. Over 2019–2022, Tesla-size PHEV models rose from 18 to 25, while Tesla-size gasoline models stayed between about 140 and 155.

3.4 Attribute improvements through changes in product offerings

Average attributes of the BEVs on sale improved mainly through new models rather than through changes in continuing models. Between 2019 and 2022, the average electric range across rival BEV models on sale rose from 354 to 454 km, and their average footprint from 7.88 to 8.39 square meters. Among the 68 models sold in both years, electric range rose much

less, from 366 to 384 km, and footprint also changed little, from 7.95 to 7.96 square meters. Changes within these continuing models account for only about 7 percent of the 2019–2022 increase in average electric range across all rival BEV models on sale and 1 percent of the increase in their average footprint. Most of the change therefore came from the composition of models on sale: new models had longer electric ranges and larger footprints than the models they replaced. Appendix Table B1 reports the full comparison.

These patterns support treating new product offerings as the main margin of adjustment, while holding the characteristics of continuing models fixed. New models also improved on earlier models in the same size class, with longer electric ranges and larger batteries. In the empirical model of Section 4, potential products take their characteristics from new models in the same size class introduced around the same time, and thus reflect these improvements. Section 5.3 describes this construction.

4 Empirical Model

In this section, I develop a model of demand, pricing, and new product offerings to quantify the mechanisms behind the patterns in Section 3, Tesla's contribution to them, and their welfare implications for consumers and firms. Following the product-entry models of Eizenberg (2014), Wollmann (2018), and Fan and Yang (2020), the model has three stages.

In the first stage, at the start of each year, firms simultaneously choose their new product offerings. A potential product is an introduction opportunity defined by firm, size class, powertrain, and year. I treat existing product portfolios and their observable characteristics, subsidy schedules, and market size as known to all firms. Firms also know the fixed cost of each potential product and the distributions of the subsequent demand and marginal-cost shocks, but not their realizations. In the second stage, the shocks are realized and observed by firms each quarter, and firms set national prices. In the third stage, households in each province choose which car, if any, to buy. I describe the model in reverse order, starting with household demand, followed by pricing and product offering decisions.

4.1 Demand

Household i in province m and quarter t chooses among the products on sale in that market, $\mathcal{J}_{mt}$, and the outside option of not buying. Utility from product j is

$$u_{ijmt} = \delta_{jmt} - \alpha_i P_{jmt} + \left(\sigma_{\text{EV}}\,\nu_{1i} + \pi_{\text{EV}}\,y_i\right)\text{EV}_j + \sigma_0\,\nu_{2i} + \varepsilon_{ijmt}, \tag{4}$$

where the mean utility δ_{jmt}, common to all households in the market, is

$$\delta_{jmt} = x'_{jt}\beta^d + \mu_{g(j)} + \mu_t + \lambda_m + \lambda_m^{\text{EV}} \text{EV}_j + \xi_{jmt}. \tag{5}$$

The mean utility of the outside option is normalized to zero. The indicator EV_j equals one for BEVs, PHEVs, and extended-range EVs. The price P_{jmt} is the consumer price in Equation (1), the MSRP net of the central and local subsidies and inclusive of the purchase tax. The term ε_{ijmt} is an idiosyncratic shock, assumed to have an i.i.d. type-I extreme value distribution.

The mean utility includes a rich set of demand shifters, following the literature on the Chinese EV market (e.g., Barwick et al., 2024): product characteristics x_{jt} and fixed effects. The characteristics in x_{jt} are footprint (length $\times$ width), log electric range for BEVs,[16] fuel consumption, horsepower per kilogram, an EV time trend, and the log of the share of the quarter in which the product was on sale.[17] The fixed effects absorb several sources of unobserved demand shocks. The firm $\times$ segment $\times$ fuel type effect $\mu_{g(j)}$ captures persistent differences in brand appeal and in a firm's positioning within each segment and powertrain. The quarter effect μ_t absorbs changes in nationwide market conditions that affect all products, such as aggregate demand and seasonality. The province effect λ_m captures persistent differences across provinces in the propensity to buy a car. The province $\times$ EV effect λ_m^{EV} absorbs persistent differences in the local appeal of EVs beyond income, including those associated with license-plate rules and charging infrastructure. Finally, ξ_{jmt} is the remaining unobserved demand shock for product j in province m and quarter t.

The other terms in Equation (4) let households differ in three ways. First, price sensitivity depends on income,

$$\alpha_i = \exp(\pi_0 + \pi_y y_i) > 0, \tag{6}$$

where y_i is the household's standardized log income. Every household dislikes a higher price. High-income households are less price sensitive if $\pi_y < 0$. Second, the taste for an EV varies randomly across households (σ_{EV}) and with income (π_{EV}). Third, households differ in their taste for buying any car: the term $\sigma_0\nu_{2i}$ shifts the utility of every car relative to not buying. I assume that the draws ν_{1i} and ν_{2i} follow standard normal distributions.

[16] Log electric range is zero for other products and for BEVs in Autohome's microcar and microvan segments, which consist mostly of low-priced city EVs. Within these segments, electric range varies mainly across trim levels of the same car, and longer-range trims also differ in price and equipment. This variation does not isolate the value of electric range. The shifter therefore uses only BEVs in other segments.

[17] The share of the quarter on sale is the number of months with registrations divided by three. New models often reach the market partway through a quarter, and models leaving the market sell for only part of their last quarter. Without this control, their low quarterly sales would be read as low appeal.

I specify the household-specific utility as

$$\mu_{ijmt} = -\alpha_i P_{jmt} + \Big(\sigma_{\text{EV}}\,\nu_{1i} + \pi_{\text{EV}}\,y_i\Big)\,\text{EV}_j + \sigma_0\,\nu_{2i}, \tag{7}$$

which gives total utility $u_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt}$. Integrating over the extreme-value shocks, household i's choice probability is

$$s_{ijmt} = \frac{\exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{k \in \mathcal{J}_{mt}} \exp(\delta_{kmt} + \mu_{ikmt})}. \tag{8}$$

The product's market share is the average of these probabilities over the distribution of income and taste draws,

$$s_{jmt} = \int s_{ijmt}\, dF(y, \nu). \tag{9}$$

4.2 Pricing and marginal costs

Following Barwick et al. (2024), I assume that, after observing demand and marginal-cost shocks, each pricing firm f sets a single national firm price P_{jt}^f for each product j in $\mathcal{F}_{ft}$, the set of its products on sale in quarter t, taking its rivals' prices as given. National sales add up demand across provinces, $Q_{jt} = \sum_m M_{mt} s_{jmt}$. The firm solves

$$\max_{\{P_{jt}^f : j \in \mathcal{F}_{ft}\}} \Pi_{ft} = \sum_{j \in \mathcal{F}_{ft}} \Big(P_{jt}^f - c_{jt}\Big) Q_{jt}\Big(\boldsymbol{P}_t^f, \boldsymbol{P}_t^{-f}\Big). \tag{10}$$

Under Nash–Bertrand competition, the first-order condition for each product j is

$$Q_{jt} + \sum_{k \in \mathcal{F}_{ft}} \Big(P_{kt}^f - c_{kt}\Big) \frac{\partial Q_{kt}}{\partial P_{jt}^f} = 0. \tag{11}$$

Given the demand estimates and observed prices, these conditions recover the marginal cost c_{jt}.

To describe how marginal cost varies across products, I regress the log of the recovered costs on product characteristics and fixed effects:

$$\log c_{jt} = w_{jt}'\beta^c + \eta_{f(j)}\text{Gas}_j + \eta_{\text{body}(j)} + \eta_{e(j)} + \eta_{y(t)} + \eta_{q(t)} + \omega_{jt}. \tag{12}$$

The characteristics w_{jt} are footprint, curb weight, wheelbase, battery capacity, log electric range (entered the same way as for demand shifters), fuel consumption, horsepower per kilogram, and engine displacement for models with an engine. The regression also includes firm, body-style (sedan, SUV, MPV, or light commercial vehicle), powertrain, year, and

quarter-of-year fixed effects.[18] The residual ω_{jt} is the unobserved component of marginal cost, the cost counterpart of the demand shock ξ_{jmt}. I estimate Equation (12) by ordinary least squares on the recovered costs.[19]

4.3 Shared suppliers and marginal costs

The marginal costs recovered from pricing make it possible to ask whether Tesla's local production and component sourcing spill over to rival EV models that share its suppliers. As explained in Section 1, Tesla's orders can lower rivals' input costs through suppliers' gains from scale and learning, but capacity constraints or preferential terms for Tesla can instead raise them. Whether Tesla's suppliers lower or raise its rivals' marginal costs is therefore an empirical question.

I estimate that effect with a difference-in-differences design. Among domestic rival EV models, I compare models that share a supplier with Tesla's Shanghai plant for the same part and models that do not, before and after Tesla's first China-built deliveries. The main comparison uses core EV-specific parts, such as traction batteries and electric drives, which account for a large share of an EV's production cost. For a compact BEV in 2020, the battery accounted for an estimated 33 percent of production cost and the electric drive 11 percent (Shaikh and Sharpe, 2023).

I also estimate the effect separately for general parts that are not specific to EVs, such as seats and tires. Comparing the effects of the two types of parts shows which components carry the potential spillover. Tesla's orders were a much larger share of the output of battery and electric-drive suppliers than of general-part suppliers, which mostly sell established products to many automakers. In addition, unlike a traction battery or an electric drive, each general part is a small share of a car's cost. A spillover through suppliers' scale and learning should therefore appear mainly for core EV-specific parts. The comparison also checks for selection: if models that buy from Tesla's suppliers were on a lower cost path for other reasons, their costs could also fall when they share suppliers of general parts with Tesla, not only suppliers of core EV-specific parts.

4.4 Product offerings

At the start of each year, firms observe their fixed costs and simultaneously choose their new product offerings from predetermined sets of potential products. As in Section 3, a *potential*

[18] Firm fixed effects apply only to gasoline models. For EVs, I pool across firms to predict costs for potential products beyond a firm's observed EV line-up. Appendix F.2 explains this choice.

[19] The cost function predicts the costs of potential products, all of which lie in the four size classes. The estimation therefore excludes the low-priced city EVs in the microcar segments.

product $g = (f, c, e, y)$ is an introduction opportunity defined by firm f, size class $c \in \{\text{Small, Compact, Mid, Upper-mid}\}$, powertrain $e \in \{\text{BEV}, \text{Gas}\}$, and year y. Let $\mathcal{G}_{fy}$ denote the set of these opportunities available to firm f in year y, and let $\mathcal{D}_f^y \subseteq \mathcal{G}_{fy}$ denote the subset it chooses to introduce, which I observe in the data. Five JVs and other foreign automakers with an average model price of at least RMB 300,000, which I call luxury makers, have line-ups largely set by their global parents.[20] They set prices like other firms, but I do not model their product offering decisions, so they have no potential products. For each $g \in \mathcal{G}_{fy}$, let $d_g = 1$ if firm f introduces at least one new model in size class c and powertrain e during year y, so that $g \in \mathcal{D}_f^y$, and $d_g = 0$ otherwise. Multiple new models within this combination count as one new product offering; continuing to sell an existing model does not count as a new offering. Appendix F explains how I construct the set of potential products.

Introducing potential product g incurs a one-time fixed cost F_g, counted once regardless of the number of new models introduced. It thus captures the sunk cost of introducing new models within that firm–size–powertrain–year cell.

Log fixed cost has a systematic component, $X_g\beta$, and a disturbance. The systematic component depends on size class, powertrain, firm type, year, and whether Tesla has begun local production. The disturbance is the difference between the model's computed net return from introducing g and the firm's own expected net return. Section 5.3 specifies both.

Let $\mathcal{D}_{-f}^y = (\mathcal{D}_h^y)_{h \neq f}$ collect the other firms' offering choices in year y. Taking these choices as given, firm f selects

$$\mathcal{D}_f^y \in \arg\max_{\mathcal{D} \subseteq \mathcal{G}_{fy}} \left\{ \mathbb{E}_{\xi,\omega}\left[\Pi_f(\mathcal{D}, \mathcal{D}_{-f}^y)\right] - \sum_{g \in \mathcal{D}} F_g \right\}, \tag{13}$$

where Π_f is the present value of the firm's total variable profits, evaluated at the quarterly Nash–Bertrand pricing equilibria in Equation (10). When the firm decides whether to introduce a potential product, its continuing models remain on sale.

The present value of a new model equals its average quarterly incremental profit over the four quarters beginning in its introduction quarter, capitalized over a common 15-quarter horizon at a quarterly discount factor of 0.975. Averaging over a full year removes seasonal variation in profits, and the present value holds this first-year average constant over the horizon. The common horizon is calibrated to a Kaplan–Meier estimate of the median

[20] The five luxury makers are Beijing Benz, BMW Brilliance, Chery Jaguar Land Rover, Dongfeng Infiniti, and Mercedes-Benz.

registration lifetime of domestically produced EV models first observed by 2020Q4.[21]

Firms choose their new product offerings before knowing the demand and marginal-cost shocks their new models will face or how the shocks to existing models will change in future quarters. Therefore, the expectation in Equation (13) averages profits over these unknown shocks. Section 5.3 explains how I compute expected incremental variable profits.

I treat each firm's observed product offerings as a solution to Equation (13), given its fixed costs and rivals' offerings. Following the baseline specifications of Wollmann (2018) and Fan and Yang (2020), I assume no economies or diseconomies of scope in fixed costs. Adding or dropping one potential product therefore leaves the fixed costs of the firm's other offerings unchanged.

Following Pakes et al. (2015), Eizenberg (2014), and Wollmann (2018), I use necessary conditions for equilibrium: no firm can increase its expected profit net of fixed costs by unilaterally adding or dropping a single potential product. For $g \in \mathcal{G}_{fy}$, define its expected incremental variable profit as

$$V_g = \mathbb{E}_{\xi,\omega}\Big[\Pi_f(\mathcal{D}_f^y \cup \{g\}, \mathcal{D}_{-f}^y)\Big] - \mathbb{E}_{\xi,\omega}\Big[\Pi_f(\mathcal{D}_f^y \setminus \{g\}, \mathcal{D}_{-f}^y)\Big]. \tag{14}$$

This compares the firm's total variable profits with and without g, holding all other offering choices fixed; in both, all firms' prices are at the Nash–Bertrand equilibrium for that set of products. For an introduced potential product, this contribution must cover its fixed cost; for one not introduced, it cannot exceed that cost:

$$d_g = 1 \;\Rightarrow\; V_g \geq F_g, \qquad d_g = 0 \;\Rightarrow\; V_g \leq F_g. \tag{15}$$

5 Estimation and Identification

I estimate the model sequentially. First, I estimate demand using aggregate market shares and household-level moments. Second, I recover marginal costs from the first-order conditions of the pricing model and estimate the marginal-cost spillover through shared suppliers. Third, I use observed product offering decisions to estimate fixed costs. Each step takes the estimates from the preceding steps as given.

[21] The lifetime calculation excludes models already on sale at the start of the registration panel, recognizes exit after at least four consecutive quarters without registrations through the end of the panel, and treats models without a verified exit as censored. The common horizon sets the monetary scale of the fixed costs. By comparison, Wollmann (2018, Assumption 1 and Section III.C) compares expected annual incremental profit with sunk cost multiplied by a hurdle rate, identifying sunk costs only up to that rate. The two approaches relate a flow profit to an upfront cost, but use different scaling conventions.

5.1 Demand

The estimation of demand parameters follows the literature (Berry et al., 1995; Petrin, 2002; Berry et al., 2004). I estimate the demand parameters by the generalized method of moments (GMM), combining aggregate share moments with micro moments constructed from the China Family Panel Studies (CFPS). For a candidate value of the nonlinear demand parameters, I invert observed market shares to recover mean utilities and the unobserved demand shocks ξ_{jmt}. The aggregate moments impose

$$\mathbb{E}\Big[\xi_{jmt}(\theta^d)Z_{jmt}\Big] = 0, \tag{16}$$

where θ^d collects the demand parameters and Z_{jmt} contains the six observed characteristics in Equation (5) and four excluded instruments.

Price endogeneity and instruments. Firms set prices after observing ξ_{jmt}, making price positively correlated with the unobserved demand shock. I instrument price with two measures based on the central purchase subsidy and two counts of rival products.

The subsidy instruments exploit the steps and revisions in the national subsidy schedule. The subsidy depends on a product's year, powertrain, and electric-range band; both the payments and the range thresholds changed during 2017–2019. I apply the schedule to each product's initial range to compute its subsidy, and interact this subsidy with its initial battery capacity. I hold both values fixed, and later redesigns therefore do not affect the instruments. Because range enters utility directly, identification comes from the schedule's discontinuities and revisions, not from range itself. The central government sets the schedule nationwide, beyond the control of any individual firm.

The other instruments count rival EV and gasoline products. Following Berry et al. (1995), these counts shift markups: a product with more close substitutes faces more competition and carries a lower markup. In the model, firms choose their product portfolios before the transitory demand shocks are realized, making the product counts predetermined with respect to ξ_{jmt}.

Conditional on the characteristics in x_{jt} and the firm $\times$ segment $\times$ fuel type, quarter, province, and province $\times$ EV effects, I assume all four instruments are uncorrelated with ξ_{jmt}. By shifting consumer prices through subsidies and markups, they help identify average price sensitivity in demand.

Micro moments. Following Petrin (2002) and Berry et al. (2004), I add micro moments from the CFPS to identify how preferences vary with income. For each survey wave $w \in$

$\{2018, 2020, 2022\}$, the model must reproduce two statistics of the households that bought a car: their mean standardized log income, $\mathbb{E}[y_i \mid \text{buy}, w] = \bar{y}_w$, and the slope from regressing the log price paid on income, $\text{Cov}(\log P_{jmt}, y_i \mid \text{buy}, w)/\text{Var}(y_i \mid \text{buy}, w) = b_w$. The left-hand sides are the model's predictions for that year's markets, and $\bar{y}_w$ and b_w are the CFPS values. The first moment disciplines how the propensity to buy a car varies with income, and the second how willingness to pay varies with income. Appendix C describes the CFPS targets and reports the fit of the micro moments.

5.2 Marginal costs and shared suppliers

Given the demand estimates and observed prices, I invert the Nash–Bertrand first-order conditions in Equation (11) to recover c_{jt} for each product in each quarter. I then estimate whether Tesla's local production changed the marginal costs of rival EVs through shared suppliers. The research design is a difference-in-differences comparison between models that share a supplier with Tesla's Shanghai plant and models that do not, before and after Tesla's first China-built deliveries. I make this comparison separately for core EV-specific parts and for general parts.

For rival EV product j, I measure exposure to Tesla's suppliers, Exposed_j^C, in two ways. In the main measure, $\text{Exposed}_j^C = 1$ if j shares at least one supplier of core EV-specific parts with Tesla's Shanghai plant, and 0 otherwise. The core parts are traction batteries and electric drives. In the second, Exposed_j^C is the number of core-part suppliers that j shares with Tesla's Shanghai plant. Let $\text{After}_t = 1$ from 2019Q4, the quarter of Tesla's first China-built deliveries. I estimate

$$\log c_{jt} = \psi \left(\text{Exposed}_j^C \times \text{After}_t \right) + \gamma \log S_{b(j)t} + \phi_{n(j)} + \phi_t + \phi_{k(j)t} + e_{jt}, \tag{17}$$

where $S_{b(j)t}$ is the cumulative output of the battery maker $b(j)$ that supplies j, $\phi_{n(j)}$ is a nameplate $\times$ powertrain effect, ϕ_t is a quarter effect, $\phi_{k(j)t}$ is a battery-size-bin $\times$ quarter effect, and e_{jt} is the error.

The nameplate $\times$ powertrain effects absorb persistent differences across model lines, and the quarter effects absorb cost changes common to all rival EVs. I also include battery-size-bin $\times$ quarter fixed effects to compare models with similarly sized packs in the same quarter. They absorb industry-wide declines in battery prices that differ by pack size. The battery maker's cumulative output absorbs cost reductions from the supplier's overall growth across all its customers. The coefficient ψ therefore measures the additional cost change for models that share Tesla's suppliers. Because Tesla's own purchases add to its suppliers' output, the battery maker's cumulative output may also absorb part of the spillover that works through

suppliers' scale. Section 6.2 shows that the estimates are similar without it.

I also estimate Equation (17) for general parts, such as braking systems (ABS/ESC), cameras, seats, tires, or window glass, with Exposed_j^G defined in the same two ways; Appendix E lists all 16 categories. With either measure, I estimate the equation in two forms, with the same controls and fixed effects: with general-part exposure in place of core-part exposure, and with both in the same regression, so that each estimate controls for the other type of exposure.

The identifying assumption is that, conditional on the controls and fixed effects in Equation (17), the marginal costs of models that share Tesla's suppliers would have followed the same path as the costs of other rival EVs had Tesla not begun local production. Exposure is fixed at the model level: a model is exposed if any of its recorded suppliers also supplies Tesla's Shanghai plant for the same part. Under the identifying assumption, ψ measures the marginal-cost spillover through shared suppliers: a negative ψ means that the marginal costs of models sharing Tesla's core-part suppliers fell relative to those of other rival EVs after Tesla began local production.

Three endogeneity concerns arise in interpreting this comparison as a causal effect. First, rival models may have begun using Tesla's suppliers after it began local production. Shared suppliers would then reflect a response to it rather than prior exposure. Second, cost declines among Tesla's suppliers could also reflect broader changes in the battery industry. Third, Tesla may have chosen suppliers that were already likely to improve, in which case their customers' costs might have fallen even without Tesla's local production.

On the first concern, few rival models switched into Tesla's supplier pool.[22] To check that the estimate does not depend on such switches, I also measure exposure using only supplier records from 2019 or earlier and, separately, exclude models whose shared-supplier links are first recorded from 2020 onward, after Tesla's first China-built deliveries. For the second and third concerns, I control for the battery-size-bin $\times$ quarter effects and the battery maker's cumulative output, which absorb broader declines in battery costs. I also add a separate cost trend for each battery maker, which absorbs differences in cost trends across makers, such as a faster decline at the makers Tesla chose. With these trends, ψ measures a shift in exposed models' costs at 2019Q4 beyond the steady decline that each battery maker's trend captures. An event study tests whether exposed models were already on a different cost path before local production began. The general-part estimates provide a further check on selection: a cost advantage unrelated to Tesla would also appear among models that share

[22] Among the 29 models in the broader cost sample with supplier information both before 2020 and from 2020 onward, 26 have the same supplier-overlap status in both periods; two switch into Tesla's supplier pool and one switches out. Only one switch-in is recorded strictly after Tesla's first recorded use of the shared supplier.

only general-part suppliers with it. Section 6.2 reports these results.

5.3 Fixed costs

I estimate a parametric model of the fixed costs of potential products, combining revealed-preference inequalities with restrictions on introduction frequencies.

The value of a potential product. For every potential product, including those not introduced, I compute a counterpart of its expected incremental variable profit V_g in Equation (14). A potential product leaves the body style and introduction quarter unspecified. I therefore define K_g as its set of up to eight hypothetical designs: a sedan and an SUV, each introduced in one of the four quarters. Each design takes its characteristics from models in the same size class, powertrain, and body style introduced around the same time, and its appeal and marginal cost are predicted from observed products. For a design $k \in K_g$ entering in quarter t,

$$\mathrm{IVP}_k = \frac{1}{4}\sum_{s=t}^{t+3}\frac{1}{256}\sum_{\ell=1}^{256}\Big[\Pi_{fs}\big(\mathcal{J}_s \cup \{k\}\big) - \Pi_{fs}\big(\mathcal{J}_s\big)\Big]_\ell, \qquad \mathrm{PDV}_k = A \cdot \mathrm{IVP}_k, \tag{18}$$

where $\Pi_{fs}(\mathcal{J})$ is the firm's equilibrium variable profit in Equation (10) in quarter s with products $\mathcal{J}$ on sale. The index ℓ denotes one of the 256 draws of the demand and marginal-cost shocks. The first term, IVP_k, is the design's incremental variable profit per quarter, averaged over its first four quarters. Its present value, PDV_k, scales it by A, which capitalizes first-year profit over the horizon in Section 4.4. Appendix F.2 provides more details. I denote the number of designs in K_g by n_g. The value of the potential product is the log of the average present value over these designs,

$$r_g = \log\Big(\frac{1}{n_g}\sum_{k\in K_g}\mathrm{PDV}_k\Big), \tag{19}$$

in log RMB 100 million. It is the counterpart of $\log V_g$, the expected incremental variable profit defined in Equation (14); Equation (21) below relates the two.

Fixed-cost specification. I measure fixed costs in RMB 100 million and specify the systematic part of log fixed cost as

$$\begin{aligned} X_g\beta = \beta_0 + \textstyle\sum_{y' \in \{2018,2020,2021,2022\}} \beta_{y'} \mathbf{1}\{y = y'\} + \beta_N \text{Near}_g \\ + \tau\, \text{Near}_g \times \text{Post}_y \times \text{BEV}_g + \beta_{NP}\, \text{Near}_g \times \text{Post}_y \\ + \beta_G \text{Gas}_g + \beta_{GP}\, \text{Gas}_g \times \text{Post}_y + \beta_{GN}\, \text{Gas}_g \times \text{Near}_g \\ + \beta_{JV} \text{JV}_f + \beta_{SU} \text{StartUp}_f + \beta_S \text{Small}_c + \beta_U \text{UpperMid}_c. \end{aligned} \tag{20}$$

Year effects let fixed costs change over time for every potential product, with 2019 as the omitted year. The indicator Near_g equals one for the Mid and Upper-mid classes, where Tesla's cars mainly compete, and Post_y equals one from 2020, the first full year of Tesla's local production. The indicators BEV_g and Gas_g equal one for a BEV and a gasoline model, respectively. The interaction $\text{Near}_g \times \text{Post}_y \times \text{BEV}_g$ is the term for a Tesla-size BEV after local production begins. EV start-ups, as well as JVs and other foreign automakers, have their own cost levels relative to established Chinese automakers. The Small and Upper-mid classes have theirs relative to Compact and Mid. The base category is an established Chinese automaker's Compact BEV in 2019.

Each term in Equation (20) other than τ removes a source of variation that would otherwise be attributed to τ. The year effects capture changes common to all potential products, such as the market-wide decline in new product offerings in 2020. The Tesla size $\times$ post term captures changes in the cost of introducing a larger model that are common to both powertrains. The gasoline terms let gasoline models differ in level, in their change after 2019, and in their Tesla-size premium. The firm-type and size-class terms capture persistent cost differences across firms and classes.

The parameter of interest is τ, a triple difference in fixed costs. It is the post-2019 change in the cost of introducing a Tesla-size BEV, relative to the same change for smaller BEVs, which the year effects absorb, and to the change in the gasoline Tesla-size premium, β_{NP}. Gasoline is the comparison powertrain because Tesla sells no gasoline cars, and τ measures only the part of the change specific to BEVs.[23] A negative τ means that a Tesla-size BEV became cheaper to introduce, relative to these comparisons, after Tesla began local production. The identifying assumption is that, without Tesla's local production, the Tesla-size premium in BEV fixed costs would have changed as it did for gasoline models.

[23] This comparison does not remove changes specific to larger BEVs, such as advances in battery technology; Section 7.2 examines that possibility.

Alternative specifications. The main specification controls for changes in fixed costs common to all potential products and for size-specific changes common to both powertrains. Smaller BEVs may still have faced cost changes of their own after 2019: the rising range thresholds for central subsidies, for example, bore most heavily on the smallest BEVs. Because τ measures a relative change, such a cost increase would make it larger in magnitude. I therefore estimate alternative specifications that let the costs of Small BEVs change separately after 2019, control for smaller BEVs' exposure to the subsidy range thresholds, drop the Small class, or adjust smaller BEVs' computed profits. I also use 2019 alone as the period before local production, because 2018 covers only three quarters and preceded the 2019 subsidy reform, which cut subsidies for short-range BEVs. Section 6.3 reports these estimates and shows that the main specification gives the largest decline, the upper end of the range.

Size class as the measure of similarity. The fixed-cost spillover is estimated by comparing potential products similar to Tesla's models with those that are not, which requires a measure of similarity. I measure similarity by size class for four reasons. First, size class is where Tesla competes: the Model 3 and Model Y mainly compete in the Mid and Upper-mid classes. Second, as Figure 3 and the descriptive evidence in Section 3 show, rivals' new BEV offerings shifted toward these classes after Tesla's local production began, while gasoline offerings did not follow this pattern. Third, a potential product's size class is fixed in advance: by construction, every firm has a potential product in each size class in every year in which it sells cars. Tesla's entry can change which potential products firms introduce, but not which size class each belongs to.[24] Fourth, other attributes, such as price and electric range, are endogenous: firms choose them when designing a model, and Tesla's entry could move models into or out of a group defined by them. They would also add little as measures of similarity: range rose in smaller classes as well as in Tesla's, and most new models priced near Tesla's were in Tesla's size classes.[25] Size class is therefore the dimension along which I allow the fixed cost to change with Tesla's entry.

[24] A model's size class is set by its body and platform and does not change over its sales life: each of the 1,555 models in the registration data stays in one class.

[25] Electric range, a central attribute of a BEV, followed the subsidy rules rather than Tesla. The 2019 subsidy reform ended subsidies below 250 km and widened the premium for a range of 400 km or more (Ministry of Finance, Ministry of Industry and Information Technology, Ministry of Science and Technology, and National Development and Reform Commission, 2019). The share of new rival BEV models with at least 400 km rose from 20 percent in 2018 to 70 percent in 2019 and 96 percent in 2020. The rise occurred in smaller classes as well as in Tesla's and began before Tesla's first local deliveries. New models also cluster just above 400 km, as Appendix Figure B1 shows. Price, in contrast, moved with size: from 2020, 23 of the 30 new rival BEV models priced near the Model 3 and Model Y were in Tesla's size classes.

The disturbance. As defined in Section 4.4, the firm introduces potential product g if and only if its expected incremental variable profit V_g is at least its fixed cost F_g, as in Equation (15). I observe neither. I use r_g as the counterpart of $\log V_g$ and $X_g\beta$ as the counterpart of $\log F_g$, and let $z_g = r_g - X_g\beta$ denote the computed log net return. Following Crawford et al. (2018) and Luo (2024), the disturbance $\sigma\nu_g$ is the gap between the computed log net return and the firm's own:

$$\sigma\nu_g = \Big(r_g - X_g\beta\Big) - \Big(\log V_g - \log F_g\Big). \tag{21}$$

It includes errors in the computed profits, simulation error, which is small,[26] and parts of profits and fixed costs that the model leaves out. The firm therefore introduces g if and only if $z_g \geq \sigma\nu_g$, given the observed decisions on other potential products. As a result, introduced potential products tend to have favorable disturbances.

I assume that ν_g is standard normal and independent across potential products, so that the disturbance $\sigma\nu_g$ has standard deviation σ in log points. Because r_g, the computed log present value of incremental profit, already accounts for firm-specific appeal, marginal costs, subsidies, and rivals' products on sale, I also assume that ν_g is independent of r_g and of the cost shifters X_g. I compute r_g at the observed decisions on the firm's other potential products and on its rivals' offerings.[27] Under these assumptions, the probability that the firm introduces potential product g is

$$\Pr(d_g = 1 \mid r_g, X_g) = \Phi\Big(z_g/\sigma\Big). \tag{22}$$

Revealed-preference inequalities. The introduction rule $z_g \geq \sigma\nu_g$ involves the unobserved disturbance, but its distribution is known up to σ. Following Dickstein and Morales (2018, eq. (17)), I replace the terms involving ν_g with observed terms that have the same expected value given z_g, which gives the moment functions

$$\mathrm{RU}_g = d_g\, z_g + (1 - d_g)\,\sigma\frac{\varphi(s_g)}{1 - \Phi(s_g)}, \qquad \mathrm{RL}_g = -(1 - d_g)\, z_g + d_g\,\sigma\frac{\varphi(s_g)}{\Phi(s_g)}, \quad s_g = z_g/\sigma, \tag{23}$$

[26] With 256 draws per design, the median simulation standard error of r_g is 0.02 and its 90th percentile is 0.04. At $\hat{\sigma} = 0.63$, the variance of the simulation error is less than 0.2 percent of the variance of the disturbance. Appendix F.2 provides further details.

[27] These decisions change r_g little. Appendix F.2 shows that the profit a new model takes from the firm's other models averages less than 1 percent of its own profit. Appendix I.2 shows that, near the introduction threshold, changing all other decisions together (about 13 on average) changes the expected profit by at most about 2.1 percent. These changes are small relative to $\hat{\sigma} = 0.63$: the value of a potential product hardly depends on how the others are decided.

where φ and Φ are the standard normal density and distribution functions. At the true parameters, both expressions in Equation (23) have nonnegative expectations: RU_g says that introduced potential products were worth their fixed cost, and RL_g says that products not introduced were not. I average RU_g and RL_g within 20 groups of potential products: the eight powertrain × Tesla size × period cells, the three firm types, the four size classes, and the five years. This gives 40 moment inequalities. Appendix G provides the derivation and further details.

Count equalities. Equation (22) gives the probability that each potential product is introduced. The expected number of new product offerings in any group of potential products is therefore the sum of these probabilities. I match it to the observed number:

$$\log\left(\sum_{g\in C}\Phi\big(z_g/\sigma\big)\right)-\log\left(\sum_{g\in C}d_g\right)=0, \tag{24}$$

for twelve groups C: the eight powertrain × Tesla size × period cells of the triple difference in Equation (20), and all potential products in each of 2018, 2020, 2021, and 2022. These restrictions match model-implied product introduction frequencies to the data.[28]

Identification. The fixed cost is identified by comparing the computed profits of potential products that firms did and did not introduce. The computed profit of an introduced product bounds its fixed cost from above, and that of a product not introduced bounds it from below. The disturbance allows some introduced products to have lower computed profits than some products not introduced. Given these comparisons, the count equalities set the level of the fixed cost at which the model reproduces the observed number of new product offerings. The annual counts identify the constant and the year effects, and the counts in each powertrain × Tesla size × period cell identify the Tesla-size, gasoline, and post-2019 terms of Equation (20). In particular, conditional on computed profits, τ is identified by the post-2019 shift in rivals' new product offerings toward Tesla-size BEVs, relative to the same shift for gasoline models. The inequalities, averaged separately by firm type, size class, and year, identify how fixed costs differ across firm types and size classes. The inequalities and count equalities together identify σ, the scale of the disturbance.

Estimation and inference. As in Dickstein and Morales (2018), I estimate σ together with the coefficients in Equation (20). The point estimates minimize the largest standardized

[28] Under these assumptions on the disturbance, the odds-based moments of Dickstein and Morales (2018) hold with equality, and Equation (24) imposes the same restriction, reweighted so that it does not divide by small introduction probabilities. Appendix G provides further details.

violation of the revealed-preference inequalities while satisfying the count equalities. For each coefficient and for σ, I construct an individual nominal 95 percent range using the penalized-resampling (PR) component of Bugni et al. (2017). For each candidate value, I allow the remaining coefficients and σ to vary to minimize violations of the moment restrictions. I compare the resulting test statistic with the 95th percentile of a reference distribution constructed from 1,000 resampling draws, treating each firm-year as an independent resampling unit. The reported range extends to the first rejected value at each end. I examine firm-level clustering as a sensitivity check. I hold the earlier demand and cost estimates and computed profits fixed throughout these calculations. Appendix G details the moment construction, estimation, and inference procedures.

6 Estimates

I report the estimates in the same order as the estimation steps in Section 5: demand, the marginal-cost spillover, and fixed costs.

6.1 Demand

Table 3 reports the demand estimates. For comparison, columns (1) and (2) are logit models without household heterogeneity. They use the same province-quarter markets, product characteristics, and fixed effects as the full model in column (3). In the OLS logit in column (1), the median own-price elasticity is only -0.23, and demand is inelastic for 98 percent of product-quarters. The price coefficient is biased toward zero because products that buyers value for unobserved reasons also have higher prices. Instrumenting price with the two subsidy instruments in column (2) raises the price coefficient more than fivefold and the median elasticity to -1.28.[29]

Column (3) reports the full model. At the mean of log income, the price coefficient is $e^{-1.595} = 0.20$ per RMB 10,000, and richer households are less price sensitive. Richer households also value EVs much more: one standard deviation of log income raises the utility of an EV by 2.31. Households prefer larger cars, longer electric range, and better performance. The median own-price elasticity is -2.52 and the sales-weighted mean is -3.16.[30]

[29] The two counts of rival products are left out because, in a logit model, they are correlated with the error term if EV buyers prefer other EVs.

[30] These estimates are broadly comparable to recent estimates of automobile demand in Germany and China (Remmy, 2026; Barwick et al., 2024).

Table 3: Demand estimates

	(1) OLS logit	(2) IV logit	(3) Full model
Price (per RMB 10,000)	−0.015	−0.085	—
	(0.004)	(0.029)	
Heterogeneity			
Price, constant (π_0)	—	—	−1.595
			(0.192)
Price × income (π_y)	—	—	−0.272
			(0.073)
EV × income (π_{EV})	—	—	2.310
			(0.466)
EV taste dispersion (σ_{EV})	—	—	2.511
			(1.205)
Taste for buying any car (σ_0)	—	—	1.014
			(1.274)
Mean utility			
Footprint (m^2)	0.635	0.896	1.390
	(0.178)	(0.219)	(0.277)
Log range, non-micro BEV	1.366	1.601	1.194
	(0.467)	(0.521)	(0.598)
Fuel consumption (L/100 km)	−0.116	−0.084	−0.028
	(0.053)	(0.067)	(0.086)
Horsepower per kg	0.740	2.282	6.873
	(2.325)	(2.717)	(3.312)
EV trend (per quarter)	0.069	0.055	0.065
	(0.010)	(0.011)	(0.018)
Log share of quarter on sale	2.060	2.048	2.051
	(0.095)	(0.098)	(0.104)
Implied			
Median own-price elasticity	−0.23	−1.28	−2.52
Sales-weighted own-price elasticity	−0.29	−1.59	−3.16
Median markup (share of firm price)	—	—	0.417

Notes: Column (1) is an ordinary least squares regression of $\log(s_{jmt}) - \log(s_{0mt})$ on price and the characteristics. Column (2) is two-stage least squares with the two subsidy instruments; their first-stage F statistic, clustered by demand product, is 12.6. Column (3) is the full model, estimated by GMM with the micro moments. Its price coefficient is $\alpha_i = \exp(\pi_0 + \pi_y y_i)$, per RMB 10,000, with y_i standardized log household income. All columns use the same 868 province-quarter markets, 2017–2023 (732 products), and the same fixed effects: firm × segment × fuel type, quarter, province, and province × EV. Standard errors are clustered by demand product. Elasticities and markups are computed on national quantities.

Substitution from Tesla. The full model predicts much closer competition between Tesla and other EVs than the logit models do. When a Tesla model's price rises slightly, about 32 percent of the buyers who leave it switch to other BEVs, PHEVs, or extended-range EVs, compared with about 1 percent under either logit model. This is because households in the full model differ in their taste for EVs. Figure C1 in Appendix C reports what these buyers choose instead, including not buying a car.

6.2 Marginal costs and shared suppliers

Table 4 reports estimates of Equation (17). Column (2) is the preferred specification. From 2019Q4, marginal costs are 0.215 log points lower for rival models that share a supplier with Tesla in core EV-specific parts than for other rival EVs, a decline of about 19 percent. The estimate is statistically significant. Measuring exposure by the number of shared suppliers gives a similar decline for each additional supplier, and that estimate is significant in every column. Column (1) drops the control for the battery maker's cumulative output. This extends the sample to all 105 nameplates with a known battery maker, and the estimate is unchanged at -0.215.

Figure 4 plots event-study estimates, with a separate coefficient for each half-year relative to 2019Q2–Q3. Panel (a) measures exposure by any shared supplier and panel (b) by the number of shared suppliers, as in the two core-part rows of Table 4. Before Tesla's first China-built deliveries, the coefficients are small and jointly insignificant in both panels: exposed and unexposed models followed similar cost trends. From the first half-year after local production began, exposed models' costs are 0.15 to 0.25 log points lower, with a similar decline per shared supplier in panel (b), and the gap persists through 2023. The average coefficient in panel (a) after local production began, -0.213, is close to the difference-in-differences estimate.

The bottom panel of Table 4 reports the same regressions for general parts. In every column, the general-part estimates are roughly a third of the core-part estimates and are not statistically significant. When core-part and general-part exposure enter the same regression, the core-part estimate is nearly unchanged, -0.221 in the preferred specification, and the general-part estimate remains small and insignificant. An event study for general parts also shows no change in exposed models' marginal costs relative to those of unexposed models after Tesla began local production. The decline in marginal costs therefore occurs for core parts but not for general parts. This suggests that the spillover works through suppliers of EV-specific parts, not through suppliers of general parts used in both gasoline cars and EVs. The general-part estimates also give little sign that models buying from Tesla's suppliers

Table 4: Supplier overlap with Tesla and rivals' marginal costs

	(1)	(2)	(3)	(4)
Core parts (battery, electric drive)				
Any shared supplier × 2019Q4 onward	−0.215	−0.215	−0.215	−0.203
	(0.081)	(0.086)	(0.110)	(0.111)
Number of shared suppliers × 2019Q4 onward	−0.200	−0.214	−0.220	−0.221
	(0.047)	(0.045)	(0.047)	(0.048)
General parts				
Any shared supplier × 2019Q4 onward	−0.087	−0.071	−0.068	−0.082
	(0.120)	(0.124)	(0.120)	(0.118)
Number of shared suppliers × 2019Q4 onward	−0.078	−0.077	−0.064	−0.063
	(0.064)	(0.069)	(0.071)	(0.071)
Battery maker's cumulative output		✓		✓
Battery maker's linear trends			✓	✓
Nameplates	105	75	75	75

Notes: Dependent variable: log recovered marginal cost of rival domestic EVs (Tesla excluded), 2017–2023, price and marginal cost at least RMB 50,000. Each coefficient is from a separate regression. Core parts are traction batteries and electric drives; general parts are listed in Appendix E. General-part rows use models with general-part supplier records: 99 of the 105 nameplates in column (1) and all 75 in columns (2)–(4). All columns include nameplate × powertrain, quarter, and battery-size-bin × quarter effects. Column (1): models with a known battery maker. Columns (2)–(4): models whose battery maker is one of six with published output data (987 product-quarters). Column (2) is the preferred specification used in the counterfactual. Standard errors clustered by nameplate in parentheses.

were already on a lower cost path. Appendix E reports these checks.

The decline in marginal costs for models that share Tesla's core-part suppliers is robust to the checks in Table E1 in Appendix E. The decline persists when exposure is limited to supplier links observed through 2019, and when the sample drops models whose shared supplier first appears in 2020 or later. The estimated decline therefore does not depend on rivals adopting Tesla's suppliers after it began local production. A related concern is that Tesla chose suppliers, in particular CATL, whose costs were already falling. The preferred specification addresses this concern by controlling for the battery maker's cumulative output. Columns (3) and (4) of Table 4 add a separate linear cost trend for each battery maker and give similar estimates. Samples restricted by a floor on each product's minimum price, which do not select on recovered marginal costs, also yield a similar decline. Because Tesla may have begun sourcing parts before its first China-built deliveries, and the spillover may take time to appear, I also move the assumed start date of local production anywhere from 2019Q2 to 2020Q3. The estimate remains negative and statistically significant.

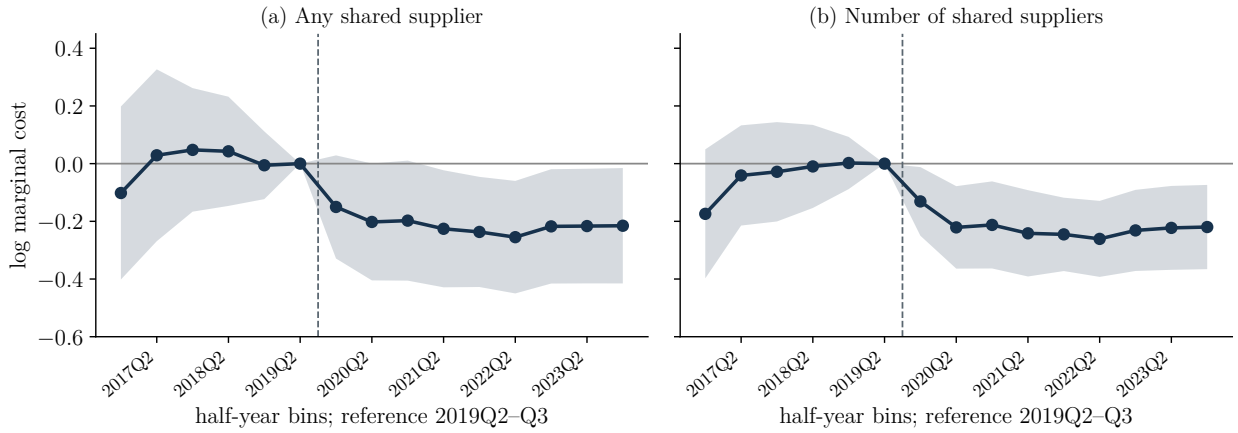


Figure 4: Event study: marginal costs of rival models that share Tesla's suppliers

Notes: Coefficients on any shared supplier (panel a) and the number of shared suppliers (panel b) × half-year bins, relative to 2019Q2–Q3, with 95 percent confidence intervals. All rival domestic EVs with price and marginal cost of at least RMB 50,000 (114 nameplates); nameplate × powertrain, quarter, and battery-size-bin × quarter effects; no battery-maker control. The first bin, 2017Q1, contains one exposed model. Standard errors clustered by nameplate. The dashed line marks Tesla's first China-built deliveries.

6.3 Fixed costs

Table 5 reports the main estimates, from the specification in Equation (20). They imply that, after Tesla began local production, the fixed cost of introducing a Tesla-size BEV fell by about 68 percent relative to smaller BEVs, the upper end of the range across the specifications in Section 5.3. The estimate $\hat{\tau} = -1.14$ measures this decline net of the change in the Tesla-size premium for gasoline models. It reflects how differently the two BEV size groups moved after 2019. Rivals introduced Tesla-size BEVs about three times as often, from 2.7 to 8.5 percent of potential products, although their computed profits rose only modestly; a lower fixed cost reconciles the two. Smaller BEVs moved the other way: their introduction rate fell from 15.5 to 9.6 percent even though their computed profits rose with EV demand. Relative to the period before 2020, the implied fixed cost of a Tesla-size BEV fell by about a quarter and that of a smaller BEV rose, with no comparable divergence for gasoline models. The estimate of τ therefore measures this relative change, not a change in the level of the Tesla-size cost.

Table 5 also reports the implied cost levels. Across introduced potential products, the systematic BEV cost rises from RMB 0.96 billion before 2020 to RMB 2.52 billion afterward, while the gasoline cost falls. This rise has two sources: new offerings shift toward larger, more costly size classes, and the fixed cost of introducing a smaller BEV rises. Accounting for the favorable disturbances of introduced potential products lowers the implied BEV cost

Table 5: Fixed-cost estimates and implied levels

A. Coefficients (log RMB 100 million)

Coefficient	Estimate	Individual 95% PR range
Constant	1.76	$[1.4, 3.0]$
Year 2018	0.29	$[-0.2, 1.7]$
Year 2020	0.77	$[0.2, 1.4]$
Year 2021	0.97	$[0.5, 1.6]$
Year 2022	1.00	$[0.5, 1.6]$
Tesla size	2.15	$[1.8, 3.1]$
$\boldsymbol{\tau}$: Tesla size × post × BEV	−1.14	$[-2.3, -0.2]$
Tesla size × post	0.04	$[-1.0, 0.9]$
Gasoline	1.72	$[1.0, 2.3]$
Gasoline × post	−1.16	$[-2.1, -0.5]$
Gasoline × Tesla size	−1.72	$[-2.6, -1.1]$
JVs and other foreign automakers (non-luxury)	0.41	$[0.1, 1.7]$
EV start-ups	0.41	$[0.1, 0.7]$
Small class	−0.26	$[-1.4, 0.1]$
Upper-mid class	−0.49	$[-1.0, -0.2]$
Scale of the disturbance, σ	0.63	$[0.45, 1.65]$

B. Fixed-cost levels (RMB billion)

	Systematic cost	Cost conditional on introduction
BEV, before 2020	0.96	0.26
BEV, 2020 onward	2.52	0.60
Gasoline, before 2020	4.70	1.22
Gasoline, 2020 onward	3.16	0.85

Notes: Estimates of Equation (20), with σ estimated jointly. The base category is an established Chinese automaker's Compact BEV in 2019; "post" is 2020 onward. Panel A reports individual nominal 95 percent PR ranges under firm-year clustering. Ranges are rounded outward to 0.1 log point (0.05 for σ). Each range runs to the first value rejected under both of two independent sets of resampling draws, with all other coefficients and σ re-estimated; Appendix G describes the procedure. Appendix H.2 reports the test of $\tau = 0$ under firm clustering. Panel B summarizes introduced potential products. Systematic cost is the geometric mean of $\exp(X_g\beta)$. Cost conditional on introduction counts the whole disturbance in the fixed cost and replaces it with its mean given introduction, which accounts for the favorable disturbances of introduced potential products. Appendix H.1 defines these levels. The sample contains 2,427 potential products and 367 firm-year clusters; inference uses 1,000 resampling draws.

to RMB 0.26 billion before 2020 and 0.60 billion afterward.[31]

Alternative specifications. Several factors may have raised the cost of introducing BEVs after 2019. If they raised the costs of both size groups in similar proportions, the year effects absorb them, leaving τ unaffected. If they raised the costs of smaller BEVs by more, however, the estimate of τ would overstate the relative decline for Tesla-size BEVs. In China's EV market during the sample period, some factors applied to BEVs of every size, such as the battery safety standard mandatory from 2021 (State Administration for Market Regulation and Standardization Administration of China, 2020) and the dedicated BEV platforms that leading automakers launched in 2020 and 2021.[32] Others bore most heavily on the smallest BEVs. For example, the minimum range for central subsidies rose from 150 km in 2018 to 250 km in 2019 and 300 km in 2020 (Ministry of Finance, Ministry of Industry and Information Technology, Ministry of Science and Technology, and National Development and Reform Commission, 2018, 2019, 2020b). Half of the Small BEV designs available in 2018 had a range below 300 km, and none did by 2021. The lost subsidies enter computed profits, but meeting the higher thresholds may also have made smaller BEVs more costly to develop, which the model would record as a higher fixed cost of introducing them.

The alternative specifications introduced in Section 5.3 address this possibility in four ways. First, Small BEVs receive their own post-2019 change in fixed costs, which gives $\hat{\tau} = -0.82$. Second, a control for each size class's 2018 share of designs below 300 km, a measure of its exposure to the higher thresholds, gives $\hat{\tau} = -0.85$. Third, dropping Small potential products, which faced the thresholds most directly, gives $\hat{\tau} = -0.98$. Fourth, I adjust computed profits instead of costs. After 2019, the computed profits of the smaller BEVs actually introduced rose 0.31 log points more than the profits these models realized. Lowering smaller BEVs' computed profits by this amount gives $\hat{\tau} = -0.83$. In addition, using 2019 as the only year before local production gives $\hat{\tau} = -0.90$. Across these specifications, the estimated relative decline ranges from 56 to 68 percent, and the main estimate is the

[31] The size of this adjustment depends on the estimated scale of the disturbance, $\hat{\sigma} = 0.63$, with a 95 percent range of 0.45 to 1.65. Appendix H.3 reports the tests behind this range. These costs conditional on introduction are broadly in line with what Chinese automakers report for developing new models. Great Wall Motor's 2021 bond prospectus (*China Securities Journal*, June 8, 2021, p. A42 and p. A43) budgets RMB 0.36 to 0.87 billion for each of three new-energy models and RMB 0.59 to 1.00 billion for each of four SUVs and two pickups, including model-specific tooling but no new plants. BAIC BluePark's filings (February 2023 reply to regulators, pp. 3 and 6; December 2023 notice, pp. 3–4) report budgets of RMB 3.88 billion for the ARCFOX αT and αS and RMB 2.68 billion for four later ARCFOX BEVs, one of them a facelift. Leapmotor's chairman put R&D at about RMB 0.5 billion per model (Cailian Press, September 29, 2022), and Li Auto's president put the investment in each new model at about RMB 2.5 billion (China Daily, September 6, 2021).

[32] Examples are Geely's SEA architecture (2020), BYD's e-platform 3.0 (2021), whose first model was a small hatchback, and the architecture under Wuling's Hongguang MINI EV (2020).

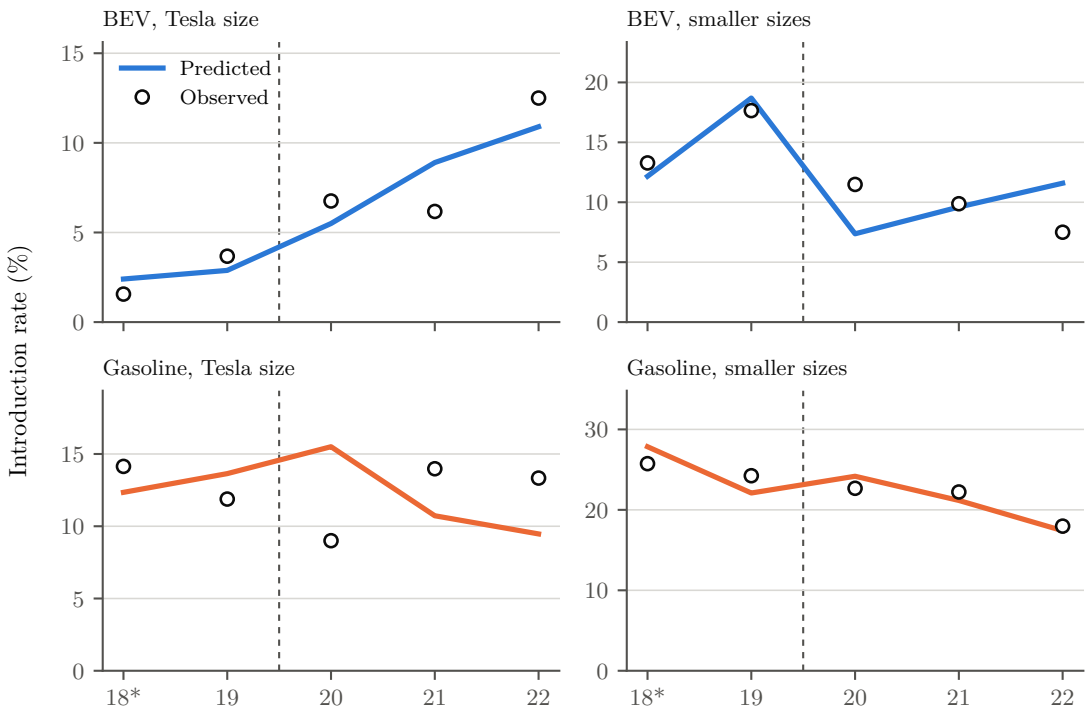


Figure 5: Predicted and observed new-model introduction rates

Notes: Lines: predicted new-model introduction rates at the main estimates. Circles: observed rates. Rates are the percentage of potential products introduced in each panel and year. The count equalities target each panel's totals before 2020 and from 2020 onward and the annual totals across panels. *2018 covers 2018Q2–Q4.

largest. The main counterfactual therefore gives the upper end of the effects of the fixed-cost spillover. Section 7.2 also reports counterfactuals that attribute less of the decline, or none of it, to Tesla's local production. Appendix H.4 reports all the estimates.

The estimated decline also does not rest on any single firm. Because only six firms introduced Tesla-size BEVs before 2020, I re-estimate the model excluding each of these firms in turn. The estimates of τ range from -1.01 to -1.18, close to the main estimate, and Appendix H.4 reports them.

Model fit. The count equalities match new product offerings in each cell before 2020 and from 2020 onward, as well as annual totals across cells. Annual introduction rates within each cell are not targeted and therefore provide a check on model fit. Figure 5 shows that, at the main estimates, the model captures the rise in Tesla-size BEV introductions: the predicted introduction rate increases from 2.4 percent in 2018 to 10.9 percent in 2022, compared with 1.6 and 12.5 percent in the data. It also reproduces the 2019 peak and the 2020 fall in smaller-BEV introductions. The fall reflects the market-wide decline in new product offerings

in 2020, which the common year effect captures. The alternative specifications fit the data similarly: across them, the predicted Tesla-size BEV introduction rate in 2022 ranges from 10.6 to 11.6 percent, and each reproduces the same pattern for smaller BEVs. Appendix H.4 reports their fit.

7 Counterfactual

This section quantifies the effects of Tesla's local production and sourcing on welfare, rivals' new product offerings, and profits across firm types. I compare the observed 2020–2022 market with a simulated market without Tesla's Shanghai-built products or its supply-side spillovers. I then separate the effect of competition from that of the supply-side spillovers, which comprise the marginal-cost and fixed-cost spillovers. I first describe the scenarios, the equilibrium adjustment, and the welfare measure, and then report the main results. Finally, I examine how the results change with the attribution of the fixed-cost decline, alternative welfare measures, and earlier local production.

7.1 Scenarios, equilibrium adjustment, and welfare

Scenarios and channel decomposition. I consider three scenarios. The first, "Observed market," is the 2020–2022 market in the data: the Shanghai-built Model 3 and Model Y are on sale, and both supply-side spillovers are present. The second, "Local production without spillovers," keeps those two models on the market but removes both supply-side spillovers, which are the reduction in the marginal cost of rival models that use Tesla's suppliers and the reduction in the fixed cost of introducing Tesla-size BEVs. The third, "No local production," removes the Shanghai-built models and both supply-side spillovers; Tesla continues to import.[33] The scenarios differ only in Tesla's locally produced products and the supply-side spillovers. All other estimated parameters, firms' potential products, the unobserved shocks to demand and costs, and the draws of the disturbance are the same in all three.

Comparing the second scenario with the third gives the competition effect: costs are the same, and only the presence of the Shanghai-built Tesla models differs. Comparing the first scenario with the second gives the effect of the supply-side spillovers: the Shanghai-built models are on sale in both scenarios, and only the spillovers differ. These two effects sum

[33] Tesla's imported Model S and Model X remain on sale in all three scenarios. In the data, the Shanghai-built Model 3 replaced the imported Model 3; without local production, the imported Model 3 continues at Tesla's average 2019Q2–Q4 import volume.

to the total effect, which is "Observed market" minus "No local production." Table I1 in Appendix I.1 summarizes the three scenarios.

The supply-side spillovers consist of a marginal-cost spillover and a fixed-cost spillover, and I separate the contribution of each. To remove the marginal-cost spillover, I reverse the estimated cost reduction for rival models that use Tesla's suppliers. To remove the fixed-cost spillover, I set τ—the post-2019 change in the fixed cost of introducing a Tesla-size BEV, relative to smaller BEVs and to gasoline models—to zero and hold the other fixed-cost coefficients fixed. Because either spillover's effect depends on whether the other is present, I compute each contribution twice, once with the other spillover and once without it. The Shapley decomposition averages the two contributions (Shapley, 1953; Shorrocks, 2013). Those averages sum to the combined effect of the supply-side spillovers. Appendix I.4 reports the separate contributions.

Equilibrium adjustment. For each scenario in each year, I simulate two cases. In the first case, with *product offerings fixed*, rival firms keep every observed product that was on sale and change only prices. In the second case, in *full equilibrium*, rival firms change prices and that year's product offerings. A rival may drop a BEV or gasoline car introduction observed in that year, or introduce a BEV or gasoline potential product it did not introduce (Eizenberg, 2014; Wollmann, 2018; Fan and Yang, 2020). PHEV introductions and luxury makers' introductions stay as observed.[34]

In both cases, following Crawford et al. (2018) and Fan and Yang (2025), I draw each potential product's disturbance conditional on its observed introduction decision. In full equilibrium, rival firms choose their best responses sequentially, starting from the observed product offerings. On its turn, a firm repeatedly introduces or drops the one potential product that most increases its profit net of fixed costs (Wollmann, 2018; Lee and Pakes, 2009). The process stops when no firm has a profitable single-product deviation, holding all other introduction decisions fixed. I average outcomes over 30 draws of the disturbance. Appendix I.2 describes the order of moves and the checks on the solution.

Welfare accounting. For each year y, moving between two scenarios changes domestic welfare by

$$\Delta W_y = \frac{A}{4}\Big(\underbrace{\Delta \mathrm{CS}_y}_{\text{consumers}} + \underbrace{\Delta \Pi_y^D}_{\text{producers' variable profits}} \Big) - \underbrace{\Delta K_y}_{\text{new-model fixed costs}} . \tag{25}$$

[34] In both cases, every firm except Tesla, importers, and very small sellers sets new prices. Those three groups keep their prices.

Consumer surplus and domestic producers' variable profits are annual flows. Dividing by four gives their average quarterly flow, and $A = \sum_{u=0}^{14} 0.975^u = 12.64$ capitalizes it over 15 quarters. This is the horizon firms weigh against the one-time fixed costs ΔK_y when deciding on new products. Domestic producers are all firms producing in China other than Tesla, including JVs and foreign-owned producers, with their full profits. Domestic welfare excludes the profits of Tesla and importers, as well as government spending and revenue; Section 7.2 reports a measure that includes them. Reported effects average ΔW_y over 2020–2022. Appendix I.3 gives the details.

7.2 Local production: competition and supply-side spillovers

Figure 6 reports the total effect of Tesla's local production and sourcing, measured as "Observed market" minus "No local production," and separates it into competition and the supply-side spillovers. The results use the main fixed-cost estimates, which give the upper end of the effects of the fixed-cost spillover. The last two rows show how the results change with the share of the estimated fixed-cost decline attributed to Tesla's local production. Consumer surplus, profits, and domestic welfare are 15-quarter present values, while new product offerings are annual counts. The figure reports each outcome with *product offerings fixed* and in *full equilibrium*.

Three margins in the model shape these results. Substitution patterns determine which rivals lose sales to Tesla. Supplier overlap determines which rivals benefit from lower marginal costs, and similarity in size to Tesla's models determines which new BEVs become cheaper to introduce.

Welfare. Panel A of Figure 6 shows that consumers receive most of the gain. Tesla's models expand consumer choice, while the marginal-cost spillover puts downward pressure on rivals' prices. With product offerings fixed, consumer surplus rises by RMB 126.6 billion and domestic producers' net profits by RMB 46.0 billion. The producer gain comes mainly from lower fixed costs of introducing the observed new models, which rivals introduce both with and without Tesla's local production.

When firms can adjust their offerings, lower fixed costs bring more Tesla-size BEVs to market. The additional models expand consumer choice, but they also intensify competition and require more fixed-cost spending. Consumer surplus rises further, to RMB 160.6 billion. For domestic producers, gains from the two spillovers more than compensate for losses from competition, leaving a net gain of RMB 9.6 billion, much smaller than with offerings fixed. Domestic welfare is similar in the two cases: RMB 172.7 billion with offerings fixed and

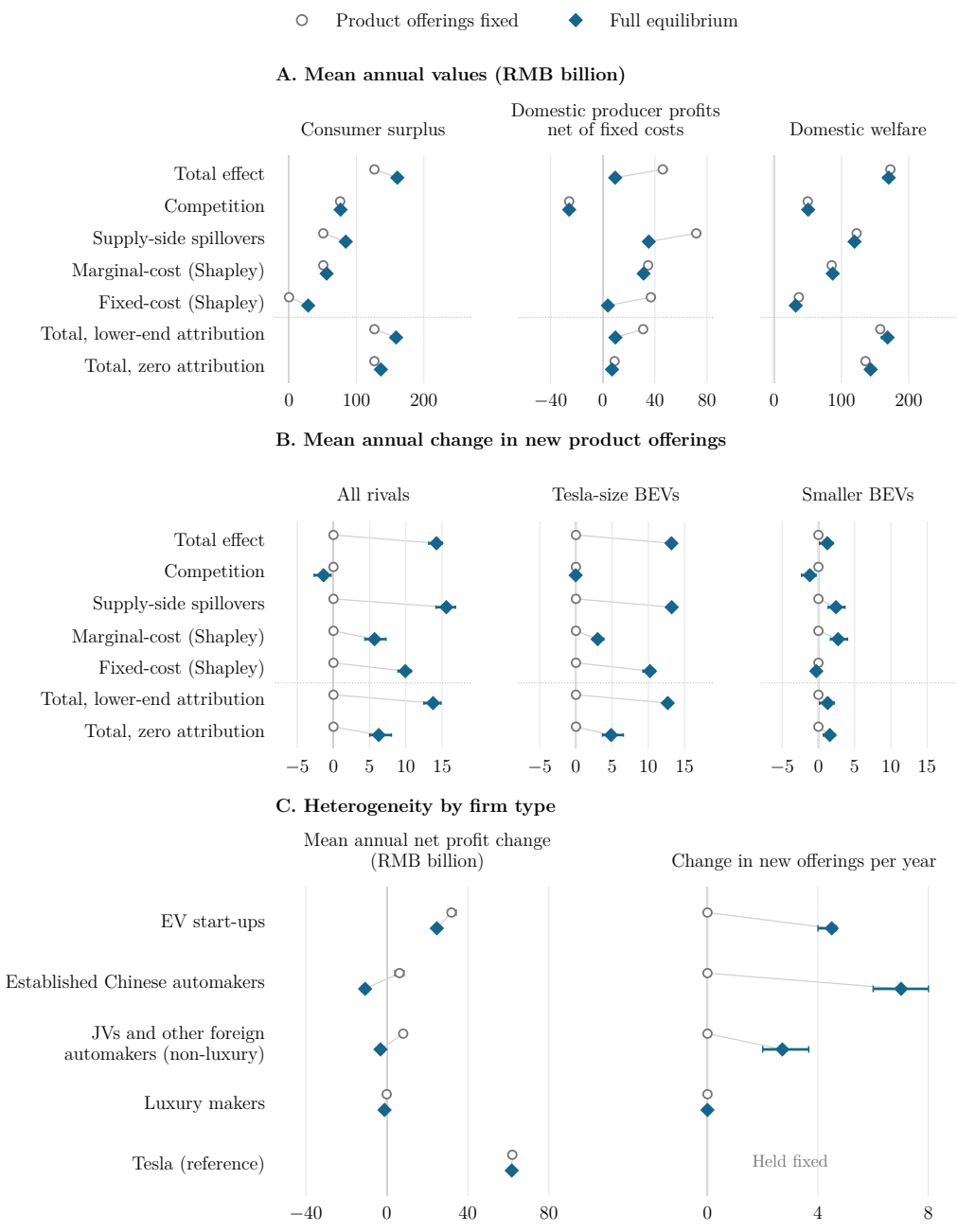


Figure 6: Tesla's local production: welfare, product offerings, and firm types

Notes: Changes from the market without Tesla's local production; imported Tesla models remain. Monetary values average the annual effects for 2020–2022, each valued over 15 quarters; offering counts are annual averages. A new product offering is an introduced potential product (firm × size class × powertrain × year). Shapley values average the two orders of adding the supply-side spillovers. Points are means over 30 conditional draws of the disturbance; bands are the paired 5th–95th percentiles across these draws, not confidence intervals for the estimated parameters. Domestic welfare excludes Tesla's and importers' profits. With offerings fixed, rivals keep their observed offerings. The last two rows attribute the lower-end estimate of the fixed-cost decline, 56 percent, or none of it to Tesla's local production; the rest of the decline occurs in both markets. PHEV, luxury-maker, and Tesla offerings are held fixed.

RMB 170.2 billion in full equilibrium.[35] Allowing product offerings to adjust thus shifts gains from producers to consumers. The totals are similar because the two shifts largely offset: consumer surplus rises by RMB 34.0 billion more than with offerings fixed, while producers' net profits rise by RMB 36.4 billion less.

New product offerings. Panel B shows that competition from Tesla's models and the supply-side spillovers pull rivals' new product offerings in opposite directions. Because Tesla's models compete closely with other EVs, competition alone deters 1.4 new product offerings per year, mainly BEVs outside Tesla's size classes. The supply-side spillovers instead add 15.6, about 64 percent of which is attributable to the fixed-cost spillover. This spillover directly lowers introduction costs for Tesla-size BEVs. The marginal-cost spillover operates across size classes: it lowers production costs for rival EVs that share Tesla's suppliers and makes them more profitable to introduce. On net, Tesla's local production and sourcing add 14.2 new product offerings per year, a 32 percent increase over the market without Tesla's local production. Almost all of the increase, 13.2 per year, comes from Tesla-size BEVs; other BEVs and gasoline models change little on net.

The two spillovers reinforce each other. With the fixed-cost spillover present, the marginal-cost spillover adds 8.4 new product offerings per year, rather than 3.0 without it. Lower fixed costs bring more Tesla-size BEVs close to being profitable to introduce, and the reduction in marginal costs then pushes more of them over the introduction threshold. Appendix I.4 reports this interaction, and Appendix Table J2 also reports the results when the fixed-cost decline is removed from both markets.

Firm types. Panel C shows that exposure to the two spillovers differs across firm types. EV start-ups gain RMB 24.7 billion in profits net of modeled fixed costs because their spillover gains more than compensate for losses from competition. Compared with established Chinese automakers, more of their EV sales come from models that share core-part suppliers with Tesla's Shanghai plant, and more of their BEV sales are in Tesla's size classes. They therefore benefit more from the marginal-cost and fixed-cost spillovers. Established Chinese automakers add 7.0 new product offerings per year, but their variable profits fall and their fixed-cost spending rises. Their net profits therefore fall by RMB 10.7 billion. JVs and other foreign automakers also lose in full equilibrium. EV start-ups thus receive the largest profit gain among rival producers, while Tesla's own profits rise by RMB 61.6 billion. Appendix I.4 reports the complete decomposition by firm type.

[35] Both comparisons count scenario-specific fixed costs of introducing new models, including cost changes on offerings retained in both scenarios. Appendix I.3 describes the welfare accounting.

Attributing the fixed-cost decline to Tesla. The main results attribute the whole estimated decline in the fixed cost of introducing Tesla-size BEVs to Tesla's local production, the upper end across the specifications in Section 6.3. EV policies or advances in battery technology may also have contributed, and the last two rows of Figure 6 attribute less of the fixed-cost decline to Tesla. At the lower-end estimate from Section 6.3, which gives Small BEVs their own post-2019 change, Tesla's local production accounts for a 56 percent decline, and the rest of the decline also occurs in the market without Tesla's local production. Under this attribution, the counterfactual shows that rivals' new product offerings rise by 13.8 per year and domestic welfare by RMB 168.5 billion, close to the main results: the part of the decline not attributed to Tesla is too small to make many Tesla-size BEVs worth introducing without Tesla's local production.

In the zero-attribution case, the whole decline also occurs in the market without Tesla's local production, and the comparison isolates competition and the marginal-cost spillover. Offerings still rise by 6.3 per year and domestic welfare by RMB 143.4 billion, about 84 percent of the main estimate. Because fixed costs are lower in both markets, more Tesla-size BEVs are close to being profitable. The marginal-cost spillover then adds 8.4 offerings per year, more than offsetting the 2.1 that competition deters. Appendix Table J2 reports consumer surplus and producers' profits for each case.

Alternative welfare measures. I also consider two alternative welfare measures: one that excludes the disturbance from fixed costs and one that includes government spending and revenue.

First, the main welfare calculation counts the entire disturbance as fixed-cost spending. As defined in Section 5.3, the disturbance is the gap between the model's computed net return and the firm's own expected net return. Because it can reflect omitted components of profits as well as omitted fixed costs, not all of it need represent resource spending. I therefore recalculate welfare after excluding the disturbance from fixed costs while holding firms' choices unchanged. Domestic producers' net profits fall by RMB 32.8 billion. Consumer surplus is unchanged, and domestic welfare still rises by RMB 127.8 billion, about three-quarters of the main estimate.

Second, the main welfare measure excludes government spending and revenue. Accounting for the additional subsidy spending and the change in purchase-tax revenue lowers the welfare gain to RMB 154.4 billion.

Parameter estimates. To see how the results depend on the fixed-cost estimates, I resolve the counterfactual at 32 fixed-cost parameter vectors spanning the 95 percent ranges.

Tesla's local production adds 3.8 to 14.1 new product offerings per year and RMB 142.6 to 174.9 billion in domestic welfare.[36] At every vector, competition reduces rivals' offerings, and the spillovers more than offset this reduction. Appendix J reports these exercises.

Earlier local production. The balance between competition and the spillovers may depend on the size of the domestic EV market when local production begins: in a smaller market, fewer rival sales benefit from lower marginal costs. To examine this, I move Tesla's locally produced line-up two years earlier, to 2018–2020. Because the estimated fixed-cost decline applies only after 2019, this exercise excludes the fixed-cost spillover, and I compare it with the 2020–2022 exercise that also excludes it.

In the smaller 2018–2020 market, competition deters more new product offerings, and the marginal-cost spillover makes up for less of this reduction. Rivals' new product offerings therefore fall by 12.8 per year, mainly among smaller BEVs. Domestic welfare still rises, by RMB 90.0 billion, compared with RMB 128.7 billion in the 2020–2022 exercise. In both periods, Tesla's local production raises consumer surplus and domestic welfare. Its effect on rivals' offerings depends on how many rival sales benefit from the marginal-cost spillover. That number rises with the size of the domestic EV market. Appendix K reports the full analysis.

8 Conclusion

A foreign manufacturer that produces and sources locally can divert customers from domestic rivals. It can also change rivals' costs, both the marginal cost of producing products that share its suppliers and the fixed cost of introducing products similar to its own. Suppliers' economies of scale and learning can lower these costs, while supplier capacity constraints and preferential terms for the entrant can raise them. This paper quantifies this trade-off in China's EV market after Tesla began producing cars in Shanghai and sourcing their components locally in 2019. A model of demand, pricing, and new-model introduction connects the competition and cost channels to consumer surplus and rivals' profits.

I find that the marginal costs of rival EV models sharing core-part suppliers with Tesla's Shanghai plant declined by about 19 percent relative to those of other rival EVs, and the fixed cost of introducing BEVs in Tesla's size classes fell relative to smaller BEVs. Competition from Tesla's Shanghai-built models alone slightly reduces rivals' new product offerings, but the spillovers more than reverse this: on net, rivals' new offerings rise by about a third.

[36] Each vector is evaluated with five draws of the disturbance, compared with 30 for the main estimates.

Consumers receive most of the domestic welfare gain from Tesla's local production, while rival producers gain modestly in aggregate. Allowing rivals to adjust their offerings raises the consumer gain but shrinks producers' net gain, leaving total domestic welfare almost unchanged. Even if Tesla did not cause the fixed-cost decline, the marginal-cost spillover still more than offsets competition's effect on rivals' offerings, and most of the domestic welfare gain remains.

Taken together, the results show that a foreign entrant's local production can do more than draw customers away from domestic rivals: it can also benefit them through supply-side spillovers. The balance between these forces depends on how many of rivals' models share the entrant's suppliers, how similar they are to its products, and how large the domestic market is when local production begins. For Tesla in China, EV start-ups gain because their models more often share Tesla's suppliers and compete in its size classes, while established Chinese automakers lose. Had Tesla begun local production two years earlier, in a smaller EV market, rivals would have introduced fewer new products than without it.

Evaluating foreign entry and policies that encourage local production and sourcing therefore requires weighing product-market competition against supply-side spillovers. These evaluations should account for rivals' product choices as well as their prices. Finally, they should distinguish consumers' gains from domestic producers' gains: the two can move in opposite directions when rivals adjust their product choices. In China's EV market, the premise of policies that tie foreign entry to local production and sourcing incentives or requirements partly holds. Tesla's local production and sourcing benefited some domestic rivals but not others. For the domestic economy as a whole, however, it was a clear and robust gain.

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Appendix

A Data Construction

Products. A demand product combines operating entity, model, segment, powertrain, import status, and a band of electric range or engine displacement. A new model year or generation does not create a new product. Within a product-quarter, the price and the characteristics are sales-weighted means of the trims that fall in that product.

For a BEV the range bands are below 200 km; 200–299, 300–399, 400–499, and 500–599 km; and 600 km and above. For a PHEV or an extended-range EV the bands are below 50 km, 50–79, 80–119, 120–199 km, and 200 km and above. For a gasoline car the displacement bands are up to 1.0 liter, 1.0–1.5, 1.5–2.0, 2.0–2.5, 2.5–3.0, 3.0–4.0, and above 4.0 liters.

Sample. The registration panel has 3,760 products, 37,717 product-quarters, and 134.3 million registrations. Of these products, 2,594 are gasoline, 764 are BEVs, 251 are PHEVs, and 21 are extended-range EVs. The remaining 113 diesel products and 17 products of other powertrains do not enter the demand sample. A gasoline product enters if, in its best quarter, it sold at least 0.3 percent of that quarter's gasoline registrations; an EV enters if it sold at least 0.1 percent of that quarter's EV registrations. I drop product-quarters that lack a usable price or a characteristic used in estimation. The remaining demand sample has 732 products and 10,002 product-quarters, and it accounts for 78 percent of registrations.

Models and size classes. A model is defined by firm, nameplate, and powertrain. A model's introduction is its first quarter with registrations; models already registered in 2017Q1, when the data begin, are not counted as introductions. Size classes (Small, Compact, Mid, Upper-mid) pool Autohome's sedan and SUV segments of the same size, as described in Section 2.3.

Households. Each market has 200 simulated households drawn from the CFPS with probability proportional to the survey weight. The 2016 wave serves 2017, the 2018 wave 2018–2019, the 2020 wave 2020–2021, and the 2022 wave 2022–2023. I shift each household's log income by the difference in log per-capita income between the province it represents and its own province.

A.1 Firm classification

Section 2.4 defines the three firm types. JVs and other foreign automakers are the producers whose registrations mostly carry a foreign partner's brand. This rule follows the brands and pricing units in the data rather than legal ownership alone: SAIC–GM–Wuling is classified with established Chinese automakers, while SAIC–GM is classified with JVs and other foreign automakers. Zeekr, Aion, and Ora remain with Geely, GAC, and Great Wall, respectively.

Table A1: Firm types and leading manufacturers in the product offering samples

Firm type	Firms	Five largest firms	Registration share (%)
Established Chinese automakers	40	Geely, SAIC–GM–Wuling, Changan, Great Wall, BYD	66.2
EV start-ups	30	Li Auto, XPeng, NIO, Leapmotor, Neta	90.3
JVs and other foreign automakers (non-luxury)	18	FAW–Volkswagen, SAIC–Volkswagen, SAIC–GM, Dongfeng–Nissan, FAW–Toyota	63.4

Notes: The 88 firms are those in the product offering samples. Within each group, firms are ranked by registrations of China-produced vehicles over 2017–2023; the last column is the five firms' share of the group. Affiliated brands remain with their firm. Tesla and the five luxury makers defined in Section 4.4 are excluded.

B Attributes of BEV Models on Sale

Table B1 gives the attribute comparison behind Section 3 for BEV models on sale in 2019 and 2022. The sample covers models produced in China in the four size classes, excluding Tesla and the five luxury makers. It contains 106 models in 2019 and 178 in 2022, with 68 sold in both years. These continuing models show much smaller changes in attributes than the overall set of models.

To measure the contribution of changes within continuing models, I multiply their change in mean attributes by their share of models in 2022 (68/178), and divide by the change in the mean across all models. This contribution is 1.0 percent for footprint and 6.9 percent for electric range. The remaining change comes from the composition of models on sale, including both introductions and exits. Most of this compositional change comes from new models. The 110 models sold in 2022 but not in 2019, nearly all introduced after 2019, average 498 km of electric range, compared with 384 km for continuing models.

Electric range of new BEV models. Figure B1 shows that the range of new rival BEV models followed the central purchase-subsidy rules rather than Tesla's models. From 2019,

Table B1: BEV model attributes and changes in models on sale, 2019–2022

	Mean over models			
	All models 2019 → 2022	Continuing models 2019 → 2022	2019 only	2022 only
Footprint (m^2)	7.88 → 8.39	7.95 → 7.96	7.75	8.66
Electric range (km)	354 → 454	366 → 384	332	498
Battery capacity (kWh)	48.1 → 60.7	48.7 → 51.0	47.0	66.8
Horsepower	149 → 206	159 → 163	130	232
Number of models	106 → 178	68	38	110

Notes: Models produced in China in the four size classes, excluding Tesla and the five luxury makers. A model is a firm–nameplate–powertrain combination with positive registrations in the year. Each model's attributes are sales-weighted across its trims and quarters, then averaged across models without sales weights. Continuing models are sold in both years; "2019 only" and "2022 only" refer to models sold in one of these two years. Of the 110 models sold only in 2022, 108 first appear after 2019.

models below 250 km received no subsidy and those of 400 km or more received the largest subsidy; from 2020 the minimum was 300 km (Ministry of Finance, Ministry of Industry and Information Technology, Ministry of Science and Technology, and National Development and Reform Commission, 2019, 2020b). Panel (a) shows that the share of new models with a range of at least 400 km rose sharply in 2019, for both Tesla-size and smaller BEVs. Panel (b) shows bunching at the 400 km subsidy threshold. Of the 32 models first sold from 2019Q3 to 2020, all rated on the NEDC cycle, 6 have a longest range of 400 to 409 km, and none falls between 330 and 399 km. The shift began in 2019, before Tesla's local production, and in smaller classes as well as Tesla's. Range therefore tracked the subsidy rules, which is why I measure similarity to Tesla by size class, as discussed in Section 5.3.

C Demand Estimation

Micro moments. The targets of the micro moments come from the CFPS households with positive income in each wave, weighted by their survey weights. A household counts as a buyer if its reported spending on a vehicle purchase in the past year lies between RMB 50,000 and RMB 2 million; the lower bound screens out small vehicle expenditures that are not car purchases. The 2018, 2020, and 2022 waves have 412, 346, and 328 buyers. The price paid is that spending, and income is standardized with the same fixed mean and standard deviation as the income of the simulated households. On the model side, each wave's two moments pool that year's 124 province-quarter markets, weighted by market size. Table C1 reports the targets and the fit.

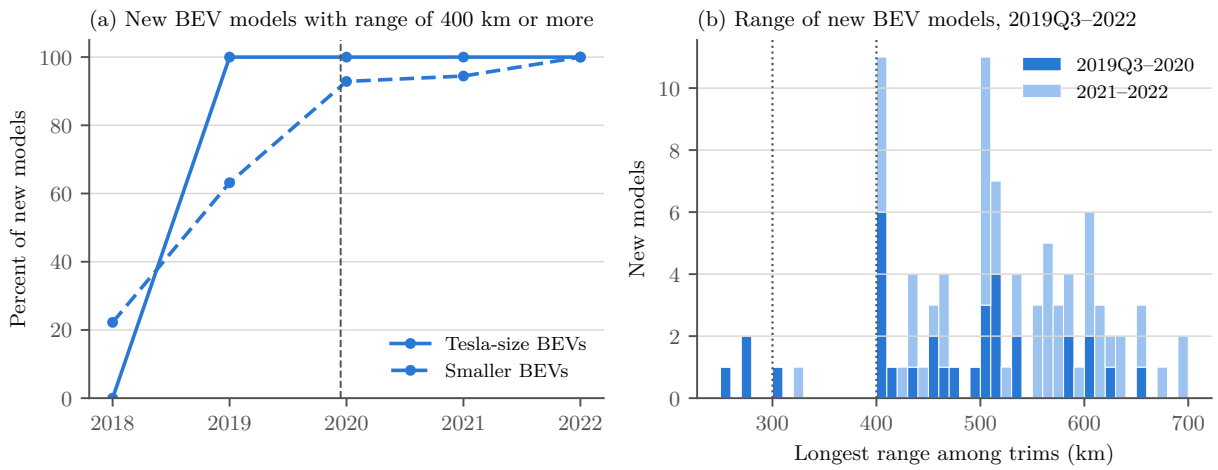


Figure B1: Electric range of new rival BEV models

Notes: BEV models produced in China in the four size classes, excluding Tesla and the five luxury makers, with 100 or more registrations in their first year. Range is the longest range among a model's trims in its first year. Panel (a): 20 to 29 new models a year; Tesla-size models number 2 in 2018 and 4 in 2019. The dashed line marks Tesla's first China-built deliveries in December 2019. Panel (b): dotted lines at 300 and 400 km, the subsidy thresholds from 2020. Models introduced from 2021 may report the CLTC cycle, which gives ranges about 2 percent above NEDC for the same trim.

Table C1: Micro moments: targets and fit

	2018		2020		2022	
	Mean income	Slope	Mean income	Slope	Mean income	Slope
CFPS target	0.452	0.124	0.644	0.106	0.798	0.200
Model	0.411	0.201	0.596	0.177	0.887	0.114

Notes: Mean income: mean standardized log income of households that bought a car. Slope: coefficient from regressing the log price paid on standardized log income among buyers. Each wave uses that year's 124 province-quarter markets weighted by market size.

Diversion from Tesla. Figure C1 compares substitution patterns on the common province-quarter demand sample used in Table 3. For each Tesla model, diversion to another product is the increase in that product's sales divided by the decrease in the Tesla model's sales after an infinitesimal increase in its price, holding all other prices fixed. Destination shares are averaged over Tesla product-market observations using observed Tesla sales as weights. In either standard logit, diversion from product j to product k is $s_k/(1-s_j)$, and diversion to no purchase is $s_0/(1-s_j)$. Because the price coefficient cancels, the OLS and IV logit models imply identical diversion ratios at observed shares, and the figure shows them together.

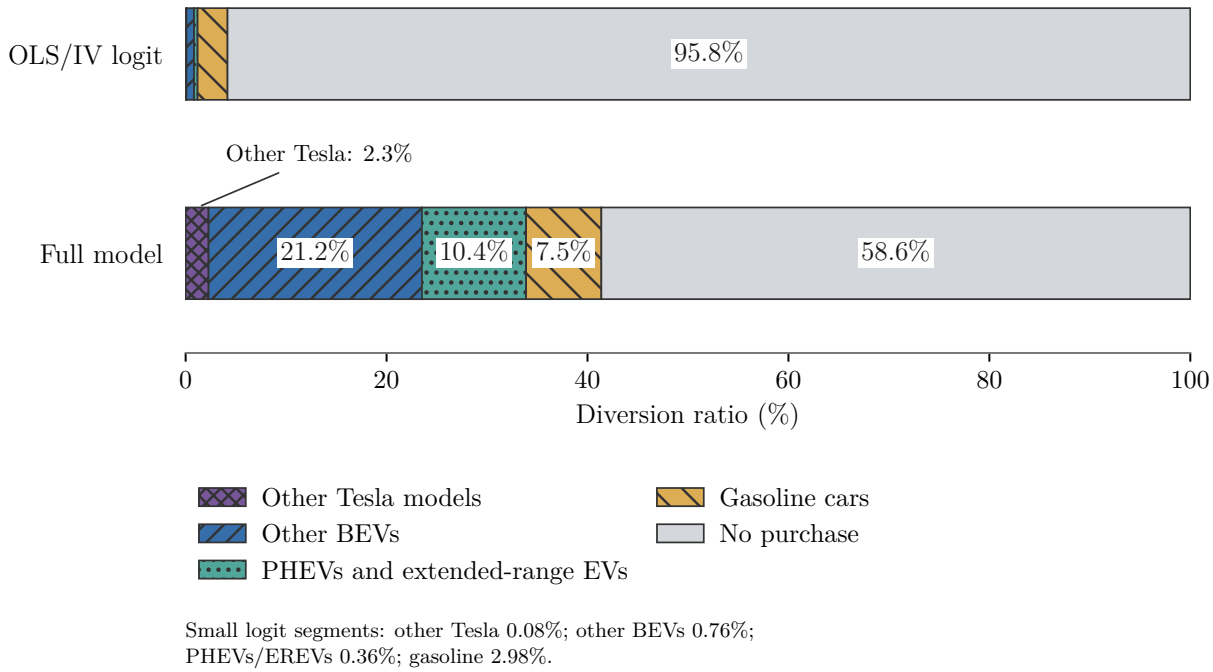


Figure C1: Where Tesla's marginal buyers go: logit and full model

Notes: Each bar sums to 100 percent. OLS/IV logit combines columns (1) and (2) of Table 3; Full model is column (3). Other Tesla models exclude the model whose price changes, and other BEVs exclude all Tesla models. No purchase is the outside option. Values too small to display in the logit bar are listed below the legend.

D The National Market for Price and Profit Simulations

Demand is estimated on province markets because variation across provinces helps identify the price and EV taste parameters. Product offering decisions and prices are national. The simulations of prices and profits, used both to estimate fixed costs and in the counterfactuals, therefore use one national market per quarter, built in three steps to reproduce the province model. First, I take each province's estimated effects for buying any car and for EVs, λ_m and λ_m^{EV}. Second, I pool the simulated households of all provinces, weighted by market size, and each household keeps its province's effects. Third, each observed product receives a product $\times$ province shift in mean utility that reproduces its province shares. At observed prices, this market reproduces the province shares and recovered marginal costs of the demand-sample products to numerical precision. Hypothetical products, such as the potential products whose profits Appendix F computes, have no observed province shares. They therefore receive no province shift and are offered in every province. Appendix F.2 measures their appeal under

Table E1: Marginal-cost spillover: robustness

	Any shared supplier	Number shared
Preferred (Table 4, column 2)	−0.215 (0.086)	−0.214 (0.045)
Same sample, no battery-maker control	−0.245 (0.090)	−0.230 (0.047)
Samples that do not select on recovered marginal cost		
Product's minimum price ≥ RMB 120,000	−0.204 (0.095)	−0.188 (0.046)
Product's minimum price ≥ RMB 150,000	−0.229 (0.139)	−0.213 (0.047)
Exposure timing		
Exposure from supplier records up to 2019 only	−0.183 (0.126)	−0.185 (0.084)
Drop models whose shared supplier first appears from 2020	−0.287 (0.093)	−0.269 (0.041)
Inference for the preferred estimate		
Wild cluster bootstrap p-value	0.019	0.005
Permutation p-value (exposure permuted across nameplates)	0.038	0.007
Leave one nameplate out: range	[−0.276, −0.168]	[−0.239, −0.172]

Notes: All rows include the battery maker's cumulative output and the fixed effects of Table 4, except the second row. Standard errors clustered by nameplate. The price-floor samples fix the sample by each product's minimum firm price over the panel, before marginal costs are seen.

the same convention, as if sold in every province while competitors remain where they were actually sold. Each quarter's simulations use 500 of the 6,200 pooled households: the 155 with the strongest taste for EVs, who account for most of Tesla's purchases, and 345 drawn by province and income tercile in proportion to market size. With this draw, Tesla's diversion ratios are within one percentage point of those computed with all households.

E Marginal-Cost Spillover: Robustness

Table E1 reports checks of the preferred specification, column (2) of Table 4. Across the alternative controls, samples, and exposure definitions in the table, the estimates range from −0.18 to −0.29. When I move the assumed start date of local production anywhere from 2019Q2 to 2020Q3 in the specification of column (1) of Table 4, the estimate stays between −0.16 and −0.22 and is significant at the 5 percent level.

Most of the overlap runs through CATL, which supplies 46 of the 54 exposed models. Two further checks ask whether the estimate reflects CATL's own falling costs rather than Tesla's local production. The first compares models supplied by the CATL entity that supplies Tesla with models whose batteries come from makers other than CATL, excluding models supplied only by other CATL entities. The second adds a quadratic cost trend for each battery maker.

Table E2: Supplier overlap in general parts: further checks

	Any shared supplier	Number shared
General parts, preferred (Table 4, column 2)	−0.071 (0.124)	−0.077 (0.069)
Core and general parts in one regression		
Core parts (battery, electric drive)	−0.221 (0.091)	−0.200 (0.047)
General parts	−0.089 (0.104)	−0.051 (0.073)
General parts, excluding braking systems	−0.077 (0.138)	—
General parts, all rival EVs (103 nameplates), no battery-maker control	−0.085 (0.121)	−0.077 (0.064)

Notes: Controls and fixed effects as in Table 4. Rows other than the last use the sample of column (2) of Table 4 (75 nameplates) and include the battery maker's cumulative output. Braking systems are excluded only for the any-shared measure. Standard errors clustered by nameplate in parentheses.

The estimates are −0.211 and −0.285, both statistically significant at the 5 percent level.

General parts. General parts are the 16 categories in my MarkLines supplier data that are not specific to EVs: braking systems (ABS/ESC), driver-assistance control units, domain controllers, cameras, radar, seats, window glass, tires, headlamps, rear lamps, air conditioning, steering, suspension, bumpers, instrument panels, and wiring harnesses. Other EV-specific parts, such as inverters and battery materials, enter neither measure. A rival's supplier counts as shared only if Tesla's Shanghai plant uses it for the same part. Sharing a general-part supplier with Tesla is common: 56 of the 75 models in the preferred sample do. The share is similar whether or not a model also shares a core-part supplier (34 of 47 versus 22 of 28). Much of this overlap comes from a single supplier: for 27 of the 56 models, the only shared general-part supplier is Bosch, for braking systems.

Because only 19 of the 75 models share no general-part supplier, the general-part estimates are less precise than the core-part estimates. Table E2 reports further checks. With core-part and general-part exposure in the same regression, the core-part estimates are nearly unchanged and the general-part estimates remain small and insignificant. Excluding braking systems, or using all rival EVs as in Figure 4, gives similar general-part estimates.

Figure E1 repeats the event study of Figure 4 for core-part and general-part overlap on the 103 nameplates with general-part records. The core-part coefficients follow the pattern of Figure 4. The general-part coefficients do not change at Tesla's entry: from 2019Q4 on they lie between −0.08 and 0.02. The earliest pre-entry general-part coefficients lie above zero, but they rest on only two to six models without a shared general-part supplier.

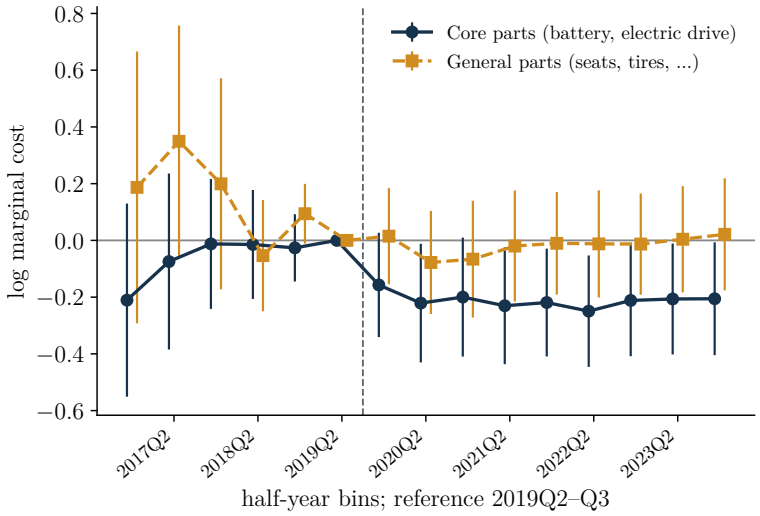


Figure E1: Event study: core-part and general-part supplier overlap

Notes: Coefficients on any shared supplier of core parts (battery, electric drive) or of general parts × half-year bins, relative to 2019Q2–Q3, from separate regressions, with 95 percent confidence intervals. Specification as in Figure 4, on the 103 nameplates with general-part supplier records. Standard errors clustered by nameplate. The dashed line marks Tesla's first China-built deliveries.

F Potential Products and Incremental Variable Profits

F.1 The set of potential products

Endowment. A firm has a BEV potential product in every size class in every year in which it sells any car, and a gasoline potential product in every size class in every year in which it sells a gasoline car. Most EV start-ups hold licenses only for EVs and therefore have no gasoline potential products. PHEV offerings are held at their observed levels and are not chosen in the model. The decision is annual, as in Wollmann (2018), because new models are planned ahead of the quarter in which they are introduced. The fixed cost in a year does not depend on the firm's earlier new product offerings, and an introduction does not change the potential products available later. Every potential product, including one the firm did not introduce, is treated as technically feasible in its year.

Body style. Each potential product specifies a firm, size class, powertrain, and year, but not a body style. In the data, a firm that introduces a sedan of a given size and powertrain rarely introduces the SUV version in the same year, even when the two would earn similar profits. I therefore treat the sedan and the SUV as alternative designs of the same potential product.

F.2 Incremental variable profits

Estimating fixed costs requires the incremental variable profit of every potential product, including products that were never introduced. Each profit simulation therefore needs a hypothetical model's characteristics, its appeal to buyers, and its marginal cost. I run these simulations in the national market of Appendix D.

Designs. For each candidate quarter and body style, a *design* is a hypothetical model with the median first-year characteristics of new models of the same size class, powertrain, and body style introduced from four quarters before to three quarters after the candidate quarter. When fewer than two such models exist, I widen the window symmetrically until it contains two. The prices of these models serve only as starting values, because each design's price is solved in market equilibrium.

Appeal and marginal cost. I predict a design's appeal in its first year from its characteristics, using an equation estimated on observed products. The estimation also includes new models that sold too few cars to enter the demand sample, whose appeal I recover from their first-year sales. Appeal is measured as if each product were sold in every province while its competitors are sold only where they actually were, the situation a new model faces. For BEVs, the prediction also includes a firm-specific appeal level. It is a weighted average of the residuals of the firm's own BEVs and those of its firm type, adjusted for the appeal of the firm's other models. The weight on the firm's own BEVs rises with the number it sells. I predict marginal cost from Equation (12), pooling EV cost levels across firms so as not to extrapolate a firm's EV cost level to categories in which it has little or no EV experience. Each design also receives appeal and marginal-cost shocks drawn from the residuals of observed products' predictions.

Profit simulation. For each of the 16,402 candidate designs, I use 256 draws of the demand and marginal-cost shocks that the firm does not know at the start of the year. For models already on sale, the draws are forecasts from their last four quarters plus forecast errors drawn jointly for demand and cost from a held-out sample. Domestic producers' other models first sold in the decision year receive draws like the design's, and the markets with and without the design share the same draws. Imported models, the models of very small sellers, and Tesla's models keep their realized appeal and cost; I treat them as known to rivals when they decide. I drop designs whose expected profit exceeds 1.42 times that of the most profitable observed product of the same size class and powertrain sold in the same

quarters; for gasoline designs, the benchmark is the firm's own most profitable product when one exists.

Present values. Equations (18) and (19) define the design's present value and the potential product's value r_g. The factor $A = \sum_{u=0}^{14} 0.975^u = 12.64$ capitalizes first-year average quarterly incremental profit over the 15-quarter horizon of Section 4.4, calibrated to the median registration lifetime of EV models.

Simulation precision and cannibalization. Two checks support assumptions in Section 5.3. First, simulation error in r_g is small. Its standard error, computed by the delta method and allowing for draws shared across designs in the same year, has a median of 0.021, a 90th percentile of 0.036, and a 99th percentile of 0.055. On average, simulation variance is 0.16 percent of the variance of the disturbance at $\hat{\sigma} = 0.63$. Second, cannibalization is small: the profit a design takes from the firm's other models averages 0.4 percent of its own profit, and 0.6 percent of total profit summed over all designs. Valuing each potential product at the firm's observed decisions on its other potential products therefore changes little. For introduced potential products, the firm's actual new models are on sale when each design is valued.

G Fixed-Cost Estimation

Appendix F.2 describes the simulated profit inputs. This appendix explains how I construct the moments, obtain the point estimate, and calculate individual coefficient ranges.

G.1 Moment construction

The fixed-cost sample has 2,427 potential products in 367 firm-years. Let q index firm-years and $G = 367$.

Revealed preference. At the true parameters, an introduced potential product satisfies $z_g \geq \sigma\nu_g$ and one not introduced satisfies $z_g < \sigma\nu_g$, so $d_g(z_g - \sigma\nu_g) \geq 0$ and $(1 - d_g)(\sigma\nu_g - z_g) \geq 0$. Because ν_g is standard normal and independent of z_g, $\mathbb{E}[d_g\nu_g \mid z_g] = -\varphi(s_g)$ and $\mathbb{E}[(1 - d_g)\nu_g \mid z_g] = \varphi(s_g)$, with $s_g = z_g/\sigma$. The moment functions in Equation (23) replace the unobserved terms $-d_g\sigma\nu_g$ and $(1 - d_g)\sigma\nu_g$ with observed terms that have the

same conditional means:

$$\mathbb{E}[\mathrm{RU}_g \mid z_g] = \mathbb{E}[d_g(z_g - \sigma\nu_g) \mid z_g] = \Phi(s_g)z_g + \sigma\varphi(s_g) \geq 0,$$
$$\mathbb{E}[\mathrm{RL}_g \mid z_g] = \mathbb{E}[(1 - d_g)(\sigma\nu_g - z_g) \mid z_g] = -(1 - \Phi(s_g))z_g + \sigma\varphi(s_g) \geq 0.$$

These are the moments in Equation (17) of Dickstein and Morales (2018). I build each moment from firm-year sums, the units that the inference resamples. For each group b, firm-year q contributes $\sum_{g \in q} w_g H_{gb} \mathrm{RU}_g$ and $\sum_{g \in q} w_g H_{gb} \mathrm{RL}_g$, where H_{gb} indicates membership in group b and w_g is one over the number of potential products in g's size class $\times$ powertrain $\times$ year. Averaging these sums over firm-years gives the 40 inequality moments.

Introduction counts. Let P_{qc} and O_{qc} denote predicted and observed counts in firm-year q for count group c. Their totals are $P_c = \sum_q P_{qc}$ and $O_c = \sum_q O_{qc}$, and the sample log gap is $D_c = \log P_c - \log O_c$. A count equality compares aggregate totals rather than averages over firm-years. To resample it with the other moments, I linearize the log gap D_c by the delta method and write it as an average of firm-year terms:

$$\psi_{qc} = D_c + G\left(\frac{P_{qc}}{P_c} - \frac{O_{qc}}{O_c}\right), \qquad \frac{1}{G}\sum_q \psi_{qc} = D_c.$$

Each term ψ_{qc} is firm-year q's influence on D_c, and their spread across firm-years measures the sampling variability of D_c. Each of the twelve count equalities enters as two inequalities, in ψ_{qc} and $-\psi_{qc}$, so that the tests detect both overprediction and underprediction. These 24 inequalities bring the total to 64 moments.

Connection to odds-based moments. Under the same assumptions, the odds-based moments of Dickstein and Morales (2018) hold with equality. Writing $p_g = \Phi(s_g)$, multiplying the odds residual $d_g(1-p_g)/p_g - (1-d_g)$ by p_g gives $d_g - p_g$, the count residual. Using the count residual avoids dividing by small probabilities: about 38 percent of potential products have estimated introduction probabilities below 0.001, implying odds weights above 999 for introductions among them.

G.2 Point estimation

The point estimator minimizes the largest standardized violation of the revealed-preference inequalities, subject to eleven independent count equalities. The twelfth, the 2022 total, is implied by the others and remains in the inference tests. For each value of σ on a grid with steps of 0.01, I minimize this criterion over the coefficients and take the value with the

smallest criterion, $\hat{\sigma} = 0.63$. The point estimates pass the joint test below.

G.3 Inference

Let $m_{qj}(\beta, \sigma)$ be firm-year q's term in moment j, for the 64 moments, with sample mean $\bar{m}_j$ and sample standard deviation $\hat{s}_j$. The test statistic measures the largest standardized violation:

$$T(\beta, \sigma) = \max_j \left[-\frac{\sqrt{G}\, \bar{m}_j(\beta, \sigma)}{\hat{s}_j(\beta, \sigma)} \right]_+, \qquad [x]_+ = \max\{x, 0\}.$$

Individual coefficient ranges. The parameter space Θ of the cost coefficients keeps the systematic fixed cost of every potential product between RMB 50 million and RMB 10 billion. For a candidate value a of coefficient β_ℓ, define $\Theta_a = \{(\beta, \sigma) : \beta \in \Theta,\ 0.2 \le \sigma \le 2,\ \beta_\ell = a\}$; for σ itself, the candidate value fixes $\sigma = a$ instead. I minimize the statistic over the remaining coefficients and σ and construct its penalized-resampling reference as

$$\mathcal{T}(a) = \inf_{(\beta,\sigma)\in\Theta_a} T(\beta, \sigma),$$
$$\mathcal{T}_b^*(a) = \inf_{(\beta,\sigma)\in\Theta_a} \max_j \left[-\frac{\mathbb{G}_{bj}^*(\beta, \sigma) + \sqrt{G}\, \bar{m}_j(\beta, \sigma)/\kappa}{\hat{s}_j(\beta, \sigma)} \right]_+,$$

where $\mathbb{G}_{bj}^*(\beta, \sigma) = G^{-1/2} \sum_q e_{bq}\{m_{qj}(\beta, \sigma) - \bar{m}_j(\beta, \sigma)\}$, e_{bq} are independent standard normal multipliers, and $\kappa = \sqrt{\ln G}$. I compute the empirical 95th percentile of 1,000 PR draws for each of two independent sets of multipliers, and I retain a candidate when $\mathcal{T}(a)$ does not exceed this cutoff under at least one of the two sets. Inverting these tests gives the range, using the PR component of Bugni et al. (2017). All other parameters remain free, including τ and σ when another coefficient is tested. Coverage is individual nominal 95 percent, rather than simultaneous across coefficients.

Joint tests of coefficient vectors. I also test specified coefficient vectors using generalized moment selection (Andrews and Soares, 2010). A moment enters the bootstrap when $\sqrt{G}\, \bar{m}_j/\hat{s}_j \le \kappa \approx 2.43$. The cutoff is the 95th percentile over 1,000 firm-year bootstrap samples of the maximum recentered standardized violation of the selected moments. Unlike a PR range, which re-estimates the other coefficients, a joint test evaluates a complete coefficient vector. I apply it to the main estimates, the alternative specifications of Appendix H.4, and the parameter vectors of Appendix J, and report the ratio of the statistic to its cutoff; a vector passes when the ratio is below one.

G.4 Sampling and computation

Sampling. The main resampling scheme allows dependence within firm-years, while treating different firm-years as independent. Firm-level clustering instead allows dependence across a firm's years; both schemes maintain independence across firms. Fixed-cost inference is conditional on the estimated demand parameters, recovered marginal costs, and computed profit inputs. I maintain the regularity and identification conditions of Bugni et al. (2017).

Computation. I compute profiles using constrained nonlinear optimization with multiple starting values. I locate each end of a range by numerical search between a value that is not rejected and one that is, and report the outer value, rounded outward to 0.1 log point, or to 0.05 for σ.

H Fixed-Cost Sensitivity and Robustness

H.1 Implied fixed-cost levels

Panel B of Table 5 reports two fixed-cost levels, evaluated at the main estimates for introduced potential products in each powertrain and period. Both are geometric means, the exponential of mean log cost. The systematic cost is $\exp(\overline{X_g\beta})$. The cost conditional on introduction follows the main counterfactuals, which count the whole disturbance in the fixed cost, $\exp(X_g\beta + \sigma\nu_g)$. It replaces $\sigma\nu_g$ with its mean given introduction, $-\sigma\varphi(s_g)/\Phi(s_g)$, where $s_g = (r_g - X_g\beta)/\sigma$, giving $\exp\left(\overline{X_g\beta - \sigma\varphi(s_g)/\Phi(s_g)}\right)$. Changes across periods reflect both the cost function and the mix of introduced potential products.

H.2 Tests of a zero fixed-cost effect

Table H1 reports the PR test of $\tau = 0$, re-estimating σ and the other coefficients. For the main specification, the test rejects $\tau = 0$ at the 5 percent level under firm-year clustering, the main resampling scheme. Under firm clustering, which also allows dependence across a firm's years and leaves 88 clusters, it rejects at the 10 percent level. The table also reports the test for the four alternative specifications of Appendix H.4 that change the cost function or the sample. Two of them, one giving Small BEVs their own post-2019 change and one dropping the Small class, reject $\tau = 0$ at the 10 percent level under firm-year clustering.

Table H1: PR tests of a zero fixed-cost effect

Specification and clustering	Clusters	$\mathcal{T}(0)$	PR cutoff	p	Reject $\tau = 0$ at 5 percent	Reject $\tau = 0$ at 10 percent
Main						
Firm-year	367	1.101	1.006	0.03	Yes	Yes
Firm	88	0.869	0.946	0.09	No	Yes
Small BEVs with their own post-2019 change						
Firm-year	367	0.837	0.901	0.08	No	Yes
Firm	88	0.659	0.896	0.21	No	No
Control for range-threshold exposure						
Firm-year	367	0.769	0.873	0.13	No	No
Firm	88	0.597	0.857	0.26	No	No
Small class dropped						
Firm-year	367	0.897	0.956	0.08	No	Yes
Firm	88	0.717	0.932	0.16	No	No
2019 the only year before 2020						
Firm-year	367	0.703	0.947	0.21	No	No
Firm	88	0.590	0.862	0.25	No	No

Notes: Each row re-estimates the other cost coefficients and σ. The PR cutoff is the 95th percentile of 1,000 PR resampling draws, and the 10 percent test compares $\mathcal{T}(0)$ with their 90th percentile; Appendix G describes the procedure. The p-value is the share of draws whose statistic is at least $\mathcal{T}(0)$. Because additional starting values are used only for draws near the 95th percentile, p-values above 0.05 are upper bounds and 10 percent rejections are conservative.

H.3 Scale of the disturbance

The point estimate, $\hat{\sigma} = 0.63$, comes from the grid search in Appendix G.2. Table H2 reports PR tests of individual values of σ, each re-estimating all cost coefficients. Under the main resampling draws, no value from 0.50 to 1.55 is rejected. The value 1.60 is rejected under the main draws but not under a second, independent set, and therefore stays in the range. Both sets reject 0.45 and 1.65. Following the rule in Appendix G.4, these first rejected values are the reported bounds, giving a range of 0.45 to 1.65.

Table H2: PR tests of individual values of σ

		Main draws		Second draws	
σ	Statistic	Cutoff	Reject?	Cutoff	Reject?
0.40	1.084	0.967	Yes	—	—
0.45	1.002	0.937	Yes	0.928	Yes
0.50	0.923	0.929	No	—	—
1.15	0.989	2.085	No	—	—
1.20	1.171	2.200	No	—	—
1.50	2.628	2.772	No	—	—
1.55	2.824	2.859	No	—	—
1.60	3.008	2.933	Yes	3.015	No
1.65	3.183	3.000	Yes	3.098	Yes
1.80	3.648	3.198	Yes	—	—

Notes: The tests use firm-year clustering. Each cutoff is the 95th percentile of 1,000 PR resampling draws, and the second draws use an independent set of multipliers. Dashes mark values not tested under the second draws.

H.4 Robustness of the fixed-cost estimates

Panel A of Table H3 re-estimates the model, including σ, excluding in turn each of the six firms that introduced a Tesla-size BEV before 2020. Estimates of τ remain between -1.18 and -1.01, and estimates of σ between 0.49 and 0.65, close to the main estimate. No single firm drives the decline.

Panel B changes the specification, again re-estimating σ. The first row adds a Small BEV term and its post-2019 interaction, with separate count equalities for Small BEVs before and after 2020, so that τ compares Tesla-size BEVs with Compact BEVs. The second instead adds the interaction of BEV, post, and each size class's share of 2018 BEV designs with a range below 300 km, with a count equality that weights each class's BEV introductions by this share; the share is about one-half for Small, one-third for Compact and Mid, and zero for Upper-mid. The third drops Small potential products of both powertrains. The fourth drops 2018, which covers only three quarters, leaving 2019 as the only year before local production. The fifth lowers the computed profits of smaller BEVs from 2020 onward by 0.31 log points, the amount by which the computed profits of the smaller BEVs actually introduced rose more after 2019 than the profits these models realized. Because each powertrain $\times$ Tesla-size $\times$ period cell has its own fixed-cost level, this shift raises τ one for one and leaves σ unchanged. Every specification passes the joint test, and $\hat{\tau}$ ranges from -0.98 to -0.82, inside the 95 percent PR range of the main estimate.

The computed profits value each year's sales over 15 quarters, the median sales life of an EV model. Sales lives differ little between the two BEV size groups, and size-specific

horizons change $\hat{\tau}$ by less than 0.01.

Table H3: Robustness of the fixed-cost point estimates

Specification	$\hat{\tau}$	$\hat{\sigma}$	Joint-test ratio
A. Excluding one firm			
Without SAIC	−1.175	0.65	0.734
Without BAIC	−1.128	0.55	0.666
Without WM Motor	−1.137	0.56	0.710
Without GAC	−1.154	0.60	0.641
Without BYD	−1.008	0.57	0.787
Without NIO	−1.167	0.49	0.787
B. Alternative specifications			
Small BEVs with their own post-2019 change	−0.817	0.61	0.604
Control for range-threshold exposure	−0.846	0.66	0.610
Small class dropped	−0.981	0.60	0.534
2019 the only year before 2020	−0.901	0.89	0.296
Smaller-BEV computed profits lowered after 2019	−0.826	0.63	0.656

Notes: Ratios divide the firm-year joint-test statistic by its critical value; every specification passes the test. The main estimates are $\hat{\tau} = -1.140$, $\hat{\sigma} = 0.63$, and a ratio of 0.656.

Table H4 compares the fit of the alternative specifications with that of the main specification, at each specification's own estimates. Each captures the rise in Tesla-size BEV introductions and the 2019 peak and 2020 fall in smaller-BEV introductions about as well as the main specification.

Table H4: Model fit of the alternative fixed-cost specifications

		Tesla-size BEVs		Smaller BEVs	
Specification	$\hat{\tau}$	2018	2022	2019	2020
Observed		1.6	12.5	17.6	11.5
Main specification	−1.14	2.4	10.9	18.7	7.4
Small BEVs with their own post-2019 change	−0.82	2.4	10.7	18.5	6.9
Control for range-threshold exposure	−0.85	2.5	10.9	18.7	7.7
Small class dropped[a]	−0.98	2.5	11.6	20.1	10.1
2019 the only year before 2020	−0.90	–	10.6	17.6	7.5
Smaller-BEV computed profits lowered after 2019	−0.83	2.4	10.9	18.7	7.4

Notes: New-model introduction rates, percent of potential products. Smaller BEVs are Small and Compact BEVs. [a]Smaller BEVs are Compact BEVs only; their observed rates are 17.6 percent in 2019 and 12.2 percent in 2020. The specification with 2019 as the only year before 2020 excludes 2018.

I Counterfactual Details

This appendix documents the construction, welfare accounting, and detailed results of the 2020–2022 comparison in Section 7. Appendix J examines alternative parameters and assumptions. Appendix K applies the same solution and welfare methods to earlier local production.

I.1 Scenarios

Table I1 summarizes the three scenarios for 2020–2022. Removing the marginal-cost spillover raises the marginal cost of exposed rival EVs by $0.215 \times \text{Exposed}_j^C$ log points. For observed models, Exposed_j^C indicates a core-part supplier shared with Tesla's Shanghai plant. For candidate models, which have no supplier records, it is their maker's sales-weighted share of EV sales from such models since 2020, shrunk toward 0.47, the share among all rival EV nameplates, with a weight of two nameplates. Makers without EV records receive 0.47. The adjustment applies to models with price and marginal cost of at least RMB 50,000. Gasoline cars, imports, and Tesla's models are unaffected by this cost adjustment. Removing Tesla's products eliminates the Shanghai-built Model 3 and Model Y; imported Tesla models remain in the comparison market. From 2020, the imported Model 3 continues at its 2019Q4 price; its appeal follows the estimated time effects, less a common reduction that holds Tesla's import sales at their 2019Q2–Q4 average of about 8,800 cars a quarter. Removing the fixed-cost spillover sets $\tau = 0$, holding all other cost coefficients fixed. Re-estimating with τ restricted is a separate sensitivity exercise in Appendix J.

Table I1: Scenarios for the channel decomposition

Scenario	Locally produced Tesla products	Marginal-cost spillover	Fixed-cost spillover
Observed market	Yes	Yes	Yes
Local production without spillovers	Yes	No	No
No local production	No	No	No

Notes: The observed market is the 2020–2022 market in the data. Locally produced Tesla products are the Shanghai-built Model 3 and Model Y; imported Tesla models remain in every scenario. Removing the fixed-cost spillover sets $\tau = 0$, holding the other cost coefficients fixed.

I.2 Equilibrium solution and validation

The 2020–2022 exercise has 1,499 BEV and gasoline potential products, of which 177 are introduced, with 227 new models in all. The exercise for earlier local production has 1,421

potential products in 2018–2020, of which 182 are introduced, also with 227 new models. Each year is solved separately. Canceling an introduction removes all observed new models of that potential product in their own quarters; introducing a previously unintroduced potential product adds one model using a randomly chosen candidate design, consistent with the averaging in Equation (19). PHEV and luxury-maker offerings, and introduction decisions outside that year, remain observed. Prices adjust in a Nash–Bertrand equilibrium for the modeled firms, including their retained products; Tesla, importers, and very small sellers keep the prices specified for the exercise.

Incremental profits are calculated as in estimation, scaling each design's present discounted value by the change in its simulated profit. For potential product g, in scenario $\mathcal{E}$ with other offering changes S,

$$v_g(\mathcal{E}, S) = \log\left(\frac{1}{n_g}\sum_{k\in K_g}\exp\left[\log \mathrm{PDV}_k + \log \mathrm{IVP}_k(\mathcal{E}, S) - \log \mathrm{IVP}_k(\mathcal{E}_0, \varnothing)\right]\right), \tag{26}$$

where $\mathcal{E}_0$ denotes the observed market. Thus $v_g(\mathcal{E}_0, \varnothing) = r_g$. Effects of other offering changes use the realized shocks of models on sale.

As in Crawford et al. (2018, Appendix S.B.4) and Fan and Yang (2025), I draw the disturbance conditional on the observed introduction decisions, so that the model reproduces them. This treats ν_g as the part of the firm's net return that my computation misses, held the same in every scenario. With $s_g = z_g/\sigma$ as in Equation (23),

$$\nu_g \sim N(0,1) \text{ conditional on } \begin{cases} \nu_g \le s_g, & d_g = 1, \\ \nu_g > s_g, & d_g = 0. \end{cases} \tag{27}$$

A potential product is introduced in scenario $\mathcal{E}$ if $v_g \ge X_g\beta^{\mathcal{E}} + \sigma\nu_g$. I use the same draws in every scenario, and the main results average over 30 draws.

Starting from observed offerings, firms make sequential best responses in order of 2019 sales (Wollmann, 2018; Lee and Pakes, 2009). Each firm makes the single change with the largest increase in profit net of fixed costs, provided the gain exceeds RMB 10,000, and continues until no further single change is profitable. Passes over firms continue until no firm wishes to change an introduction decision. When several offerings change, I approximate a potential product's value by its no-change value plus the single-change effects, computed for decisions near their thresholds.

All 900 equilibrium computations of the 2020–2022 exercise converge: three years, 30 draws, five scenarios (the three in Table I1 and the two that add one spillover at a time), and two firm orders. Reversing the firm order changes mean annual effects by about 0.01

new product offerings. Recomputing the values of the 3,491 decisions within 0.3 log points of their thresholds in 60 final configurations, with all other changes simulated at once, leaves every decision unchanged. Changing all other decisions together (about 13 on average) moves these values by at most 0.021 log points, small relative to $\hat{\sigma} = 0.63$.

I.3 Welfare accounting

Equation (25) in Section 7.1 defines the welfare effect ΔW_y of moving between two scenarios in decision year y. Quarterly consumer surplus is $\mathrm{CS}_t = M_t \sum_i w_i \alpha_i^{-1} \log(1 + \sum_j e^{\bar{u}_{ijt}})$, using 500 simulated households with weights w_i, where $\bar{u}_{ijt}$ is household i's utility from product j before the extreme-value shock. Domestic producers' variable profit Π_t^D sums $(P_{jt}^f - c_{jt})Q_{jt}$ over the products of firms producing in China other than Tesla, with P^f including the central subsidy and excluding purchase tax.

Domestic producers include JVs and foreign-owned firms producing in China, with their full profits rather than only the income accruing to Chinese owners. Tesla's and importers' profits are reported separately. Subsidy outlays and purchase-tax revenue are not netted from domestic welfare; Appendix J reports this adjustment.

ΔK_y is the change in the fixed costs of new product offerings, counted once per introduced potential product. Introducing g in scenario $\mathcal{E}$ costs $\exp(X_g\beta^{\mathcal{E}} + \sigma\nu_g)$, which includes the disturbance, the part of the firm's net return that my computation misses. Favorable disturbances therefore make introduced products cheaper than their systematic costs imply. Canceling an introduction saves its cost in the comparison scenario, and a product introduced in both scenarios contributes any change in its fixed cost. Appendix J examines accounting that excludes the disturbance from realized costs.

Each decision year is a separate static comparison. The flow change has two parts: the change over the year's four quarters with offerings fixed, and the additional change from offering adjustments over each changed model's full first year, including quarters in the next calendar year. The factor $A/4$, with $A = \sum_{u=0}^{14} 0.975^u = 12.64$, capitalizes each part's average quarterly flow over 15 quarters, as in estimation, and fixed costs are deducted once. With offerings fixed, only the first part enters and fixed costs are evaluated on the observed offerings; in full equilibrium, both use the final offering sets.

Reported monetary effects average ΔW_y over 2020–2022, or 2018–2020 for earlier local production, and offering counts average the annual responses over the same years. Table I2 reports the individual years.

In the fixed-offering comparison, the observed offerings are imposed in each scenario, and the costs of those introductions are evaluated under that scenario's cost schedule. It

Table I2: Annual welfare comparisons: 15-quarter present values (RMB billion)

	Offerings fixed			Full equilibrium		
Year	CS	Net profits	Welfare	CS	Net profits	Welfare
2020	+41.1	+33.0	+74.1	+66.7	+17.1	+83.8
2021	+125.1	+30.8	+155.9	+151.6	+9.3	+160.9
2022	+213.8	+74.2	+287.9	+263.7	+2.3	+265.9
Average	+126.6	+46.0	+172.7	+160.6	+9.6	+170.2

Notes: Each row compares the observed market with the market without Tesla's local production under that year's conditions. CS is consumer surplus; net profits cover producers in China other than Tesla. The average row gives the monetary values in the main figures and tables.

therefore includes cost savings even when the offering set is unchanged. Averaged over 2020–2022, those savings are RMB 36.9 billion. Adding them to RMB 135.7 billion in capitalized consumer surplus and variable profits gives RMB 172.7 billion in domestic welfare.

Under this accounting, offering adjustment adds RMB 50.9 billion in capitalized consumer surplus and variable profits, but raises the fixed costs of introducing new models by RMB 53.3 billion relative to the observed offerings. Domestic welfare is therefore RMB 2.4 billion lower than with offerings fixed. With offerings fixed, the observed offerings are also imposed in the market without Tesla's local production, where they need not be an equilibrium.

I.4 Full results for 2020–2022

Table I3 reports the results underlying Figure 6: aggregate welfare in Panel A, the channels in Panel B, and the effects by firm type in Panel C, with variable profits and fixed costs shown separately.

Without Tesla's local production, annual new offerings of Tesla-size BEVs fall to 0.1, compared with 13.3 observed on average. Two features of the model explain this result. First, fixed costs common to all potential products rise after 2019, and removing the fixed-cost decline leaves these costs above their earlier levels. Second, conditional draws of the disturbance place observed introductions with low predicted probabilities close to their thresholds. For the average post-2019 introduction probability of 0.085 for Tesla-size BEVs, an introduced product's expected margin over its threshold is about 0.29 log points, well below the 1.14 log-point cost increase from removing the decline. Appendix J examines sensitivity to the fixed-cost parameters.

Interaction between the two spillovers. Table I4 reports each spillover's contribution when added before or after the other, starting from Tesla's products without either spillover.

Table I3: Tesla's local production: welfare and new product offerings, 2020–2022

A. Aggregate welfare (RMB billion)

	Offerings fixed	Full equilibrium
Consumer surplus	+126.6	+160.6
Domestic producer net profits	+46.0	+9.6
Domestic welfare	+172.7	+170.2
Tesla's profits	+61.9	+61.6
Importers' profits	−1.7	−2.4

B. Channels in full equilibrium

	Domestic welfare (bn)	Annual new offerings, all	BEVs Tesla size	BEVs smaller sizes
Total effect	+170.2	+14.2	+13.2	+1.2
Competition	+50.7	−1.4	0.0	−1.2
Supply-side spillovers	+119.5	+15.6	+13.2	+2.4
Marginal-cost (Shapley)	+87.1	+5.7	+3.0	+2.7
Fixed-cost (Shapley)	+32.3	+9.9	+10.2	−0.3

C. Heterogeneity by firm type, full equilibrium

	Annual new offerings	Variable profits	Fixed-cost spending	Net profits
Established Chinese automakers	+7.0	−3.0	+7.8	−10.7
EV start-ups	+4.5	+30.0	+5.3	+24.7
JVs and other foreign automakers	+2.7	+0.2	+3.3	−3.2
Luxury makers	0.0	−1.2	0.0	−1.2

Notes: Means over 30 conditional draws of the disturbance at the point estimates, relative to the market without Tesla's local production. Panel B decomposes the total: the Shapley rows average the two orders of adding the spillovers. Net profits in Panel C sum to domestic producer net profits in Panel A; positive fixed-cost spending lowers net profits. With offerings fixed, rivals keep their observed offerings. Monetary values are average annual 15-quarter present values; offering counts are annual averages.

The difference is their interaction. Both contributions are larger when the other spillover is present. The interaction adds 5.4 new product offerings per year, almost all in Tesla-size BEVs, and RMB 18.3 billion in domestic welfare.

Table I4: Interaction between marginal-cost and fixed-cost spillovers

Effects of adding each spillover in either order	Annual new offerings added first	Annual new offerings added second	Welfare (bn) added first	Welfare (bn) added second
Marginal-cost spillover	+3.0	+8.4	+78.0	+96.3
Fixed-cost spillover	+7.2	+12.6	+23.2	+41.5
Interaction	+5.4		+18.3	

Notes: Means over 30 conditional draws of the disturbance at the main estimates. "Added first" introduces a spillover with the other absent; "added second" introduces it with the other present. The interaction, the second contribution minus the first, is the same for both spillovers. Welfare is full-equilibrium domestic welfare in RMB billion.

J Counterfactual Sensitivity

The bands in Section 7 show variation across conditional draws of the disturbance at the main estimates. This appendix examines alternative fixed-cost parameters, the attribution of the fixed-cost decline to Tesla, and the two alternative welfare measures.

Table J1: Sensitivity of the effects of Tesla's local production, 2020–2022

Full-equilibrium effects	Annual new offerings	Consumer surplus RMB bn	Domestic welfare RMB bn
Main estimates	+14.2	+160.6	+170.2
32 vectors passing the joint test: range	[+3.8, +14.1]	[+133.7, +160.6]	[+142.6, +174.9]
$\sigma = 0.5$	+14.1	+154.3	+163.6
$\sigma = 1.5$	+10.8	+152.0	+165.9
Costs exclude the disturbance: main estimates	+14.2	+160.6	+127.8
Costs exclude the disturbance: range over the 32 vectors	[+3.8, +14.1]	[+133.7, +160.6]	[+108.5, +137.2]

Notes: Changes relative to the market without Tesla's local production, 2020–2022. Monetary amounts are average annual 15-quarter present values; new offerings are annual averages. Ranges are the minimum and maximum of means over the 32 parameter vectors that pass the firm-year joint test. These vectors and the σ rows use five draws of the disturbance, and the main estimates use 30. The σ rows re-estimate the other coefficients with σ fixed. Excluding the disturbance from costs changes only the fixed-cost accounting.

Parameter vectors. Following Fan and Yang (2025), I evaluate selected fixed-cost vectors, varying one coefficient at a time and re-estimating σ and the other coefficients. I also evaluate vectors at $\sigma = 0.5$ and $\sigma = 1.5$, the smallest and largest values on a grid of 0.1 at which a coefficient vector passes both the PR test for σ and the firm-year joint test. The 32 vectors reported here pass the firm-year joint test and each uses five draws of the disturbance, while

the main estimates use 30. Table J1 reports the smallest and largest vector means and, separately, results at the two values of σ.

Across the 32 vectors, Tesla's local production adds 3.8–14.1 new product offerings per year and RMB 142.6–174.9 billion in domestic welfare. Competition reduces new offerings, while the combined spillovers increase them, at every vector. The Tesla-size BEV response ranges from 3.3 to 13.3 additional offerings per year, compared with 13.2 at the main estimates. At $\sigma = 0.5$ and $\sigma = 1.5$, the estimated τ is -1.09 at both values, and local production adds 14.1 and 10.8 new product offerings per year and RMB 163.6 and 165.9 billion in domestic welfare.

The smallest effects come from the vector at the lower end of the range for the Tesla size $\times$ post coefficient. Its τ is -0.06, but the sum of τ and the Tesla size $\times$ post coefficient is -1.06, close to -1.10 at the main estimates. This vector assigns the post-2019 decline in the cost of introducing Tesla-size BEVs to the Tesla size $\times$ post coefficient, which is shared with gasoline products and is not attributed to Tesla in the counterfactual. The decline therefore occurs in both markets, as in the zero-attribution case. Tesla's local production still adds 3.8 new product offerings per year and RMB 142.6 billion in domestic welfare, close to the RMB 143.4 billion in the zero-attribution case.

Attributing the fixed-cost decline to Tesla. The estimated decline in the fixed cost of introducing Tesla-size BEVs need not be entirely due to Tesla's local production, since EV policies and battery technology also changed over the period. Table J2 reports results under four treatments of the decline, which differ in which of the two markets it occurs in.

Full attribution. The main results let the decline occur only in the observed market, attributing all of it to Tesla's local production. They give the upper end of the effects: rivals' new product offerings rise by 14.2 per year and domestic welfare by RMB 170.2 billion.

Lower-end attribution. The lower-end attribution uses $\hat{\tau} = -0.82$, the smallest estimated decline, from the specification in Appendix H.4 that gives Small BEVs their own post-2019 change. That specification keeps the 2019 subsidy changes, which hit Small BEVs hardest, out of τ. The remaining -0.32 of the main estimate occurs in both markets. Competition removes 1.4 new product offerings per year, Tesla's part of the decline adds 6.8, and the marginal-cost spillover adds 8.4, for a total of 13.8. Across the 30 draws, the 5–95 percent range of this total is 12.5 to 14.9. The results stay close to the main ones because the part of the decline not attributed to Tesla is too small to make many Tesla-size BEVs worth introducing without Tesla's local production.

Zero attribution. If other forces caused the whole decline, it would occur in both mar-

kets, and the comparison isolates competition and the marginal-cost spillover. Competition removes 2.1 new product offerings per year and the marginal-cost spillover adds 8.4, for a total of 6.3, with a 5–95 percent range of 5.0 to 8.0. Domestic welfare rises by RMB 143.4 billion, about 84 percent of the main estimate.

Decline removed from both markets. Unlike the other cases, this one does not apportion the observed decline. It removes the fixed-cost decline altogether, showing what Tesla's local production does when Tesla-size BEVs remain costly to introduce. With fewer of them near their introduction threshold, the marginal-cost spillover adds only 3.0 new product offerings per year rather than 8.4, and offerings rise by 1.6 in total. Domestic welfare still rises by RMB 128.7 billion.

Table J2: Attributing the fixed-cost decline to Tesla, 2020–2022

Attributed to Tesla	Annual new offerings	Consumer surplus	Producers' net profits	Domestic welfare	Welfare, offerings fixed
All (main)	+14.2	+160.6	+9.6	+170.2	+172.7
Lower end (56 percent decline)	+13.8	+158.8	+9.7	+168.5	+157.7
None	+6.3	+136.3	+7.1	+143.4	+135.7
Removed from both markets	+1.6	+124.2	+4.5	+128.7	+135.7

Notes: Changes from the market without Tesla's local production, as means over 30 conditional draws of the disturbance. The first four columns are full equilibrium. Monetary values are average annual 15-quarter present values in RMB billion; offering counts are annual averages. Producers' net profits are those of domestic producers, net of the fixed costs of introducing new models.

Alternative fixed-cost accounting. The main accounting counts the whole disturbance in fixed costs, as the part of firms' net returns that my computation misses. If it instead reflects components of profits that the model omits, realized fixed costs would exclude it and each introduction would cost $\exp(X_g\beta^{\mathcal{E}})$. This changes welfare accounting, while leaving equilibrium decisions and consumer surplus unchanged. At the main estimates, domestic welfare rises by RMB 127.8 billion rather than 170.2 billion. With the same accounting applied to the observed offerings, fixed-offering welfare is RMB 261.6 billion rather than 172.7 billion: the cost saving on those introductions is RMB 125.8 billion rather than 36.9 billion. Offering adjustments therefore lower welfare by RMB 133.7 billion under this alternative, compared with RMB 2.4 billion in the main accounting. The fixed-cost spillover's Shapley contribution falls from 32.3 to 1.6 billion, or to −1.6 billion when fiscal flows are also included, and the marginal-cost contribution falls from 87.1 to 74.3 billion. The welfare contribution of offering adjustments therefore depends on whether the disturbance is actual spending. Full-equilibrium domestic welfare remains positive across the evaluated parameter vectors

under either accounting, before netting fiscal flows.

Fiscal adjustment. Table J3 subtracts the change in central subsidy outlays and adds the change in purchase-tax revenue to the reported welfare contrasts, holding firms' choices and the 15-quarter horizon fixed. This lowers the main gain from RMB 170.2 to 154.4 billion. Combining the fiscal adjustment with accounting that excludes the disturbance from costs gives RMB 112.0 billion. Across the 32 vectors, the two adjustments combined leave welfare gains of RMB 87.9–119.3 billion.

Table J3: Welfare accounting and fiscal sensitivity (RMB billion)

Accounting	2020–2022 total	2020–2022 no fixed-cost spillover	2018–2020 no fixed-cost spillover
Main costs; fiscal flows excluded	+170.2	+128.7	+90.0
Main costs; fiscal flows included	+154.4	+116.8	+69.3
Systematic costs; fiscal flows excluded	+127.8	+125.6	+103.7
Systematic costs; fiscal flows included	+112.0	+113.6	+83.0

Notes: Main cost accounting includes the disturbance; systematic costs, $\exp(X_g\beta)$, exclude it. Fiscal inclusion subtracts subsidy outlays and adds purchase-tax revenue. All rows use the same decisions and prices. The last two columns exclude the fixed-cost spillover; the last column is earlier local production.

K Earlier Local Production: Competition and Marginal-Cost Spillovers

This appendix examines the balance between competition and marginal-cost spillovers when Tesla's later locally produced line-up is introduced into the historical 2018–2020 market. The comparison with 2020–2022 excludes the fixed-cost spillover. Because Tesla's line-up is the same in both periods, the comparison reflects the earlier, smaller domestic market.

Table K1 describes the historical markets. The earlier market had a much smaller base of rival BEV sales that receive the cost reduction: about 117,000 in 2018 and 103,000 in 2019, compared with 370,000 in 2021 and 638,000 in 2022. Tesla-size BEVs accounted for 2.8 and 7.1 percent of rival BEV sales in 2018 and 2019, compared with 17.3 and 19.9 percent in 2021 and 2022. The share of rival BEV sales that receive the cost reduction was nevertheless higher in 2018–2019, at 30.2 and 34.1 percent, than in 2021–2022, at 24.9 and 25.2 percent. The smaller aggregate spillover gains therefore reflect the smaller sales base rather than a lower share. Section 3 documents the accompanying changes in model offerings and attributes.

Table K1: Rival BEV sales, product mix, and cost-spillover coverage

	Rival BEV registrations (thousands)	Tesla-size sales share (%)	Sales receiving the cost reduction (thousands)	Share receiving the cost reduction (%)
2018	387.0	2.8	116.9	30.2
2019	303.1	7.1	103.3	34.1
2020	499.9	15.6	133.3	26.7
2021	1,489.1	17.3	370.1	24.9
2022	2,532.5	19.9	638.1	25.2

Notes: Observed private registrations in the counterfactual market sample. Rivals are producers in China other than Tesla, including JVs; imports are excluded. Tesla size is Mid and Upper-mid. Sales receiving the cost reduction are those of models that share a supplier with Tesla and have a price and marginal cost of at least RMB 50,000. Shares use rival BEV registrations as the denominator.

K.1 Construction

I move Tesla's locally produced line-up eight quarters earlier: the 2020 Model 3 is offered in 2018, the 2021 Model 3 and Model Y in 2019, and the 2022 line-up in 2020. The imported Model 3 leaves the market; imported Model S and Model X offerings remain observed. Each model keeps its source-quarter firm price, while its consumer price reflects the subsidies of the quarter in which it is sold. Its source-quarter appeal is adjusted for the change in EV appeal predicted by the equation in Appendix F.2. In the plant's first year, 2018, Tesla's quarterly sales are capped at its actual domestic sales in the corresponding quarter of 2020, through a common reduction in appeal. From 2019 there is no cap. Appendix K.3 examines an additional 2019 sales cap. Exposed rival EVs receive the estimated marginal-cost spillover from 2018Q1. In rivals' profit simulations, the direct effects of Tesla's earlier line-up use the same draws of unknown shocks as in estimation, and its interactions with other offering changes use realized shocks. Subsidies, credits, and ownership rules otherwise remain historical. This experiment assumes that China permits Tesla's local production two years earlier.

I exclude the fixed-cost spillover from both periods because the estimated effect describes the post-2019 cost schedule, and applying it from 2018 would require an additional extrapolation into the period before local production. The matched comparison therefore focuses on competition and marginal-cost reductions, with the remaining cost coefficients unchanged.[37]

[37] As a diagnostic of this extrapolation, applying the estimated effect from 2018 would put the fixed cost of introducing a Tesla-size BEV in 2018–2019 about 40–75 percent below its level in any observed year, before the common post-2019 increase could offset the reduction. The estimated model would then predict about 60 Tesla-size BEV introductions over those two years, compared with 7 observed.

K.2 Results

Figure K1 compares the two historical markets, each relative to its own market without Tesla's local production. The same estimates govern both comparisons: substitution patterns determine how much Tesla's models take from rivals, and supplier overlap determines whose production costs fall. What differs is the market they act on. In 2018–2020, the EV market was much smaller, and far fewer rival sales stood to benefit from lower marginal costs.

Panel A shows that consumers gain in both markets. Under earlier local production, consumer surplus rises by RMB 96.9 billion in full equilibrium and domestic welfare by RMB 90.0 billion, compared with RMB 124.2 billion and RMB 128.7 billion in the matched 2020–2022 comparison. Competition contributes more to domestic welfare in the earlier market, RMB 65.0 billion versus 50.7 billion, while the marginal-cost spillover contributes far less, RMB 25.0 billion versus 78.0 billion. The smaller welfare gain therefore reflects the much smaller contribution of the marginal-cost spillover. Domestic producers' net profits fall by RMB 6.9 billion, because the spillover offsets only part of their losses from competition.

As Panel B shows, the balance between the two forces also shifts rivals' product offerings. In the earlier market, competition deters 13.9 new product offerings per year and the marginal-cost spillover adds only 1.0. On net, rivals introduce 12.8 fewer new products per year, a 23 percent decline from the 56.2 predicted without Tesla's local production. In 2020–2022, by contrast, competition deters 1.4 and the spillover adds 3.0. Most of the contraction, 11.0 offerings per year, is among smaller BEVs, which accounted for more than 90 percent of rival BEV sales in 2018–2019. Tesla-size BEVs also decline, while gasoline offerings change little. Simulated profits show why: competition lowers smaller BEVs' incremental profits much more than in 2020–2022, and the spillover offsets only part of this loss, even for potential products whose designs all qualify for the cost reduction.

Because rivals introduce fewer models, allowing offerings to adjust lowers the consumer gain from RMB 111.2 billion with offerings fixed to 96.9 billion, and domestic welfare from RMB 108.8 billion to 90.0 billion; in 2020–2022, both change little. In both markets, Tesla's local production raises consumer surplus and domestic welfare. Its effect on rivals' offerings depends on how many rival sales benefit from the marginal-cost spillover. That number rises with the size of the domestic EV market.

Panel C shows that, as in the main results, EV start-ups gain while established Chinese automakers and JVs lose. Established Chinese automakers cut the most new offerings, 5.6 per year, and lose RMB 4.2 billion in net profits, about as much as JVs and other foreign automakers; savings in fixed-cost spending partly offset their variable-profit losses. EV start-ups gain RMB 2.5 billion, far less than their RMB 18.5 billion in the matched 2020–2022 comparison. Tesla's profits rise by RMB 57.2 billion. Appendix K.3 examines sensitivity to

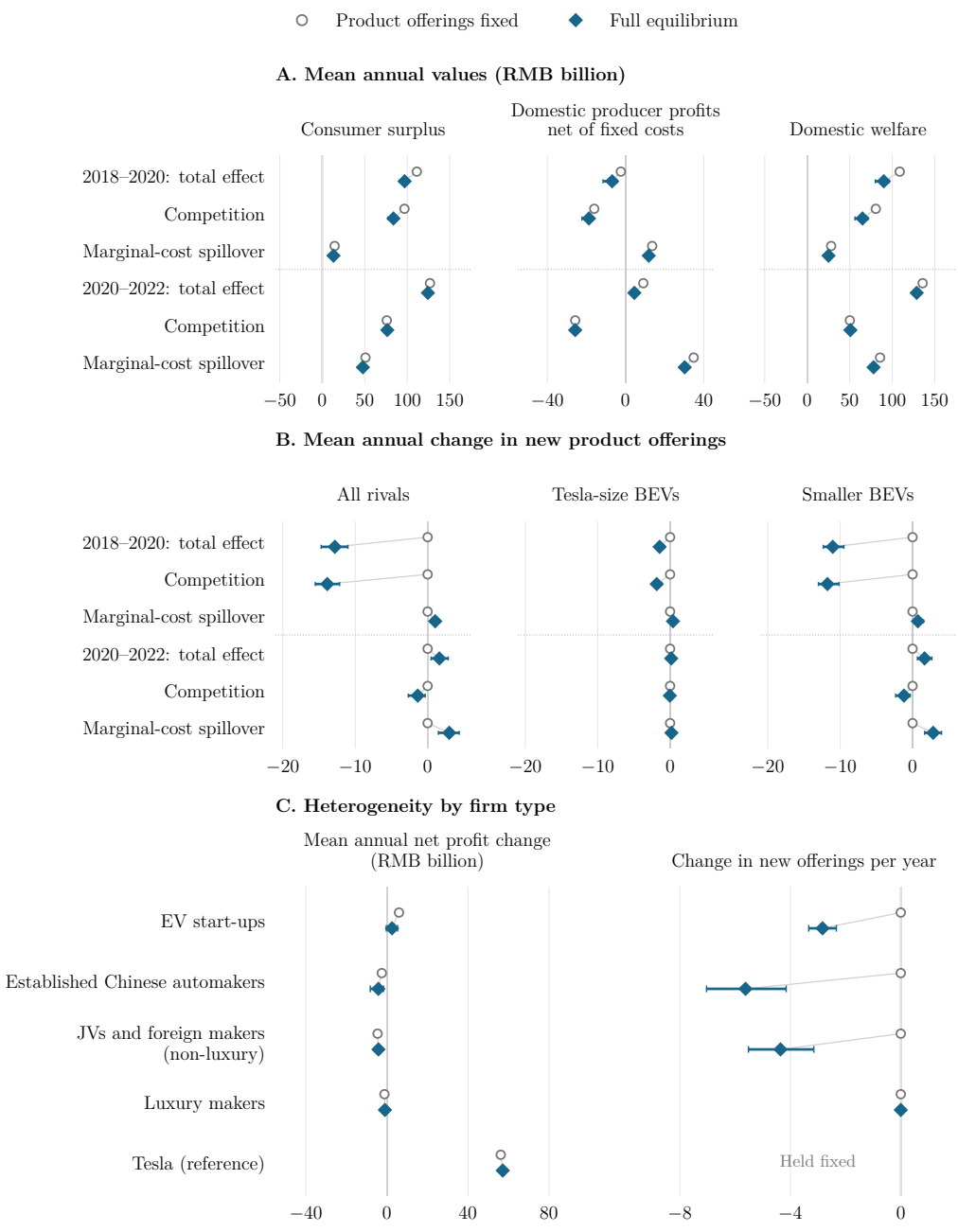


Figure K1: Competition and marginal-cost spillovers: historical market comparisons

Notes: The 2018–2020 rows are earlier local production, and the 2020–2022 rows are the matched comparison. Both exclude the fixed-cost spillover; each total is relative to its period's market without Tesla's local production, and the marginal-cost contribution adds that spillover after competition. Monetary values average the annual effects, each valued over 15 quarters; offering counts are annual averages. Panel C is earlier local production only. Points and bands are as in Figure 6.

the parameters, cost accounting, and the additional 2019 sales cap.

Table K2 reports the numbers behind Figure K1.

Table K2: Earlier local production: competition and marginal-cost spillovers

A. Aggregate welfare (RMB billion)

	2018–2020 market		2020–2022 market	
	Offerings fixed	Full equilibrium	Offerings fixed	Full equilibrium
Consumer surplus	+111.2	+96.9	+126.6	+124.2
Domestic producer net profits	−2.4	−6.9	+9.1	+4.5
Domestic welfare	+108.8	+90.0	+135.7	+128.7
Tesla's profits	+56.2	+57.2	+61.9	+63.9
Importers' profits	−4.2	−4.0	−1.7	−1.8

B. Channels in full equilibrium

	Domestic welfare (bn)	Annual new offerings, all	BEVs Tesla size	BEVs smaller sizes
2018–2020: total effect	+90.0	−12.8	−1.4	−11.0
Competition	+65.0	−13.9	−1.8	−11.8
Marginal-cost spillover	+25.0	+1.0	+0.4	+0.7
2020–2022: total effect	+128.7	+1.6	+0.2	+1.7
Competition	+50.7	−1.4	0.0	−1.2
Marginal-cost spillover	+78.0	+3.0	+0.2	+2.8

C. Heterogeneity by firm type, full equilibrium

	Annual new offerings	Variable profits	Fixed-cost spending	Net profits
Established Chinese automakers	−5.6	−7.3	−3.1	−4.2
EV start-ups	−2.8	+1.4	−1.1	+2.5
JVs and other foreign automakers	−4.4	−6.0	−1.8	−4.2
Luxury makers	0.0	−1.0	0.0	−1.0

Notes: Means over 30 conditional draws of the disturbance at the point estimates, excluding the fixed-cost spillover in both periods. Each total is relative to its period's market without Tesla's local production, and the marginal-cost contribution adds that spillover after competition. Panel C refers to earlier local production. Profits and costs are in RMB billion; negative fixed-cost spending is a saving.

K.3 Sensitivity

Parameter estimates. Table K3 repeats both comparisons at the two ends of the τ range and at $\sigma = 0.5$ and $\sigma = 1.5$, from Appendix J. Earlier local production removes 5.4 to 14.4 new product offerings per year, mostly smaller BEVs, while local production in 2020–2022 adds 1.1 to 3.1. Earlier local production raises domestic welfare at every vector, by 66 to 78 percent of the matched 2020–2022 gain. Because the exercise excludes the fixed-cost

spillover, the τ rows matter only through the other coefficients re-estimated with them; σ moves the offering response most.

Alternative welfare accounting. Earlier local production yields the smaller welfare gain under every accounting in Table J3, between 59 and 83 percent of the matched 2020–2022 gain, compared with 70 percent under the main accounting. Excluding the disturbance from realized fixed costs gives gains of RMB 103.7 and 125.6 billion. Netting subsidy outlays and purchase-tax revenue gives RMB 69.3 and 116.8 billion, or RMB 83.0 and 113.6 billion when the disturbance is also excluded.

Additional 2019 sales cap. Without a 2019 cap, and with rivals' offerings held at their observed levels, the earlier line-up sells 326,000 cars in 2019. Capping its quarterly sales at Tesla's actual domestic sales in the same quarter of 2021 lowers this to 239,000, or 27 percent less. The cap reduces the decline in rivals' new product offerings from 12.8 to 11.6 per year and the domestic welfare gain from RMB 90.0 to 78.1 billion. It changes the magnitudes, not the direction of the offering response.

Table K3: Sensitivity of the effects of earlier local production

A. Matched timing comparisons: fixed-cost spillover excluded in both periods

	Welfare (bn) 2018–2020	Welfare (bn) 2020–2022	Annual new offerings 2018–2020	Annual new offerings 2020–2022
Main estimates (30 draws)	+90.0	+128.7	−12.8	+1.6
τ at lower end of range	+99.4	+129.2	−8.5	+1.3
τ at upper end of range	+90.7	+138.4	−11.4	+3.1
$\sigma = 0.5$	+88.1	+125.6	−14.4	+1.9
$\sigma = 1.5$	+102.4	+131.3	−5.4	+1.1
Costs exclude the disturbance (30 draws)	+103.7	+125.6	−12.8	+1.6

B. Additional 2019 sales cap: earlier local production

	Domestic welfare (bn)	Annual new offerings
Without the additional 2019 cap	+90.0	−12.8
With the additional 2019 cap	+78.1	−11.6
Change caused by the cap	−12.0	+1.2

Notes: Panel A compares earlier local production with local production in 2020–2022, in full equilibrium, each relative to its period's market without Tesla's local production. Parameter rows use five draws of the disturbance. The τ rows re-estimate σ and the other coefficients; the σ rows re-estimate the other coefficients with σ fixed. Panel B adds the 2019 sales cap on the 30 draws of the main estimates; the 2018 cap applies in both rows. The change row is computed before rounding.