Subsidizing Industry Growth in a Market with Lemons: Evidence from the Chinese Electric Vehicle Market

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Abstract

Consumer subsidies are common policies to foster growth in emerging green industries, such as the electric vehicle (EV) industry. Ideally, such policies can expand the market and improve welfare by promoting firm entry and inducing technology spillovers to related industries. However, a poorly designed subsidy can attract "lemon" entrants with low and imperfectly observed quality, undermining the industry's reputation and dampening industry growth. Using Chinese EV market data from 2012 to 2018, this paper examines how subsidies affect the growth of a nascent industry. We develop a structural model of vehicle demand, firm entry and expansion, and EV reputation dynamics to analyze the subsidy's equilibrium impact. Our results suggest that the net welfare impact of the subsidy is nearly zero and that the reputation impact reduces the subsidy benefits by 10.8%. Decreasing the subsidy level can improve policy efficiency and mitigate the reputation impact, while stringency in the attribute-based subsidy can serve as a screening tool that effectively filters out lemons. This paper develops a framework for designing green industrial policies, highlighting the critical but often neglected role of the reputation channel.

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1 Introduction

Over the past decade, major markets have implemented policies promoting green industries, leading to notable growth in clean energy. In 2022, governments worldwide spent more than $40 billion to promote electric vehicle (EV) sales and approximately $10 billion toward residential solar panels. Consumer subsidies are standard policies used by most countries, among them the US, UK, Norway, and China. Ideally, such policies can attain higher welfare by enlarging the market size, promoting firm entry, and inducing technology spillovers to related industries.

However, poorly designed subsidies can draw in low-quality entrants, which reduces policy efficiency and undermines consumer perceptions of entire industries. Several markets have experienced an influx of low-quality entrants following the institution of subsidies. In Spain, around 2010, after significant public support for the development of solar energy, the market became inundated with poorly designed solar facilities.[1] California's program for residential solar panels was also associated with subpar craftsmanship.[2] In China's EV manufacturing sector, the substantial entry of low-quality EV firms offering vehicles with poor battery and engine performance or safety concerns led to consumer complaints and harmed the industry's reputation. Consumer perception plays a significant role in nascent markets, with media often noting that consumer misperceptions about EV quality are significant barriers to EV adoption.[3,4] When failing to screen for qualities, generous subsidies can lead to unintended outcomes by attracting entrants with low and imperfectly observed quality (i.e., lemons), damaging the industry's reputation, leading to underadoption of high-quality EVs, and potentially resulting in a low-quality low-reputation equilibrium.

Do subsidies attract lemon entrants, and why? How can governments design optimal consumer subsidies that effectively stimulate industry growth while avoiding lemon entrants and potential reputation losses? This paper studies these questions using data on the Chinese EV market from 2012 to 2018. While anecdotal evidence suggests a link between subsidies and the entry of lemons, systematic evidence is lacking. This paper provides novel systematic evidence on the role of consumer subsidies in attracting lemons and documents the presence of reputation externalities in the nascent Chinese EV market. We then develop and estimate a model to analyze the equilibrium impact of the subsidy on industry growth and characterize the optimal design of the subsidy.

We study optimal design considering three channels, with a particular focus on the reputation impact: (i) the subsidy brings consumer prices closer to the vehicle marginal costs and environmental benefits, expanding the market; firm entry responses and the enhanced competition make this impact permanent—denoted as the direct channel; (ii) the subsidy-induced low-quality entrants introduce

[1] Rosenthal, Elisabeth. 2010. "Solar Industry Learns Lessons in Spanish Sun." New York Times.
[2] Campaign For Accountability 2017. "What Consumer Complaints Reveal about the Solar Industry."
[3] Stenquist, Paul. 2022. "Hurdle to Broad Adoption of E.V.s: The Misperception They are unsafe." New York Times.
[4] Halper, Evan. 2022. "Getting people to accept EVs may be harder than passing climate bill." The Washington Post.

a negative reputation externality, altering reputation dynamics—denoted as the reputation channel; and (iii) the subsidy positively influences upstream sectors. Particularly, increasing EV sales lead to declining battery costs, which is reflected in future vehicle marginal costs—denoted as the upstream spillover channel. These three channels together shape the welfare impact of the consumer subsidy and inform its optimal design.

The EV industry in China is an ideal setting to study these issues. The Chinese government introduced an attribute-based consumer subsidy in 2012. The most significant subsidization occurred from 2014 to 2017, when subsidies could account for up to 50% of an EV's price, one of the world's highest rates. Consequently, EV sales surged from 8,159 in 2012 to over 2.9 million in 2021. From 2012 to 2018, EV battery costs decreased by more than 80%, and over fifty EV manufacturing firms entered the market, which attests to the subsidy's success as an industrial policy. On the other hand, the subsidy incentivized purchases among price-sensitive consumers and increased the relative profitability of cheaper cars. This attracted many lemon firms into the market, resulting in a surge in consumer complaints and damaging the industry's collective reputation. Many consumers reported engine or battery issues, and numerous fires were reported, deepening reliability concerns. Top-tier firms stated that the subsidy, by promoting low-quality cars, actually harmed the firms' profits. The government also circulated documents that discussed adverse selection, EV quality, and consumer trust.[5]

We identify lemon firms in Section 2. Lemons are defined as firms with low unobserved quality. In the context of the EV industry, these are firms with substandard production lines incapable of assembling reliable EVs. EVs from lemon firms have a higher probability of experiencing battery or engine issues and a higher fire risk, yet consumers do not have perfect information about these issues at the point of purchase. Leveraging data from the largest review website and the largest vehicle complaints filing and repair platform in China, we identify nine lemon firms that consistently demonstrate poor quality in these areas.[6,7]

We use two reputation factors to represent the collective reputation of EVs and to capture the externality throughout the paper—EV fires and the local share of lemon sales. Section 3 presents evidence regarding the existence of reputation externalities. We begin with a consumer survey that explains the externality from the consumer learning process and a social network perspective. Our results suggest that the experiences of friends who own lemon EVs can negatively impact the perceptions of potential buyers and decrease their probability of purchasing an EV. This justifies our consideration of a within-market reputation externality and use of a city-level lemon share variable.

[5]These government documents highlight the importance of quality and consumer trust and discuss potential subsidy-induced problems. Sources: https://www.gov.cn/xinwen/2016-08/16/content_5099720.htm

[6]Autohome platform (https://ir.autohome.com.cn/) is the largest vehicle review platform, from which automakers purchase data and market reports.

[7]Car Quality Network (www.12365auto.com) is also an important data source for the General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China.

We then validate these two factors using sales data. We examine the impact of EV fires on uninvolved EV firms using a difference-in-differences (DID) design that compares the sales of these firms in the event city and other cities. After an EV fire, the average sales in the event city decrease by 10% for uninvolved EV firms, and the effect lasts at least three months. Testing the impact of the lemon share on a city's future adoption of EVs, we find that a 10% increase in the local share of lemon sales would decrease future EV sales by 5.2%.

We then develop a model to formulate the subsidy's impact through the three channels—the direct channel, the upstream spillover channel, and the reputation channel—and establish the relationship between the subsidy and lemon entrants. The model features consumer choices, entry responses of lemon and nonlemon firms, and EV reputation dynamics. The demand system is a standard static discrete-choice model (Berry et al. (1995)) with random coefficients on prices and reputation factors. We then study firm entry decisions using a dynamic entry model with endogenous evolution of the market structure, EV reputation factors, and battery cost. There are four key primitives: (i) consumer price sensitivity, (ii) consumer reputation sensitivity, (iii) the battery cost reduction rate, and (iv) firm entry costs. The direct impact depends on price sensitivity, which determines how EV sales respond to lower prices. The reputation channel is influenced by both price and reputation sensitivity. In highly price-sensitive markets, subsidies tend to attract more lemons. When consumers switch to EVs in response to a subsidy, they opt for cheaper options that are more likely to be lemons. High reputation sensitivity further hurts nonlemons because consumers' perceptions are more affected by the high lemon share. The battery cost reduction rate affects the upstream spillover impact. Across all channels, entry costs are essential because entry responses contribute to both the direct channel markup changes and the amplification of the reputation impact through entry selection.

Sections 4 and 5 detail the empirical model and estimation. We first estimate the demand system using aggregate moments and micromoments, following the framework of Berry et al. (2004). Assuming that firms choose prices to maximize static profits, we back out firms' marginal costs using first-order conditions and estimate the battery cost time trend. With the estimated demand system, we can calculate the subsidy's impact on firms' per-period profits. We next study how these shifts in profit impact firm entry responses and the evolution of market structure and reputation. Using a finite-period dynamic discrete choice game of firm entry and expansion, we develop a model—comprising more than fifty firms across 20 primary markets (provinces)—of the Chinese EV industry's growth path. Our model accounts for substantial heterogeneity in firms' profits across time and markets, illustrating the diverse entry elasticities to varying profit shifts, especially across lemon and nonlemon firms. For tractability, we adopt a partially oblivious equilibrium (POE; see Benkard et al. (2015)) with three dominant firms to reduce the strategic interactions of fringe firms.

Our model includes two margins of entry in this emerging industry, representing two kinds of entry costs. First, a new firm needs to enter the industry by building a factory, hiring workers, and designing an EV production line. Second, established firms can expand into markets (provinces) by establishing sales and distribution networks, constructing retail stores, and promoting their brands and marketing initiatives. Both the industry and the market entry margins selectively filter different types of firms, resulting in significant heterogeneity in market structure and EV reputation across provinces. This two-margin setup introduces modeling challenges because the dynamics of all markets are interdependent. We use a nested-loop algorithm to reduce the computational burden caused by this interdependence: the outer loop solves the industry-level entry strategies, while the inner loop solves the entry strategies for each individual market. This approach captures entry spillovers across provinces through the outer loop. Our analysis reveals that neglecting industry-level entry results in a 25% underestimation of the subsidy's impact. Failing to consider either margin could lead to biased estimates of the entry elasticity and the subsidy's impact.

Using the estimated primitives, we quantify the impacts and evaluate whether the subsidy design can be altered to improve social surplus. Section 6 reports that the net impact of the subsidy is nearly 0. The total benefit from the subsidy is 55.7 billion RMB (8.56 billion USD), whereas the expenditure is 56.7 billion RMB (8.72 billion USD).We find that the subsidy increases EV sales by 83.5% and contributes to more than half of the firm entry. Through decomposition counterfactual analyses, we find that both the direct channel and the reputation channel introduce welfare losses but that the upstream spillover channel has a large benefit, with the reduced battery cost accounting for a reduction of more than 20% in the marginal cost of vehicles. The loss from the direct channel arises from deadweight loss (DWL) and choice distortions due to oversubsidizing. The subsidy decreases the gap between consumer prices and social marginal costs[8] from on average 31% to almost 0. Although this expands the market and notable firm entry enhances post-subsidy competition and welfare, the net impact is negative.

The subsidy attracts lemons more than nonlemons because of the high estimated price sensitivity, and the entries of 57% of the lemon entrants are subsidy induced.To quantify the losses from the reputation channel, we simulate a counterfactual scenario in which consumers have perfect information about lemons and exposure to EV fires or lemons does not generate externalities. By comparing the simulated reality with this counterfactual, we find that the reputation channel reduces the subsidy benefits by 4.3% when only the static impact is taken into account. This reduction is primarily driven by the high estimated reputation sensitivity. This effect is amplified to 10.8% when we account for equilibrium entry responses. In equilibrium, the reputation impact leads to market shrinkage, with 68.1 thousand fewer EVs sold from 2012 to 2018, corresponding to 3.1% of the total EV sales. These results suggest the value of a perfect government certification program. However, given the difficulty of monitoring every firm's quality, this paper documents how market mechanisms perform in screening entrants.

[8] We refer to vehicle marginal costs plus environment benefits as social marginal costs.

Section 7 evaluates the optimal subsidy design, focusing on two aspects: the level and stringency of the attribute-based policy. We find that the optimal level is determined mainly by the direct channel while the reputation channel pushes toward a slightly more conservative level. The optimal subsidy level is found to be 70% of the current policy; this level significantly increases policy efficiency from nearly 0 to 7.4 billion RMB (1.14 billion USD). With a move from the optimal level to the observed level, the DWL and choice distortion losses increase rapidly. However, it does not cause much of an increase in the permanent benefit from firm entry because post-subsidy sales and markups increase by only 9.2% and 1.1%, respectively. Reducing the subsidy to the optimal level slightly decreases the upstream spillover benefit, but it can also lead to a reduction in lemon firms and mitigate the reputation loss by half. Neglecting to consider the reputation impact would result in a 5% higher subsidy level and a net welfare loss of 0.36 billion RMB (51.7 million USD). The optimal stringency is determined mainly by the reputation channel. Assuming that the subsidy takes a two-part structure based on driving range, we find that increasing stringency can effectively screen lemons, thanks to the correlation between observed and unobserved quality.[9] Failing to account for the reputation channel would yield a lower than optimal stringency and lead to a welfare loss of 198 million RMB (30.46 million USD).

We also investigate alternative designs of regional policies, as provinces have varied subsidy efficiency and lemon attractiveness due to their differences in income and price sensitivity. The current policy started with 13 pilot cities and expanded to the entire nation in 2016. We simulate a counterfactual policy that delayed subsidies in four selected provinces. The results suggest that this delay can reduce the reputation loss from -10.8% to -7.9% and save 5.2 billion RMB (10.5%, 0.8 billion USD) in government expenditure. Additionally, the number of nonlemon firms in these provinces in 2018 drop only by 3.2% thanks to cross-province entry spillovers. These findings shed light on the timing of subsidy expansion to a national scale.

In summary, this paper discusses optimal subsidy design in markets with lemons. We establish the relationship between consumer subsidies and lemon entrants through the consumer price elasticity. We highlight the necessity of conservative subsidy designs and attribute-based subsidies, especially in highly price-sensitive environments. Given the widespread use of flat EV subsidies or tax reductions in many countries, this study can alert policymakers to these dynamics to inform their decision-making.

Related literature Our work is related to the following four strands of literature. First, this study is related to the large literature that examines the effects of subsidies on energy-efficient products. Many papers have evaluated the impact of various clean technology policies including solar panel subsidies (Gerarden (2023); De Groote and Verboven (2019)), EV policies (Li et al. (2017); Li (2017); Holland et al. (2021); Springel (2021); Xing et al. (2021); Li et al. (2022); Barwick et al. (2023); Kwon

[9] We assume that the subsidy takes the form $T + t \cdot DrivingRange$ and alter the stringency t.

(2023)), and other renewable energy policies (Murray et al. (2014); Novan (2015)). In evaluating these policies, most papers focus on the static environmental benefits of adoption, but dynamic entry considerations have limited empirical discussion. We point out that firm dynamic responses and enhanced competition contribute almost half of the welfare benefits. We contribute to the literature by (i) identifying a novel force to consider, lemon entrants and their reputation impact, and (ii) estimating the dynamic equilibrium impact of subsidies on industry growth.

Our study is closely related to the work of Heutel and Muehlegger (2015), who find that markets that were early to introduce lower-quality hybrid vehicles subsequently experienced reduced adoption rates, highlighting the potential unintended consequences of subsidies. We expand upon their work by examining the broader context of all electric vehicles and offering a comprehensive policy analysis. We explain why subsidies attract low-quality entrants, and we further discuss the equilibrium impact of these low-quality entrants and their reputation externalities on industry growth and social welfare.

Second, our study contributes to the literature on collective reputation. Theoretical works have modeled industry collective reputation and its dynamics (Tirole (1996); Levin (2009)). Empirical studies have quantified the impact of reputation on the vehicle (Bachmann et al. (2023)), dairy (Bai et al. (2021)), wine (Castriota and Delmastro (2015)), and pharmaceutical industries (Ching (2010)). This paper provides additional evidence regarding the emerging EV market and adds to the empirical literature by incorporating firm entry responses and their interaction with reputation dynamics.

The literature that discusses technology adoption in developing countries has documented the impact of information and quality heterogeneity on adoption (Shiferaw et al. (2015); Suri (2011)). Bold et al. (2017) point out that lemon technologies lower the adoption rate of fertilizer and hybrid seed in Uganda, and they rationalize the results by calibrating a consumer learning model with agricultural trial data. Our paper discusses similar insights in the electric vehicle industry, further explaining firm-side responses and assessing the equilibrium impact.

Finally, this paper is broadly related to the literature on industrial policy. A large theoretical literature examines industrial policies (Harrison and Rodríguez-Clare (2010); Liu (2019); Itskhoki and Moll (2019)). The empirical literature on industrial policy focuses mostly on describing the impacts on output, revenue, growth rates, and cross-sector spillovers (Head (1994); Luzio and Greenstein (1995); Hansen et al. (2003); Aghion et al. (2015), Lane (2018); Barwick et al. (2023)), with less emphasis on reputation dynamics and their influence on industry growth. This paper contributes to this literature by examining the novel reputation channel and documenting its notable impact.

To the best of our knowledge, this is the first paper to examine the reputation externality in subsidy design. We link collective reputation, adverse selection, and infant industry growth to evaluate the impact of a subsidy. We highlight the importance of the reputational impact; our findings can be extended to various green industrial policies.

2 Institutional Background and Data

2.1 EV subsidies and other policies

Since 2009, China has promoted EVs by providing generous consumer subsidies at both the national and local levels. In 2009, the subsidy was targeted at institutional sales and public transit. From 2010 to 2012, the central subsidy was ¥3,000 per kWh and could not exceed ¥60,000 for battery electric vehicles (BEVs) and ¥50,000 for plug-in hybrid electric vehicles (PHEVs).[10] Starting in 2013, the central subsidy amount became a step function of the vehicle's driving range, as shown in Table 1. The central subsidy was first introduced in 13 pilot cities, each in a different province. By 2014, the program had expanded to 88 cities.[11] In 2016, the subsidy was rolled out nationwide. Some cities also provide local subsidies, generally pegged to the amount of the central subsidy, at ratios such as 1:1 or 1:0.5.

Table 1: Central subsidy criteria: 2013–2018

	Range	2013	2014	2015	2016	2017	2018
BEV	$\geq$ 80 km	¥35,000	¥33,250	¥31,500	-	-	-
	$\geq$ 100 km				¥25,000	¥20,000	-
	$\geq$ 150 km	¥50,000	¥47,000	¥45,000	¥45,000	¥36,000	¥15,000
	$\geq$ 200 km						¥24,000
	$\geq$ 250 km	¥60,000	¥57,000	¥54,000	¥55,000	¥44,000	¥34,000
	$\geq$ 300 km						¥45,000
	$\geq$ 400 km						¥50,000
PHEV	$\geq$ 50 km	¥35,000	¥33,250	¥31,500	¥30,000	¥24,000	¥22,000

Figure 1 displays the average and the 25th and 75th percentiles of the subsidy rate from 2012 to 2019. The subsidy could account for as much as 30% of the vehicle's price on average. In the years surrounding 2016 and 2017, because of the rising complaints and concerns regarding EV quality, consumer trust, and potential adverse selection issues, the government recognized the need for adjustments. This resulted in the phase-down and decreasing patterns observed from 2017 to 2019.[12]

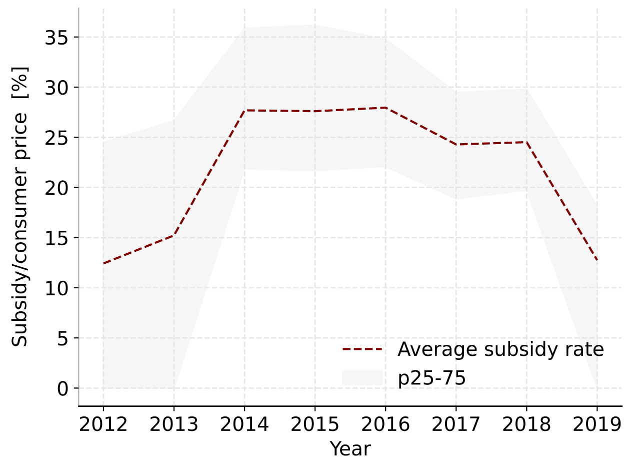
The policies have significant variation across cities and across time. This results in large differences in consumer demand and firm entry decisions. Different cities began their subsidy programs at varying times and adjusted their local policies over time. In addition to subsidies, local governments have

[10] A BEV with a driving range of approximately 100 km can reach the ¥60,000 subsidy limit; 1 kWh of battery size is equivalent to 6 to 7 km of driving range.

[11] The 13 pilot cities are Beijing, Shanghai, Chongqing, Changchun, Dalian, Hangzhou, Jinan, Wuhan, Shenzhen, Hefei, Changsha, Kunming, and Nanchang.

[12] This figure reports the subsidy statistics for only the first quarter of 2019 because of data availability. In addition, the subsidies were originally planned to be terminated in 2019. However, because EV sales experienced negative growth thereafter and because of the pandemic, the government changed the plan and kept subsidizing the industry for four more years.

Figure 1: Average subsidy rate by year [%]



Notes: This figure displays the average subsidy rate over time, including both local and central subsidies. We define the subsidy rate by dividing the total subsidy received for a model by that model's price. Subsidies vary by both model and city. We present the mean, 25th percentile, and 75th percentile of the subsidy rate. Figure A.1 plots the trend in RMB.

implemented nonmonetary policies. These include driving restrictions for gasoline vehicles (GVs),[13] plate registration restrictions for GVs,[14] and green plate benefits for EVs.[15,16] Another initiative to encourage EV adoption has been the deployment of EV charging stations. Figure A.4 illustrates the variations in the local subsidy ratios, nonmonetary policies, and number of charging stations at the city–quarter level for the 40 main cities used in the demand estimation.

2.2 Sales data

The analysis is based mainly on four data sets from 2012 to 2018: (1) vehicle registration data from the China Automotive Technology and Research Center Co. LTD. at the province level from 2012 to 2014 and at the city level from 2015 to 2018, (2) model-level attributes from major automotive websites, (3) government policies for EVs collected from government and major automotive websites, and (4) charging station data from the China Electric Vehicle Charging Infrastructure Promotion Alliance.

Our demand estimation focuses on the top 40 EV cities spanning 20 provinces from 2015 to 2018.[17] We define a model by its producer, model name, fuel type, and driving range (in the case of EVs). Table 2 reports key model attributes, prices, and sales, with Panel A for GVs and Panel B for EVs. EV

[13]For instance, Beijing adopted an end-number license plate policy: from Monday to Friday, GVs with end numbers 1 or 6, 2 or 7, 3 or 8, 4 or 9, and 5 or 0, respectively, are prohibited from using public roads.

[14]Plate registration restrictions take various forms, such as a lottery policy in Beijing and an auction policy in Shanghai. Typically, these restrictions do not apply to EVs.

[15]Green plate benefits often include reductions in parking fees.

[16]It is worth noting that driving and plate restrictions were not primarily designed to promote EV adoption. Their main aims were rather to alleviate traffic congestion and reduce on-road emissions.

[17]These 40 cities encompass all the 13 first-round pilot cities and partially overlap with the 88 second-round pilot cities.

sales almost doubled every year, while GV sales dominated the market in both number of models and sales. The total EV sales captured in our data increased from 4 thousand to 724 thousand between 2012 and 2018. GV sales decreased slightly from 2016 to 2018, indicating a substitution of GVs with EVs. Firms set the manufacturer's suggested retail prices (MSRP) at a national level, and the variations in EV prices across cities arose from local subsidies. On average, the MSRP for EVs was higher than that for GVs, indicating a passthrough. However, with an approximate 30 percent subsidy, the average consumer prices for EVs became similar to those for GVs, with those on the lowest end even lower than those of GVs. In addition, the average EV MSRP decreased, largely due to enhanced competition. Key observed attributes that influence consumer utility include driving range, engine power, and vehicle weight, which reflects the size of the vehicle. Table 2 includes summary statistics for these attributes.

Table 2: Sales data summary statistics: 2012–2018

year	2012	2013	2014	2015	2016	2017	2018
Panel A: Gasoline Vehicle Model-level Statistics							
# models	349	402	447	494	538	529	564
Total sales (1,000)	11,900	13,767	15,529	8,817	10,109	9,888	9,139
Sales per model	34,097.70	34,245.90	34,741.53	17,848.10	18,790.36	18,691.76	16,204.55
MSRP (10kRMB)	12.64	12.52	12.58	12.56	13.18	13.63	14.03
Net weight	1,349.51	1,351.23	1,356.88	1,368.24	1,404.21	1,434.43	1,457.04
Engine power	121.40	121.01	122.69	125.42	130.17	134.96	134.23
Panel B: Electric Vehicle Model-level Statistics							
# models	7	11	16	38	51	99	184
Total sales (1,000)	4	9	44	157	254	427	724
Sales per model	536.12	773.50	2459.28	3837.24	4622.29	4107.38	3751.33
MSRP (10kRMB)	23.00	22.10	20.99	22.89	23.02	20.06	19.69
Net weight	1,150.62	1,092.17	1,042.89	1,145.17	1,187.14	1,186.08	1,199.41
Engine power	47.75	48.25	50.04	63.24	72.18	73.34	85.90
Driving range	149.25	144.08	148.78	152.71	166.00	185.45	248.34

Notes: This table presents the number of vehicle models, total sales, and averages of annual sales per model, prices, and key vehicle attributes by year. Panel A reports summary statistics for gasoline vehicles and Panel B for electric vehicles. Note that, from 2012 to 2014, the numbers reflect all sales from the 20 provinces and, from 2015 to 2018, the numbers reflect sales from the top 40 cities due to data availability. This accounts for the marked drop in GV total sales between 2014 and 2015.

2.3 Lemon definition and review and repair data

Lemons are defined as firms with low unobserved quality that can be revealed through user experiences. In the context of the EV industry, these are vehicle manufacturers with substandard production lines incapable of safely assembling reliable EVs.

The key difference between lemons and nonlemons is their electronic system and platform design.

First, the electronic systems of an EV are different from those of a GV and thus lack a standardized approach. Basic features of the electronic system include a propulsion system, battery management, electric motor control, charging infrastructure, transmission, EV-specific HVAC system, and energy management. A proficiently designed system ensures optimal battery temperature, enhanced safety, and superior engine performance. In contrast, a subpar design can lead to engine issues, charging problems, and safety concerns. Second, the car platform design in EVs varies significantly from GVs. Lemons often use inferior platforms or retrofit GV platforms. Such poor designs can compromise the vehicle's structural integrity, induce battery-related issues due to misplacements or inadequate cooling, and affect the vehicle's handling. Moreover, it can lead to decreased range, inefficient charging, and reduced safety measures, heightening risks for occupants. We focus on the vehicle assembly quality of EV manufacturers because (i) batteries are manufactured mostly in the upstream industry and (ii) vehicles with the same battery supplier can exhibit different qualities.[18]

Empirical definition We rely on two main data sources to identify lemon EV firms that produce cars with poor experience quality in the above-discussed areas.[19] First, we collect consumer reviews from the Autohome platform, China's largest vehicle review platform, from which automakers purchase data and market reports. We obtain 1,138,945 reviews from 2014–2021, including 32,441 EV reviews. Second, we collect complaints and repair data on the Car Quality Network, the largest online complaints filing and repairing platform and an important data source for the General Administration of Quality Supervision, Inspection, and Quarantine of the People's Republic of China. From 2014 to 2022, 433,769 complaints were filed, 6,219 of them for EVs.

We identify nine lemon firms that consistently demonstrate poor quality in the above aspects.[20] We calculate the average review score for each firm. Compared with the GV review distribution, the EV review distribution is more spread out and has two peaks—one around 4.7 and the other around 4.0. Figure A.2 plots the distribution of review scores for EVs and GVs. We define firms with reviews lower than 4.0 as lemon firms. The review data cover only 35 EV firms in our sales data, so we supplement them with data from the complaints and repair platform. We calculate the complaint rate for each firm and define lemons as firms with a complaint rate higher than the 70th percentile of all EV models (3.0 per 1,000 sales).[21] The two definitions are aligned for the overlapping firms.[22]

[18] Figure A.5 provides a detailed illustration of the EV firm–battery firm relationships. There are no clear differences between the suppliers of lemon firms and nonlemon firms.

[19] We define lemons as firms characterized by low-quality factories, namely, those with inferior electronic systems and platforms. It is important to note that there can be variations in car quality even from the same manufacturer; for instance, not every car produced by a lemon firm necessarily catches fire. However, cars from lemon firms do have a higher average probability of catching fire or encountering other quality issues. In our analysis, we do not explicitly model this uncertainty but focus on capturing the mean difference between lemon and nonlemon firms.

[20] We focus on these five aspects: vehicle power, operation, fuel efficiency, and comfort. Unrelated aspects, such as appearance, interior design, and service, are excluded.

[21] We focus on the following vehicle issues: battery, engine, braking, steering, and suspension problems.

[22] For the 29 overlapping firms, 6 are lemons under both definitions, and 23 are nonlemons under both definitions.

Combining both definitions, we identify nine lemon EV firms, representing 19% of the EV models in our sample. We define lemons at the firm rather than the model level, as most firms, particularly the lemon ones, operate a single production line. Additionally, the review scores for models within a given firm are largely consistent.

2.4 Firm background and entry pattern

There are 57 EV firms from the sales data. Of these, 16 are prominent GV firms with a market share exceeding 1%, 24 are fringe GV firms, and 17 are newcomers to the vehicle market. Over half of these 17 newcomers originated from related sectors such as electronic buses, low-speed EVs, and battery production.[23] They typically produce EVs in the same or adjacent factories. Thus, we assume in our analysis that plant locations are exogenous in our analysis. Of the nine identified lemon firms, five belong to the fringe GV category, and three faced bankruptcy before transitioning to the EV sector. Most fringe GV firms and prominent EV firms entered the EV market between 2014 and 2016, a period of heavy subsidies, as illustrated in Figure 1. In contrast, larger GV firms, which typically produce high-quality EVs, did not participate until 2017.

Table 3: Firm entry statistics

	2012	2013	2014	2015	2016	2017	2018
Number of active EV firms	6	9	10	20	26	37	55
Number of provinces an EV firm entered							
25%	1	1	1	2	2	2	3
50%	1	1	2	3	4	4	6
75%	1	2	4	7	9	13	11

Note: There are 57 EV firms in total, 2 of which exited the market in 2018.

There are two steps in a firm's entry decision: industry-level entry (activation) and province-level entry (expansion). These steps correspond to two kinds of entry costs: A new firm first enters the industry and becomes active by building a factory, hiring relevant workers, and designing an EV production line. Active firms can expand into markets (provinces) by establishing sales and distribution networks and constructing retail stores. This decision process is supported by several firms' annual reports and press releases. According to some publicly listed firms' annual reports, industry entry costs can soar to hundreds of millions of RMB.[24] Such substantial initial costs are pivotal in assessing industry trends and the subsidy impact. We manually collect firm plant locations and their entry periods from media reports.[25] For firms that lack media coverage, we designate their entry period as

[23]Low-speed EVs include, for example, scooters and golf carts, with a speed of approximately 20 30 km/h.

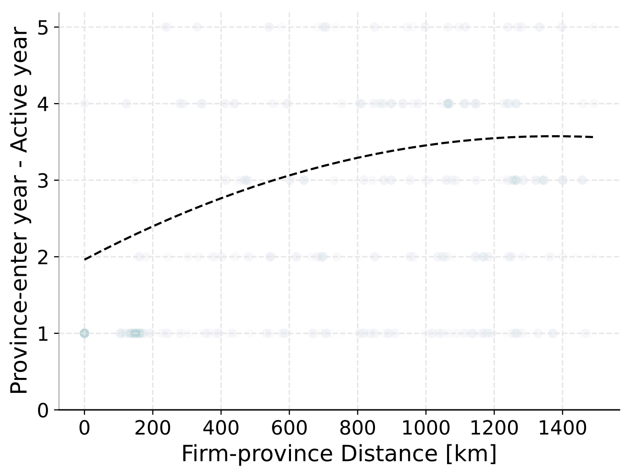
[24]BACI reported an expenditure of 1,000 million RMB, and the median investment in factory construction is cited as over 100 billion RMB (approximately 15 billion USD) (source: https://www.sohu.com/a/161723168_236020).

[25]Firms typically announce their plans. In our dataset, the plant completion dates generally align with the commence-

the time preceding any observed sales. Table 3 reports the number of EV firms during the sample period and the number of provinces that an EV firm entered by year. The number of electric vehicle firms increased from 6 in 2012 to 55 in 2018.[26] The median number of markets (provinces) that a firm entered expanded from one to six. There are variations in firm expansion decisions. By 2018, while 25% of EV firms operated in three provinces or fewer, another 25% had entered more than ten provinces. The increasing entry and expansion activities are attributed mostly to the decreasing battery cost. According to multiple industry reports, battery costs decreased by more than 80% during the sample period.

Firms typically expand first to nearby provinces, which can be attributed to supply chain efficiencies and, consequently, reduced entry costs. Some firms operate exclusively within their home province. Figure 2 plots the relationship between a firm's distance to a province and its entry timing, with the black dashed line representing a quadratic fit. On average, firms penetrate distant provinces approximately two years after penetrating the closer ones. Figure A.3 presents the expansion paths of two firms, both of which initially favored nearby markets.

Figure 2: Correlation between firm–province distance and timing of entering a province



Notes: This figure illustrates the correlation between the distance from the firm to the province and the timing of the firm's entry into that province. The shaded dots represent observed data points, and the black dashed line indicates a quadratic fit.

Because of the market-level entry margin, provinces had different market structures and EV reputations. In 2012, some provinces had one EV firm, and others did not have any. In 2015, most provinces had fewer than 10 EV firms, with the leading firms commanding a market share of between 40% and 100%. Across the 20 provinces, there were six different market leaders. By 2018, the average number of firms per province rose to 21, and the market share of top firms declined to an average of 17.5%. In the early years, a province's lemon EV share could be as large as 80%, while some

ment of sales.

[26] The number of firms producing GVs remained stable at approximately 60.

provinces had no lemon firms. In 2018, the average lemon share was 10.3%, and lemon firms did not dominate any province. Note that although these market shares in the EV sector appear significant, they represent only a minuscule portion of the overall vehicle market, implying small market power.

Modeling implications We refer to the two entry steps as "industry-level entry" (or "activation") and "market-level entry" (or "expansion") and define the market as a province in the firm-side model. We make the following assumptions based on data patterns. First, we assume that locations are exogenous in our analysis based on the discussion in the firm background section. Second, we use distance as a market-level entry cost shifter to rationalize the pattern that firms tend to enter nearby markets first. Third, we assume that there is no constraint in entering multiple provinces in the same year, given that many firms enter multiple provinces per year.

3 Evidence of the Reputation Externality

We use two reputation indicators to capture the reputation spillover—EV fires and the lemon share. The latter is defined by dividing a city's lemon EV sales by its total EV sales. We focus on within-market reputation spillover: the impact of lemons and fires on the same market's future adoption. We provide three pieces of evidence. First, We conduct a consumer survey that explains the reputation externality from the consumer learning process and a social network perspective. Results suggest that exposure to lemons, especially by means of friends' experiences, impacts potential buyers' perceptions and decreases the probability that they will purchase an EV. This justifies our consideration of a within-market reputation externality and use of the local lemon share variable. Next, we use sales data to examine the reputation externality of EV fires with a DID design that compares the same firms' sales in the event city to sales in other cities. Finally, we test the impact of the lemon share with our sales data. We hypothesize that, if a city has more lemon EVs, potential consumers are more likely to be exposed to these cars and to negative quality signals and, consequently, the probability that they will purchase EVs decreases.

3.1 Consumer survey results

We conducted an online consumer survey in three example cities with a sample size of 1,000 each. We implemented the survey in Guangzhou, Tianjin, and Qingdao, three large cities that rank in the middle tier for EV sales in our data. We asked consumers about their perceptions of EV quality and their likelihood of purchasing an EV. Additionally, we asked about their friends' experiences and tested their recognition of lemon brands. Using this information, we test the impact of friends' experiences and the presence of lemons on consumers' perceptions and their likelihood of buying EVs. We limit our sample to potential buyers who do not currently own an EV.

Table 4: Impact of reputation factors on potential buyers' EV perception

	(1)	(2)	(3)	(4)	(5)	(6)
Impact of friends' experiences						
Friends' experience score	0.640***					
	(0.019)					
Battery issues		-0.262***				
		(0.071)				
Engine issues			-0.151*			
			(0.088)			
Other quality issues				-0.298***		
				(0.067)		
Impact of lemons						
Friends' EV brand = lemon					-0.319***	
					(0.107)	
Heard of lemon brands online					0.043	
					(0.038)	
Impact of EV fires						
Local EV fire						-0.239***
						(0.071)
Aware of any EV fire						-0.420***
						(0.039)
R^2	0.409	0.053	0.030	0.060	0.085	0.098
N	738	676	672	637	248	752
Inc grp, age grp, city FEs	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is the potential buyer's perception score on a 1-to-5 scale, where higher numbers indicate more trust in EV quality. Although we collected 3,000 questionnaires, after dropping respondents who already had an EV and observations with response times of less than 2 minutes, we were left with approximately 700 observations. $*p < 0.10; **p < 0.05; ***p < 0.01$

Table 4 reports the impacts on consumer perception. The dependent variable is the potential buyer's perception score on a 1-to-5 scale, where higher numbers indicate more trust in EV quality. All regressions include income group, age group, and city fixed effects (FEs). These results confirm three key findings. First, consumers are influenced by negative reputation factors, as indicated in columns (1) to (4). Second, local lemon sales negatively impact consumer perceptions, as demonstrated in column (5). Third, these reputation spillovers are generally more pronounced locally because the coefficient for "heard of lemon brands online" is insignificant. The local EV fire coefficient is also significantly negative even when we control for the variable "aware of any EV fire". Table A.7, which reports the results when the dependent variable is changed to the probability of purchasing an EV, yields similar findings.

3.2 EV fires

We estimate the reputation externality of EV fires by comparing firm–month-level EV sales in cities with an EV fire to those in other cities. We manually collected 35 reported EV fire events in the sample cities during 2015–2018. For each event, we create a relative time measure—k-th months since EV fires—denoted by $\mathbb{1}(Fire)_{c,t-k}$ for city c and for k from -4 to 8. We drop firm–city series where a firm entered earlier than 6 months before the event. Combining all the 35 events, we estimate the following DID specification:

$$y_{jct} = \sum_{k=-4}^{k=8} \beta_1^k \mathbb{1}(fire)_{j,c,t-k}^{Involved} + \underbrace{\sum_{k=-4}^{k=8} \beta_2^k \mathbb{1}(fire)_{c,t-k}}_{\text{spillover}} + \delta_j + \xi_t + \gamma_c + \epsilon_{jct}, \tag{1}$$

where δ_j, ξ_t, and γ_c indicate firm j, period (month) t and city c, respectively. $\mathbb{1}(Fire)_{c,t-k}$ are dummy variables indicating whether the city–month is within the $(-4, 8)$ month time window, and $\mathbb{1}(Fire)_{j,c,t-k}^{Involved}$ are indicators for the involved firms. y_{jct} is the log of EV sales of firm j in city c and month t. The first part of Equation 1 represents the impact of fires on the involved firms, and the second part examines the spillover to other firms in the same city. Standard errors are clustered at the firm level.

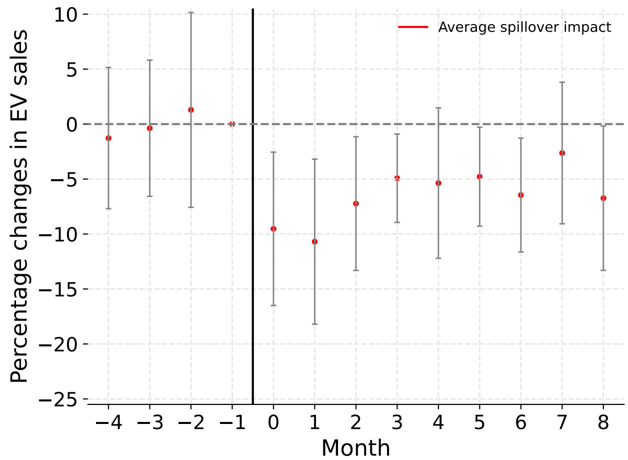
Although a fire event can have a national-level spillover, we can identify the differences only across cities. We argue that β_2^k gives a lower bound of the reputation externality because untreated cities could also be affected, but we cannot identify these impacts. Identification relies on the assumptions of no anticipation and parallel trends. The first assumption holds, as no one can anticipate EV fires. The second assumption implies that firms in the treated city and control cities would have followed the same sales time trend in the absence of EV fires. We argue that, as firms operate nationwide, supply factors remain consistent across all cities.

Figure 3 plots the estimates from Equation 1. The coefficient on relative month -1 is normalized to zero. Coefficient β_2^k represents the percentage changes in sales in each period. Two insights can be drawn from the figure. First, there is a significant spillover impact after an EV fire, with sales dropping by approximately 10% over the subsequent three months. Second, the pattern becomes less clear after three months. This can be interpreted as consumers' recollection of the event fading after this four-month period. Consequently, EV fires display a short-term 10% reputation spillover effect on firms not directly involved.

3.3 Impact of historical lemon sales

This section shows the relationship between the city's historical lemon car share and its EV sales. Our consumer survey results suggested that exposure to lemon EVs through friends' experiences decreases

Figure 3: Estimated spillover impact



Notes: This figure reports the spillover coefficients and confidence intervals from Equation 1. Standard errors are clustered at the firm level.

the probability of purchasing an EV. We construct the lemon share variable by dividing a city's lemon EV sales by its total EV sales; this measure varies at the city–quarter level.[27] We run the following regression at model–city–quarter level. The sample includes sales of all EV models at the city–quarter level from 2015 to 2018. We compare the sales of the same model–period across cities with varying lemon shares, and the coefficient η captures the reputation externality of lemons:

$$lns_{ojct} - lns_{0,ct} = \eta \cdot lemonshare_{c,t-1} - \alpha s_{ojct} + \beta policy_{ct} + \xi_{ojt} + \xi_{ct} + \varepsilon_{ojct}, \tag{2}$$

where $lns_{ojct} - lns_{0,ct}$ is the standard logit regression dependent variable, representing the log market share of model o from firm j in city c in period (quarter) t. $lemonshare_{c,t-1}$ is the lagged lemon share in city c period t, and η is the parameter of interest. It explains the impact of an increasing lemon share on future EV adoption in the same city. s_{ojct} is the city–model-specific subsidy, determined by the vehicle driving range and local subsidy policies. $policy_{ct}$ includes vehicle driving restrictions and plate restrictions. Equation 2 includes the model–period fixed effects; thus, model attributes and prices are omitted. These fixed effects control for all supply-side factors and national-level trends, such as consumer awareness of EV technology, firm production changes, and firm advertising efforts. We include a set of FEs (ξ_{ct}) to control for local unobserved demand factors. Time-invariant preferences are controlled for by means of city–fuel type fixed effects and province–firm fixed effects, which capture local preference toward green products and province-specific preferences for local firms.[28] Province–

[27]Our use of this measure can be justified by a Bayesian learning model in which the frequency of observing a car is determined by its market share. This measure is also similar to that used by Heutel and Muehlegger (2015), who also find that initial sales of low-quality EVs decrease the future adoption rate due to consumer learning.

[28]For example, some provinces might have a strong brand loyalty toward local firms; dealer presence for a certain firm–province can also affect demand.

year FEs control for province-specific unobserved policies or income shocks that vary across years.

Table 5: Impact of historical lemon share on EV sales

	Lemon share$_{t-1}$		Model-level EV sales $lns_{ojct} - lns_{0,ct}$			
			(1)	(2)	(3)	(4)
	First stage	First stage	OLS	2SLS	OLS	2SLS
$Centrals_{t-1} \times distance_{jc}^{-1}$	0.151***	0.110***				
	(0.021)	(0.025)				
Lemon share$_{t-1}$			0.002	-0.052***	0.016	-0.057***
			(0.003)	(0.016)	(0.095)	(0.019)
Subsidy			-0.166***	-0.176***		
			(0.019)	(0.021)		
Prices					-0.189***	-0.189***
					(0.022)	(0.021)
N	19,448	19,448	19,448	19,448	19,448	19,448
F-stats on excluded IVs	97.131	215.064				
Model–period	Yes		Yes	Yes		
Firm–fuel type–period		Yes			Yes	Yes

Notes: $lemonshare_{t-1}$ is rescaled to a 10% level. This table reports the main coefficients of interest. Columns (1) and (2) report ordinary least squares (OLS) and two-stage least squares (2SLS) results from Equation 2. Columns (3) and (4) relax the model–period FEs and include firm–fuel type–period FEs instead. x_{ojt} is vehicle attributes, including motor power and driving range. p_{ojt} is the price for model o from firm j. The rest of the variables and fixed effects are the same. Standard errors are clustered at the city level. $*p < 0.10; **p < 0.05; ***p < 0.01$. Table A.5 reports full results with all coefficients and more relevant tests on excluded IVs.

We use instrumental variables (IVs) for prices and the lemon share. We use two sets of IVs for consumer prices, following Barwick et al. (2023) and Kwon (2023): (i) central and local subsidies and (ii) a battery supplier dummy interacted with battery capacity.[29] All these IVs vary by model. The subsidies vary across time, and local subsidies further provide cross-sectional variation. Battery supplies and capacity are shifters for marginal costs. To deal with the potential endogeneity of the lagged lemon share variable through demand serial correlation, we use IVs that shift lemon firms' incentives and returns—that is, the distance from lemon firms to the market interacted with the central subsidy. The central subsidy provides time variation, and the distance provides geographical variation. When the central subsidy increases, the lemon firm can gain more profit from the closer city and is more likely to enter that city. The raw relationship between the IVs and lemon share is reported in Figure A.6 and Table A.3. Table A.4 details the first-stage results. We argue that the distances are exogenous, as detailed in Section 2. The central subsidy, announced well in advance, should remain unaffected by short-term local demand shocks.

Table 5 reports the results. The ordinary least squares (OLS) results suggest a slightly positive relationship between the lemon share and EV sales. City unobserved demand shocks can confound the relationship (e.g., consumers' preference for cheaper cars). The IVs help identify the reputation impact of lemon shares, and both columns (2) and (4) suggest a negative impact of the historical

[29]We categorize battery suppliers into three groups: BYD, CATL, and others. BYD supplies batteries for its own EV models, and CATL, the largest battery supplier, serves numerous EV producers.

lemon shares on EV sales. $lemonshare_{t-1}$ is rescaled to a 10% level, and the results from column (2) suggest that a 10% increase in lemon share decreases future EV sales by 5.2%. This is equivalent to a subsidy decrease of 2,954 RMB, based on the estimated subsidy coefficient $\hat{\alpha}$. These findings are robust across alternative specifications, as shown in Table A.6.

4 Model

This section develops a model to explain the subsidy's impact through the three channels. The model includes a standard discrete choice system to explain consumer responses to the subsidy and reputation. We then explain the firm responses, entry selection problem, and evolution of EV reputation with a dynamic entry model. Section 4.1 explains the models' key forces and primitives with an illustrative example. Section 4.2 explains the empirical model setup, and Section 4.3 explains equilibrium concepts and value functions.

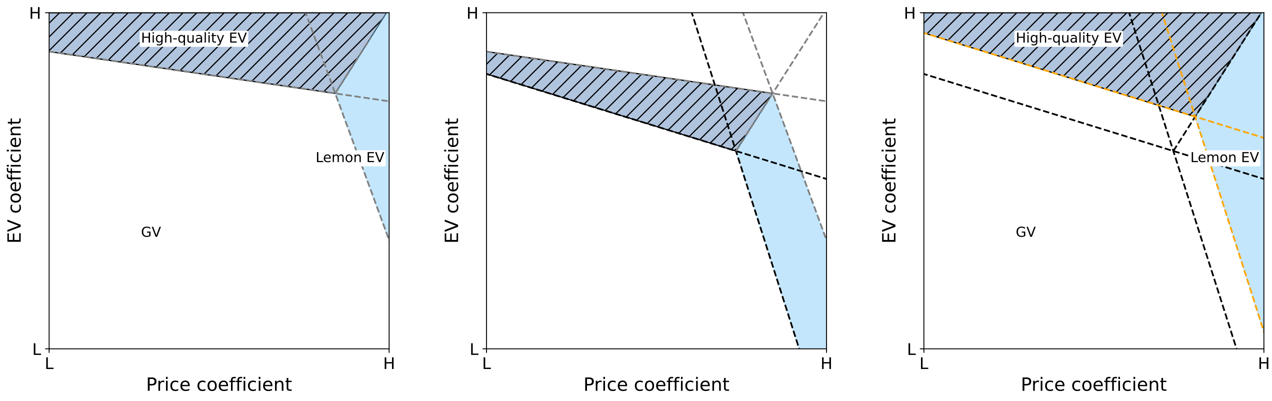
4.1 Illustrative model and key primitives

This section uses an illustrative example to explain how the three key primitives—consumer price sensitivity, reputation factor sensitivity, and entry fixed cost—affect the subsidy's impact. We focus on the reputation channel's impact and explain when and why the subsidy attracts lemons.

Consumer price and reputation sensitivities determine the profits that lemons and nonlemons derive from the subsidy and which type benefits more. We consider a market with one high-quality EV model, one lemon EV model, and one GV model. Consumers observe the prices and characteristics x of these vehicles but not the qualities of the two EVs. Thus, consumers make decisions based on the EVs' collective reputation. Consumer utility is $\beta x_j + (\theta_i^0 + \theta_i q^e)\mathbb{1}(EV) - \alpha_i(p_j - s_j)$, where x_j is the observed attribute of model j, q^e represents the EV's reputation factor (0 for the GV model), and $(p_j - s_j)$ is the consumer price with p_j representing the firm price and s_j representing the subsidy. Consumers exhibit heterogeneous sensitivity to EVs θ_i^0 and their reputation θ_i and heterogeneous price sensitivity α_i. Figure 4 explains consumer choices and shows that subsidy-incentivized highly price-sensitive consumers tend to purchase lemons.

Figure 4a depicts the space of consumer preferences, with the x-axis representing price sensitivity α_i and the y-axis representing EV preference θ_i^0. We assume that the price of the high-quality EV is greater than the lemon's price because our data suggest a negative correlation between lemons and prices. This is because there are imperfect signals of the unobserved quality, such as a lower driving range and a smaller vehicle size. Without loss of generality, we assume that both EVs' prices are lower than the GV's price. Figure 4b and Figure 4c, respectively, display the subsidy's direct impact and the effects of a reputation decrease.

Figure 4: Illustration: Subsidy's direct impact and reputation impact



(a) Baseline (b) Direct impact (c) Reputation impact

Notes: The line that depicts the high-quality EV–GV margin in panel (a) is defined by $\theta_i^0 > -(p^{GV} - p^h) \cdot \alpha_i + \text{constant}$, where p^h represents the price of the high-quality EV and p^{GV} is the price of the GV. The constant term is determined by the observed characteristic x for both models. Similarly, the lemon–GV margin in panel (a) is expressed as $\theta_i^0 > -(p^{GV} - p^l) \cdot \alpha_i + \text{constant'}$, with p^l denoting the price of the lemon EV. This constant term is also influenced by the observed characteristic x for both models. Due to the lower price of the lemon EV, this lemon–GV margin line has a steeper slope.

The mechanism of potential subsidy-induced adverse selection is as follows. In the baseline scenario without subsidies, consumers' choices are illustrated in Figure 4a. Dark blue consumers choose the more expensive EV (the high-quality one), while light blue consumers choose the cheaper EV (the lemon). The remaining, white consumers choose the GV model. When a subsidy s is introduced, it incentivizes consumers to shift from the GV to an EV. Figure 4b highlights the shifted consumers. Highly price-sensitive consumers are more inclined to switch, as indicated by the larger light blue area than dark blue area. These two areas reveal whether the lemon or nonlemon benefits more from the subsidy's direct impact. If, in reality, consumers are concentrated on the right side of the graph, lemon firms benefit more; otherwise, nonlemon firms benefit more from the subsidy. A decline in EV reputation—due to a rise in the lemon share or an occurrence of an EV fire event—causes consumers to switch back to the GV, as illustrated in Figure 4c. The magnitude of this effect is determined by consumer reputation sensitivity θ_i. If θ_i is sufficiently large, the reputational effects could outweigh the direct impact, resulting in a negative net subsidy impact on nonlemons. In this example, the dark blue area in Figure 4c is almost equal to that in Figure 4a, while the light blue area increases significantly in size.

From this illustrative analysis, we deduce the following: If consumers exhibit strong sensitivity to both reputation and prices (represented by the light blue area), then both the direct and the reputation channels have a large impact. In such scenarios, while the subsidy can substantially expand the market, it disproportionately attracts lemons. Conversely, if consumers display price inelasticity and fall within the darker blue areas, a subsidy tends to favor nonlemons and results in lower reputation concerns.

However, the subsidy-induced EV sales would be smaller because consumers are inelastic, resulting in a smaller direct impact.

Firm entry responses amplify the reputation channel's impact. When lemons derive greater benefits from subsidies, their increased entry can degrade the EV reputation. Consequently, nonlemon firms may witness diminished profits and be less incentivized to enter the market. The evolution of market structure also underscores the direct channel's impact: an increase in firm numbers can intensify competition, thereby driving prices down and increasing EV adoption. Furthermore, with more consumers shifting to EVs, battery cost decreases, reflecting the upstream spillover impact.

We next develop an empirical model and estimate the price sensitivity α, reputation sensitivity θ, and firm entry cost. To include the upstream spillover impact, we estimate battery cost time trends and calibrate the impact of EV sales on battery cost. Section 4.2 explains the empirical model with a detailed demand system, firm entry and expansion, and EV reputation dynamics. Section 5 explains the estimation.

4.2 Empirical model

Figure 5: Model Overview

Overview and timing We use a finite-period dynamic discrete choice model to explain firm entry and expansion decisions, and we assume that the last period repeats indefinitely. Figure 5 provides an overview of the model timing. There is a finite number of firms with exogenous qualities, denoted by $j \in J = [1, 2, ...]$, and M markets (provinces). Each firm, j, is distinct and has its own set of models O_{jt} by year, location m, and local advantages. Whether a firm is a lemon, along with all these features, is exogenous and known to all players.[30,31] A firm's entry and expansion process is as follows. Potential industry entrants consist of all existing GV firms and all firms that have registered to produce EVs.[32] They first decide whether to become active in the EV industry and, if so, pay the

[30] O_{jt} can include both EV and GV models. This allows us to capture the different pricing and entry incentives for GV firms and pure EV firms.

[31] In my model, firms cannot choose the characteristics of their models. Whenever firm j enters the EV industry in any given period, O_{jt} encompasses all the models observed in the data.

[32] There are 15 firms that applied for a license to produce EVs but did not enter. Source: https://www.sohu.com/a/230906728_116588.

sunk cost $\overline{FC}j$. Once activated, these firms have the option to branch out into new markets, incurring a firm–market-specific entry cost denoted by $FCjm$. A firm can enter multiple markets in the same period without any constraints or extra costs. Hence, the decisions regarding entering various markets for a firm are treated as independent actions.

In each per-period market, active firms set national prices for their models $o \in O_{jt}$ after considering the competition in the $M_j \subseteq M$ markets that they have entered and their margin costs. Based on city c' policies and the EV reputation factors—the previous period's EV fires and lemon shares—consumers in city c from market (province) m in period t choose from all available EV and GV models in the market O_{mt}. Exogenous characteristics of city c in market m include its population size, income distribution, local subsidy, and other relevant policies. We model demand at the city level to accommodate differences in city-level policies and because consumers rarely purchase cars outside their cities.[33]

The state variables include the following. Industry state includes industry structure—firms' active statuses—and the current battery cost, denoted ω_t. Each market's state includes the market structure and current EV reputation in that market. We assume that firms have perfect information on the subsidy policy path and abstract from potential policy uncertainties. We further assume that the subsidy stops in 2019, as originally planned by the government.[34] We also assume that firms anticipate changes in all exogenous conditions, including demographics and the availability of charging stations. We assume that firms know their quality and whether their rivals are lemon firms. Within each period t, the timing of the game is as follows:

1. Each firm j observes the current state for the industry and for every market.

2. Potential industry entrants, whether nonactive GV firms or nonactive new EV firms, observe the private information regarding their sunk cost shock ε_{jt}^{a} and decide whether to activate in the EV industry. Active firms observe shocks on their scrap value ε_{jt}^{ext} and decide whether to exit all markets.

3. Active firms observe their own cost shocks for entering each market ε_{jmt} and make market-level entry decisions market by market.

4. Every active firm sets national prices for all its models $o \in O_{jt}$ to maximize per-period profits.

5. For each market m, demand shocks realize. Short-lived consumers either choose a model $o \in O_{mt}$ or leave. Each firm j receives profits from the M_{jt} markets it has entered.

[33] Purchases of EVs from other cities are not eligible for the full subsidy.

[34] The government usually announces the subsidy plan ahead of time. The subsidies were originally planned to be terminated in 2019. However, because EV sales experienced negative growth thereafter and because of the pandemic, the government changed the plan and kept subsidizing the industry for four more years.

6. State $(s_I, \{s_m\}_{m \in M})$ transitions to the next period. The above activation and entry decisions become effective, and both market and industry structures evolve. This period's sales determine the next period's battery cost and EV reputation factors. Exogenous market conditions evolve.

Assumptions and information structure We make the following assumptions to simplify the analysis: (i) that whether a firm is a lemon is exogenous and (ii) that firms know their qualities but governments and consumers do not observe them. These assumptions imply that a firm draws a factory with an ex ante unknown quality, observes the realized factory quality, and then decides whether to enter the EV industry. Once lemon firms enter the market, they do not upgrade the factory, and cars from these firms have higher fire and breakdown probabilities. We focus on modeling firm responses in entry and exit instead of quality improvement decisions. We further assume that firms foresee the subsidy policy path.

Several facts support the exogenous quality simplification, and these allow us to focus on the entry–exit margin. First, we observe more entry and exit behaviors than quality changes. More than 50 firms entered the market during the sample period. Some firms exited the market when subsidies became lower and stricter in later years after 2019. These suggest that firms respond to the subsidy more on the basis of the entry–exit margin than on quality improvement decisions. One reason could be that EV firms in China are relatively small and most have only one production line. This makes the entry and exit decision more relevant. Moreover, while observed attributes such as driving range have increased, actual assembly and production quality are difficult to enhance. Improvements in these areas require redesigning and upgrading the entire production line, which is almost equivalent to paying the initial entry cost again. This high cost makes the improvement an irrelevant choice for most firms. Second, our data indicate that the review score ranking for each firm remains stable over time.[35] Third, while larger firms may have quality choices, they are not on the entry margin and are not lemons. The background subsection has explained that most EV firms are fringe. Therefore, we abstract from these decisions and focus on the entry selection issue.

Consumers and the government have imperfect information about lemon firms because electronic systems and platform designs are unobserved and vehicles are experienced goods. Several other features in new product markets further exacerbate the incomplete information environment. With more than 50 firms entering the market, it is hard for consumers to distinguish each individual firm's quality, and they tend to recognize the industry as a whole. Common mechanisms for revealing quality have not been established. Most reviews are posted 1.5 years after purchasing and in our study mainly after 2018. Table C.14 reports the number of reviews by year. The government was unaware of which quality aspects to inspect and was treating EV inspections as if they were for GVs. No third-party

[35] The review score ranking of only one firm, BYD, improved over time. We argue that quality improvement or learning by doing can occur in this industry, although it is rare. Thus, we decided not to include this in the model.

agency provided EV quality reports until 2019. These create a several-year period in the nascent EV industry where the problem of incomplete information is prevalent. Appendix C.1 provides more supporting evidence for these assumptions and simplifications.

Consumer demand We use the standard discrete-choice model with random coefficients to model consumer choice:

$$u_{i,oj,ct} = X_{oj}\beta_i \quad - \quad \underbrace{\alpha_i \cdot (p_{ojt} - s_{ojct})}_{\text{consumer price}} \quad + \quad \underbrace{q^e_{jct}\boldsymbol{\theta_i}}_{\text{reputation factors}} \quad + \quad \overline{\xi}_{jt} \quad + \quad \overline{\xi}_{ct} \quad + \quad \xi_{ojct} \quad + \quad \epsilon_{i,oj,ct}, \tag{3}$$

$$q^e_{jct} = [lemonshare_{c,t-1}, \quad \mathbb{1}(fire)_{c,t-1}, \quad \mathbb{1}(fire)_{jc,t-1}] \cdot \mathbb{1}(EV), \tag{4}$$

where X_{oj} includes observed vehicle attributes and city-level policies, including driving range, vehicle weight, motor power, fuel type, plate benefits and restrictions, and the number of charging stations. p_{ojt} is the MSRP, and s_{ojct} is the subsidy amount. Note that firms set national prices and all price variations across markets come from local subsidies. (β_i, α_i) represents individual heterogeneous preferences for prices and attributes. $\beta_{ik} = \overline{\beta}_k + \sigma_k\nu_{ik}$, where $\overline{\beta}_k$ is the mean preference for attribute k and $\sigma_k\nu_{ik}$ is the individual-specific preference following a normal distribution $\mathcal{N}(0, \sigma_k)$. We include random coefficients for fuel type and a constant. $\alpha_i = exp(\overline{\alpha}_1 + \sigma_p\nu_{ip})/inc_i$, where $\overline{\alpha}_1$ captures the mean price sensitivity, $\sigma_p\nu_{ip}$ is the consumer-specific price sensitivity following a normal distribution $\mathcal{N}(0, \sigma_p)$, and we allow price sensitivity to be affected by individual income inc_i.

$q^e_{jct}\boldsymbol{\theta_i}$ illustrates how consumers respond to the EV reputation factors. Collective reputation factors include the lagged lemon shares and last period's EV fires in the city. We allow for firm-specific reputation by including $\mathbb{1}(fire)_{jc,t-1}$ for fire-involved firm j. Vector $\boldsymbol{\theta_i}$ represents the heterogeneous taste for these reputation factors. $\theta_{ik} = -\theta_k \cdot exp(\nu_{iq})$, where θ_k captures the scale of consumer sensitivity to reputation factors k.[36] We further include firm–period fixed effects $\overline{\xi}_{jt}$ to control for national-level firm reputation changes across time and other supply-side changes.

We include other FEs that control for unobserved demand. Time-invariant preferences are controlled for by means of city–EV fixed effects and province–firm fixed effects, which capture local preferences toward green products and province-specific preferences for local firms. City–year FEs and period FEs control the city-specific unobserved policies or income shocks that vary across years. ξ_{ojct} is a product–market–time-specific idiosyncratic demand shock. $\epsilon_{i,oj,ct}$ is a consumer-specific demand shock that jointly follows a generalized extreme value distribution.

We do not allow reputation sensitivity θ_k to vary by time, as our data do not provide sufficient variation to assess temporal sensitivity changes. It is possible that consumers develop a better under-

[36] Note that different reputation factors share the same ν_{iq} random draw. Thus, a reputation-sensitive consumer is sensitive to all three reputation factors. We allow for different θ_k to capture the scale differences.

standing of each firm as time progresses and thus the impact of reputation factors diminishes. However, reduced-form regressions do not reveal significant heterogeneity in reputation factor sensitivity across time, probably due to the limited variation in the data. We argue that this simplification is acceptable because one important reputation factor, $lemonshare_{ct}$, exhibits a significant decline in later years, as detailed in Section 2.[37] Thus, reputation externalities diminish over time, despite our model's not accounting for reduced consumer sensitivity to these factors. We do not allow reputation sensitivity θ_k to vary by firm. This assumption indicates that a consumer's willingness to pay (WTP) for all EV models uniformly decreases in response to a decline in collective reputation factors. Despite this uniformity in sensitivity, our approach still captures the heterogeneous impact of EV collective reputation factors on different firms. This is because the effect of one unit change in WTP is less pronounced for more expensive models. Furthermore, because we allow heterogeneous consumer sensitivities θ_{ik}, market segmentation also contributes to the heterogeneity as explained in Figure 4. Section 5.2 and Figure 7 show significant heterogeneity in the reputation impact.

Per-period firm profit Firms choose national prices to maximize their national per-period profits.[38] The per-period profit for firm j in period t is

$$\pi_{jt} = \max_{\{p_o\}_{o\in\mathcal{O}_{jt}}} \sum_c \sum_{o\in\mathcal{O}_{jt}} (p_o - mc_{ojt}) \cdot d_{ojct}(p_o, p_{-o\in O_{jt}}, p^*_{-j}), \tag{5}$$

where o is the index for firm j's models and O_{jt} is the set of models that firm j sells in time t. Demand for model o from firm j, denoted as d_{ojct}, is a standard function of firm prices $\{p_o\}_{o\in O_{jt}}$, rivals' prices, and the market structure in markets $c \in C$ (Equation B.1). $mktsize_{ct}$ is defined by the number of households in each market–year. The pricing problem follows the standard approach in the literature; thus, we put the first-order conditions and relevant equations in Appendix Equation B.2-B.3.

We assume that the marginal cost takes the following form:

$$mc_{ojt} = \omega_t \cdot batterycapacity_{oj} + X_{oj}\omega_1 + \overline{\xi}_j + \overline{\xi}_y + \varepsilon^c_{ojt}, \tag{6}$$

where ω_t represents the per-unit battery price in period t. X_{oj} is the vector of vehicle attributes, including vehicle weight and motor power, and $\overline{\xi}_j$ and $\overline{\xi}_y$ stand for firm fixed effects and year fixed effects, respectively.

[37] In 2014–2015, the lemon share could be as large as 80%. In 2018, most markets had a lemon share smaller than 5%.

[38] We assume that firms do not use dynamic pricing strategies. This stance is supported by two primary pieces of evidence. First, our data indicate that firms set national prices that rarely change over time, pointing to a lack of dynamic pricing strategies. This trend can be partially attributed to the industry's rapid growth and the fact that many firms release new models every six months or annually while phasing out older ones. Second, firms possess limited market power. Despite the scarcity of EV firms in the early years, they confront significant competition from GVs. Consequently, the profits of rivals remain largely unaffected by the pricing decisions of EV firms. This limits the incentive for dynamic pricing.

Entry cost structure As explained above, firms' entry cost consists of two parts: (i) an active sunk cost for factory construction, $\overline{FC}_{jt}$, and (ii) a market entry sunk cost for retail store establishment, $\overline{FC}_{jmt}$. We allow these costs to differ across firm types—that is, whether a firm has experience in the GV industry and whether it is a lemon firm. The market-level fixed cost differs by firm's GV experience because GV firms usually have established their retail chains, and we observe GV firms entering more markets per period. As described in Section 2, we use firm–market distances as entry cost shifters; γ_2 and γ_3 capture the impact.

$$\overline{FC}_j = \Gamma_0 + \Gamma_1 \cdot \mathbb{1}(GV) + \Gamma_2 \cdot \mathbb{1}(Lemon) \tag{7}$$

$$FC_{jm} = \gamma_0 + \gamma_1 \cdot \mathbb{1}(GV) + \gamma_2 \cdot distance_{jm} + \gamma_3 \cdot distance_{jm} \cdot \mathbb{1}(GV). \tag{8}$$

There is an i.i.d. random cost shock for each firm–market entry decision ε_{jmt}, for firm activation decisions ε^a_{jt}, and for exit decisions ε^{ext}_{jt}. These random shocks $\sim$ type II extreme value distribution with variance ρ and mean $\rho\overline{\gamma}$.[39] These fixed costs are time invariant. According to firms that disclosed their plans, the expenditure of building a factory does not exhibit significant variation over time. Significant cost-saving advancements, which drive increased entry over time, are mostly concentrated in the battery sector and are indirectly incorporated into marginal costs. We set scrap values ν^{scrap} to zero because our dataset registers only two industry exits and thus we cannot identify the scrap values. Based on bankruptcy auction records, the scrap value is significantly lower than activation costs and is approximately zero.

Evolution of market conditions Exogenous evolution of the market includes (i) demographic and market size changes and (ii) policy changes that shift consumer demand from GVs to EVs. These affect mainly consumer choices, as defined in Equation 3. We take all these conditions as given without estimating the process. The state variables include industry structure, battery cost ω_t (referencing Equation 5), market structures, and market-specific EV reputations. We discuss the transitions of the state variables after defining the equilibrium concept.

4.3 Equilibrium concept and value functions

I assume that firms are in partially oblivious equilibrium (POE) with three dominant firms and use partially oblivious strategies to make pricing, activation, expansion, and exit decisions.[40] The in-

[39] Euler constant $\overline{\gamma} = 0.577$.

[40] The three dominant firms are BAIC, SAIC, and Zhidou, each holding a significant portion of the market. In the early years, their EV market shares in domestic and surrounding markets ranged from 30% to more than 90%, decreasing to approximately 20–30% in later years. Zhidou, identified as a lemon firm, entered the market in 2014. It accounted for 15–20% of national EV sales around 2014 and 2015, with its share in some markets exceeding 80%. However, its national EV share had dwindled to less than 2% by 2018. BYD, another major player, is incumbent in all the markets; thus, we can exclude its status from the state variables.

dustry state includes the industry structure and battery cost: $s_{It} = (str_{It}, \omega_t)$, where the industry structure $str_{It} = (\{\mathbb{1}(active)_{jt}\}_{j\in\mathcal{D}}, n_t^h, n_t^l)$ includes the three dominant firms' status, number of fringe nonlemons (n_t^h), and number of fringe lemons (n_t^l). Each market's state includes the market structure and EV reputation: $s_{mt} = (str_{mt}, q_{mt}^e)$, where the market structure is defined similarly $str_{mt} = (\{\mathbb{1}_{jmt}\}_{j\in\mathcal{D}}, n_{mt}^h, n_{mt}^l)$. We further reduce market interdependency. Industry-level actions, including activation, exit, and pricing, are determined only by the industry state s_{It}. The market-level entry strategies are determined by the specific market's state, s_{mt}, and the industry state, s_{It}, and remain unaffected by the state of other markets.

A partially oblivious strategy for a firm j, σ_{jt}, is a mapping from any state (S_t, ε_{jt}) to an action, where ε_{jt} includes $(\varepsilon_{jmt}, \varepsilon_{jt}^a, \varepsilon_{jt}^{ext})$. A firm's strategy includes activation, entry, exit, and pricing decisions. Specifically, $\sigma_{jt}(S_t, \varepsilon_{jt})$ has the following four components:

$$\sigma_{jt}(S_t, \varepsilon_{jt}) = \begin{bmatrix} \sigma_{jmt}^{ent}(s_m, s_I, \varepsilon_{jmt}) \quad \forall m \in M \\ \sigma_{jt}^{act}(s_I, \varepsilon_{jt}^a) \\ \sigma_{jt}^{ext}(s_I, \varepsilon_{jt}^{ext}) \\ \sigma_{jt}^p(s_I) \end{bmatrix}, \tag{9}$$

which include market-level entry decisions for all M markets, σ_{jmt}^{ent}, and three national-level decisions: activation σ_{jt}^{act}, exit σ_{jt}^{ext}, and pricing σ_{jt}^p. $\sigma_{jt}^p(s_I)$ is not a function of any shocks because we assume that firms set prices before observing the actual realization of s_m and before observing any demand shocks ξ_{ojmt}, according to the model's timing. The equilibrium includes the set of strategies $\{\sigma_{jt}\}_{j\in J, t\in T}$.

All of the strategies have a subscript t to capture changes in exogenous conditions across time. We aim to incorporate period-specific features, such as firm–time-specific trends and government policies, into the system's outcome, even if these elements are not included in the state variables. As previously discussed, we allow the strategies to be firm specific, highlighting the heterogeneity in their primitives, market segmentations, and entry elasticities.

Unlike most papers in the literature, this paper does not adopt the Markov perfect equilibrium (MPE) with homogeneous firms for two reasons. First, firm–markets are heterogeneously affected by the subsidy and reputation factors; ignoring this will not fit the market-level entry well and cannot explain why the subsidy attracts some firms but not others. Section 5.2 shows the large heterogeneity in firm profits and subsidy impact in the estimation results. Importantly, as explained in Section 4.1 and Figure 4, these heterogeneities from the demand system capture the two key forces—the direct impact and the reputation impact—on lemons and nonlemons. Therefore, we allow for the firm-specific value function (V_{jt} at the industry level and V_{jmt} at the market level). Second, it is not tractable to accommodate more than 50 firms with their identity in an MPE. Thus, we restrict their strategic interaction by assuming that firms track only the three dominant firms' identities. In addition, we restrict market interdependencies and allow one market to affect other markets' dynamics only through industry state s_{It}. Using POE is equivalent to using the following two simplifying assumptions:

Assumption 4.1. ***Small firm assumption*** *There are three dominant firms $j \in \mathcal{D}$ and a finite number of fringe firms $j \in \mathcal{F}$. Firms track only the identities of dominant rival firms and keep track of the number of rival fringe lemon and nonlemon firms (n^h and n^l). Fringe firms affect other firms' profits through the aggregate numbers.*

This assumption reduces the state space from the full state space to $s_{It} = (str_{It}, \omega_t)$, where $str_{It} = (\{\mathbb{1}(active)_{jt}\}_{j\in\mathcal{D}}, n_t^h, n_t^l)$ and $s_{mt} = (str_{mt}, q_{mt}^e)$ where $str_{mt} = (\{\mathbb{1}_{jmt}\}_{j\in\mathcal{D}}, n_{mt}^h, n_{mt}^l)$.

Assumption 4.2. ***Small market assumption*** *(i). Market-level entry decisions depend only on the same market's state and industry state (s_{mt}, s_{It}). This assumption restricts the impact of another market m''s strategy on market m's future value. Conditional on current industry state s_{It}, each market's future value and strategy are independent.*

(ii). Industry-level strategies depend only on industry state s_{It}. This assumption restricts the impact of each market $\{s_{mt}\}_{m\in M}$ on industry-level activation, exit, and pricing decisions. Conditional on s_{It} and all firms' POE strategies, a firm forms beliefs about the evolution of each market's state $\{s_{mt}\}_{m\in M}$ and makes the industry-level decision based on these oblivious beliefs.

To summarize, the POE model captures the following strategic interactions and equilibrium impacts. First, firms are aware of their own state and have knowledge of the relevant state variables as defined above. In making market-level entry decisions, they take into account the market's EV reputation and competition factors—such as the presence of dominant firms and the number of lemons to nonlemons. For industry-level activation and exit decisions, firms consider the industry structure and battery costs. When making industry-level pricing decisions, we assume that they maximize static profits, as explained earlier. This indicates that the reputation impact and the upstream spillover impact are nonstrategic. They do not lower prices and increase sales in early periods to obtain cheaper battery costs or a better EV collective reputation in later periods.[41]

Per-period profit and state transition approximations Firms' per-period profits are functions of the exact market state. We approximate a firm's per-period profit with the oblivious state variables by simulating firm profits in counterfactual full market states with the estimated demand system and fitting it with functions of the oblivious market state variables. We approximate the reputation factor transition by calibrating the probability of fires for lemons and nonlemons and simplifying the

[41] Both EV reputation factors and battery costs are determined by aggregate actions. Thus, the individual firm's power to strategically alter these dynamics is limited.

lemon share definition from the share of sales to a weighted fraction of lemon and nonlemon firms.[42] Appendix B.2 details these approximations.

Value functions In POE, all firms use strategy $\sigma_{jt}(S_t, \epsilon_{jt})\ \forall j, t$. We first define the market-specific value functions. For each market, firms can have two statuses: incumbent in market m (with superscript 1) or potential entrant (with superscript 0). We assume that the last-period value for incumbent firms is the continuation value given the current state (s_m, s_I) (Equations B.4) and that for potential entrants is 0. The value function of firm j in period $t < T$ market m is denoted $V^0_{jmt}(s_m, s_I, \varepsilon^j_{mt}|\sigma_m, \sigma_I)$ and $V^1_{jmt}(s_m, s_I, \varepsilon^j_{mt}|\sigma_m, \sigma_I)$, depending on its own status $\in \{0, 1\}$. The net present value of market m to incumbent firm j is

$$\begin{aligned} V^1_{jmt}(s_m, s_I, \varepsilon_{jmt}) = {} & E\pi_{jmt}(s_m, s_I|\sigma_I) + \\ & \beta \iint_S V^1_{jm,t+1}(s'_m, s'_I) dF(s'_m|s_m, s_I; \sigma_m, \sigma_I)(1 - P^j_t(ext|s_I; \sigma^{ext}_{jt}))dG(s'_I|s_I; \sigma_I), \end{aligned} \tag{10}$$

where $E\pi$ represents the per-period profit, the second part represents the expected future profit, and β is the discounted factor. We denote the static part $E\pi$ instead of π to distinguish it as an approximation based on the oblivious states, rather than as a function of the exact full market states. $F(s'_m|s_m, s_I; \sigma_m, \sigma_I)$ is the transition probability when firms use entry strategy σ_m in market m and use activation and exit strategies σ_I. The next two elements capture the impact of the industry-level strategies. $P^j_t(ext|s_I; \sigma^{ext}_{jt})$ is the probability of firm j exiting the industry in period t. Given the distribution of the random shocks, we map firm j's strategy $\sigma^{ext}_{jt}(s_I)$ onto conditional choice probability $P^j_t(ext|s_I; \sigma^{ext}_{jt})$. $G(s'_I|s_I; \sigma_I)$ is the transition probability of industry state s_I. The entire integral integrates over the rivals' entry strategy for market m, the self's exit strategy, and the rivals' entry and exit strategies because all these decisions are made simultaneously, according to the model timing. $E\pi$ captures the self's and the rivals' pricing strategy in σ_I. Similarly, the net present value of market m to activate potential entrant j is

$$V^0_{jmt}(s_m, s_I, \varepsilon_{jmt}) = max \begin{cases} -FC^j_{mt} + \beta \iint_S V^1_{jm,t+1}(s'_m, s'_I) dF(s'_m|s_m, s_I) dG(s'_I|s_I; \sigma_I) + \epsilon_{jmt}(1) \\ \beta \iint_S V^0_{jm,t+1}(s'_m, s'_I) dF(s'_m|s_m, s_I) dG(s'_I|s_I; \sigma_I) + \epsilon_{jmt}(0) \end{cases}, \tag{11}$$

where the first line represents the value of entering market m and the second line represents the value of waiting.

We then define the industry-level value function for each firm j in period t. A nonactive firm j

[42] We assume that the probability of catching fire is 0.002% for lemons and 0.001% for nonlemons. This roughly matches the relevant industry report and our data pattern. In approximating the lemon share, we assign different weights to the three dominant firms, which include one lemon firm and two nonlemon firms, for various markets. All fringe firms are uniformly assigned a weight of 1.

chooses whether to become active in the EV industry. The Bellman equation for firm j is

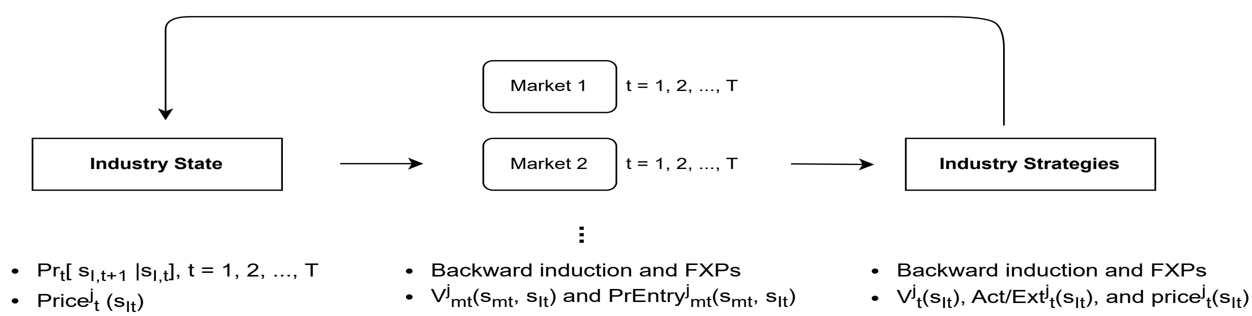
$$V_{jt}^{pa}(s_I, \varepsilon_{jt}) = \max \begin{cases} -\overline{FC}_j + \beta \sum_m \iint_S V_{jmt'}^0(s_m', s_I'|\sigma_m, \sigma_I) d\widetilde{F}(s_m'|s_I; \sigma_m, \sigma_I) dG(s_I'|s_I; \sigma_I) + \epsilon_{jt}^a(1) \\ \beta \int_{s_I'} V_{jt'}^{pa}(s_I'|\sigma_{mkt}, \sigma_I) dG(s_I'|s_I; \sigma_I) + \epsilon_{jt}^a(0) \end{cases}, \quad (12)$$

where the last-period value for nonactive firm $V_{jT}^{pa}(s_I) := 0$ for all $j \in J, s_I \in \mathcal{S}^I$. Firms' exit decision is defined similarly in Equation B.6. Details about the conditional choice probabilities of activation, exit, and market-level entry are provided in Appendix B.1.[43]

4.4 Solution method

We use a nested-loop algorithm to reduce the computational burden caused by the market interdependence. The outer loop solves the industry-level entry strategies, while the inner loop solves the entry strategies for each individual market. Figure 6 outlines the nested-loop methods.[44] As shown in the first part of Figure 6, we first guess a transition probability of the industry state and firm pricing strategies. Then, we move to the inner loop and solve each market's dynamics by backward induction and fixed points (FXP). Each market is solved independently. Given the value functions and entry probabilities at the market level, we move back to the outer loop and solve the industry-level activation, exit, and pricing strategies for each industry state. We also accommodate the impact of aggregate EV sales on battery costs in the outer loop. The detailed algorithm is presented in Appendix B.2.

Figure 6: Nested-loop method



[43]In Equations 11 and 12, we add a term $-\rho\overline{\gamma}$ to normalize the εs. This compensates for the fact that incumbents do not obtain a ε every period.

[44]Benkard et al. (2015) introduce an iterative algorithm to solve a partial oblivious equilibrium, accommodating the beliefs for fringe firms and dominant firms. We extend the iterative idea to accommodate multiple markets.

5 Estimation and Results

5.1 Estimation and identification

We estimate the demand parameters and the dynamic parameters separately. We first estimate the demand system, obtain the consumer preference parameters $(\beta, \alpha, \sigma, \theta)$, and back out firms' marginal costs. This step follows a standard approach. The second step is to estimate the fixed cost parameters, γ, Γ, and the variance of the action-specific type II extreme distributed shock, ρ, using the POE model and a pseudo-likelihood procedure.

Demand parameters We follow Berry et al. (1995), Berry et al. (2004), and Nevo (2001) to estimate the demand parameters $(\beta, \alpha, \sigma, \theta)$ in Equation 3. The demand estimation is done at the city–quarter level. We assume that model attributes, including driving range, vehicle weight, and motor power, are exogenous. We also assume that local policies, including GV plate restrictions, EV plate benefits, and the number of charging stations, are exogenous. The two major sources of endogeneity are prices and lemon shares, as explained in Section 3. We use these three sets of IVs: (i) central subsidy and local subsidy for EVs, (ii) the interaction of battery supplier and battery capacity, and (iii) the interaction of distance of lemon firms to markets and central subsidies. The first two are price IVs, and the third is an IV for the lemon share in a city–period. Section 3 discusses the IVs' exogeneity and relevance and shows first-stage results.

The following variations support identification. First, micromoments help identify the income coefficients. We use the income–vehicle segment micromoments from a new buyer survey to identify the price random coefficients.[45] The vehicle segments include compact sedan, sedan, sports utility vehicle (SUV), and multipurpose vehicle (MPV). Second, the central subsidy changes considerably across time, and the local subsidy provides cross-sectional variation in prices. Figure A.4 provides the detailed variation. Third, the large variation in choice sets across cities and across time helps identify other random coefficients. We assume that these variations are independent of city–quarter demand shocks. As stated in the entry model timing assumptions, we assume that firms make entry decisions before the realization of market–period-specific shocks. Fourth, geographical differences and variations in central subsidy levels and selected pilot cities provide the lemon share IVs and identify consumer sensitivity to reputation factors, as explained in Section 3.

Dynamic parameters We estimate the dynamic entry model separately with a maximum likelihood approach. The estimation of the dynamic model follows a procedure similar to the solution method outlined in Figure 6 yet requires fewer iterations. In the spirit of Bajari et al. (2007), we utilize

[45] We use the household surveys of new vehicle buyers from 2011 to 2017, following Barwick et al. (2023) and Kwon (2023).

the data as much as possible to approximate the outer loop strategies, which avoids the costly outer loop calculation. In our calculation, the initial guess of industry structure transition probability G is estimated from the observed number of active firms and the initial guess of firms' pricing strategies is equal to observed prices. We then solve the inner loop and update the outer loop strategies once to correct for the poorly estimated conditional choice probability (CCP) from the data. This idea comes from Aguirregabiria and Mira (2002).[46] In estimating the entry costs, we consider the decreasing trend in battery costs as observed in the data, without estimating the causal impact of EVs. This simplifies the off-equilibrium path calculations. This trend is driven by aggregate EV sales and is thereby exogenous to the actions of any individual firm. The pseudo-likelihood functions for market-level entry and industry-level actions are detailed in Appendix B.1

Table 6: Number of observations in MLE

	2012	2013	2014	2015	2016	2017	2018
Number of new firm–province $\mathbb{1}_{jmt} == 1$	10	31	54	39	152	273	–
Number of firm–province $\mathbb{1}_{jmt} == 0$	110	149	166	301	308	427	–
Number of new firm $\mathbb{1}^{a}_{jt} == 1$	3	2	6	6	12	20	–

Notes: This table reports the number of observations in the MLE. The last column is "–" because we do not observe 2019 market structures. The first row reports the number of new firm–markets per year, and the second row is the number of active firms × 20 markets minus the number of incumbent firm–markets. The third row reports the number of new active firms per year.

Identification is given by the parametric assumptions and relies on rich variation in market-level and industry-level profit changes and entry decisions. Market-level fixed costs are identified from profit variations across markets and time. The main exogenous shifter is the large variation in subsidies over time and the decreased vehicle marginal cost, as explained in Section 2. We observe a large number of entry decisions. Table 6 reports the number of firms entering the industry. The first two lines are the number of observations in the likelihood function (Equation B.10), and the last line is the number of active firms per year.

5.2 Estimation results

Demand parameters Table 7 reports the estimated demand parameters from logit regression and from the random taste discrete-choice model. The coefficients on observed vehicle attributes align with intuition. Consistent with the reduced-form evidence, consumers respond to negative reputation signals, and the effect is significant in both specifications.

We then back out the vehicle marginal cost using firms' first-order conditions and the estimated

[46] The algorithm usually converges within 5 iterations of the outer loop. The inner loop's beliefs on transitions G and profits $E\pi$, which are associated with outer loop strategies, update very little after 2 iterations, although the outer loop strategies can update. Thus, in the estimation, updating the outer loop once already provides accurate information for inner-loop decisions.

Table 7: Demand estimation results

	Logit		BLP	
	Coef.	S.E.	Coef.	S.E.
Prices				
Prices	-0.163	(0.018)		
$\overline{\alpha}$			1.589	(0.102)
σ_p			0.298	(0.014)
Reputation factors				
L.fires	-0.092	(0.021)	-0.151	(0.013)
L.fires$_{involved}$	-0.049	(0.018)	-0.067	(0.029)
L.lemon share	-0.046	(0.014)	-0.137	(0.015)
Other characteristics				
Engine power	0.162	(0.049)	0.104	(0.031)
Driving range	0.179	(0.044)	0.365	(0.071)
Net weight	0.260	(0.047)	0.482	(0.049)
GV (σ_{gv})			1.732	(0.212)
Constant (σ_0)			0.680	(0.093)
N	140,711		140,711	

Note: This table reports estimates of Equation 3. We include estimates of key primitives (price and reputation sensitivities) and coefficients for observed vehicle attributes. The first three coefficients in the other characteristics are estimated mean taste parameters, and the last two rows are variances in consumer taste for GVs and a constant (or outside options).

consumer price elasticities.[47] Table 8 reports the marginal cost estimates. The coefficients on observed vehicle attributes align with intuition. The estimated marginal cost of adding 10 kg of vehicle weight is ¥5,014. EV engines are cheaper than GV engines. This observation coincides with industry knowledge and discussions on the relatively low technology barrier associated with electric engines.

Table 8: Marginal cost estimation results (¥10K)

		Coef.	S.E.
Battery capacity (kWh)	2015	0.415	(0.016)
	2016	0.344	(0.013)
	2017	0.264	(0.027)
	2018	0.215	(0.019)
Vehicle weight		5.014	(0.063)
Engine power (GV)		9.955	(0.042)
Engine power (EV)		0.207	(0.045)

Note: This table reports estimates of Equation 6. We include estimates of key primitives (battery cost time trend) and coefficients for observed vehicle attributes.

The coefficients on battery capacity reflect a decreasing battery costs over time. Increasing battery capacity by 1 kWh would have cost ¥4,152 in 2015. The battery cost declines by approximately 20% each year during our sample period, and the marginal cost of battery capacity becomes ¥2,154 per

[47] These first-order conditions assume that firms observe the full market structures.

kWh in 2018. Our findings are consistent with the results from Barwick et al. (2023) and industry reports.[48] Batteries account for 57.3% of the marginal cost, a figure aligned with industry reports.[49]

In the counterfactual analysis, we extend our model to allow the battery price ω_t to be affected by aggregate historical EV sales, reflecting the subsidy's effect through the upstream spillover channel. Comparing the estimated battery costs with aggregate EV sales, we calibrate the impact of EV sales on future battery cost, following Nykvist and Nilsson (2015) and Ziegler and Trancik (2021). The calibration results suggest that, without EV sales, the baseline battery cost annual reduction rate is 9% in the main specification.[50] Discussions on the calibration and sensitivity tests appear in Appendix C.2.

To understand the implications of these demand parameters for firm profits and disentangle the direct monetary impact, the reputation impact, and the battery cost reduction impact, we decompose observed firm profits into three parts, as shown in Equation 13:

$$\begin{aligned}
&\pi_{jt}(s, q^{e*}, mc^*) = \\
&\underbrace{\pi_{jt}(s, q^{e*}, mc^*) - \pi_{jt}(s, 0, mc^*)}_{\text{reputation impact (?)}} + \underbrace{\pi_{jt}(s, 0, mc^*) - \pi_{jt}(0, 0, mc^*)}_{\text{direct impact (+)}} + \underbrace{\pi_{jt}(0, 0, mc^*) - \pi_{jt}(0, 0, mc^0)}_{\text{upstream spillover impact (+)}} \\
&+ \underbrace{\pi_{jt}(0, 0, mc^0)}_{\text{baseline}}.
\end{aligned} \tag{13}$$

We calculate firm profits in the following four scenarios: (i) the observed scenario with the current subsidy, reputation factors, and battery cost $\pi_{jt}(s, q^{e*}, mc^*)$; (ii) the full-information scenario $\pi_{jt}(s, 0, mc^*)$;[51] (iii) a scenario with full information and no subsidy, but the battery cost decreases as in reality $\pi_{jt}(0, 0, mc^*)$; and (iv) the baseline without any government intervention, and the battery cost decreases at a baseline rate $\pi_{jt}(0, 0, mc^0)$. The difference between (i) and (ii) is the reputation impact; the difference between (ii) and (iii) is the direct impact; and the difference between (iii) and (iv) is the upstream spillover impact. In all these calculations, we allow firm price responses but keep the market structures the same as in reality to develop a sense of how much the three channels change per-period profits and entry incentives.

Firms are differently affected by the subsidy because of consumer heterogeneity and market segmentation, and this is determined by the key primitives α and θ, as explained in Section 4.1. Figure 7

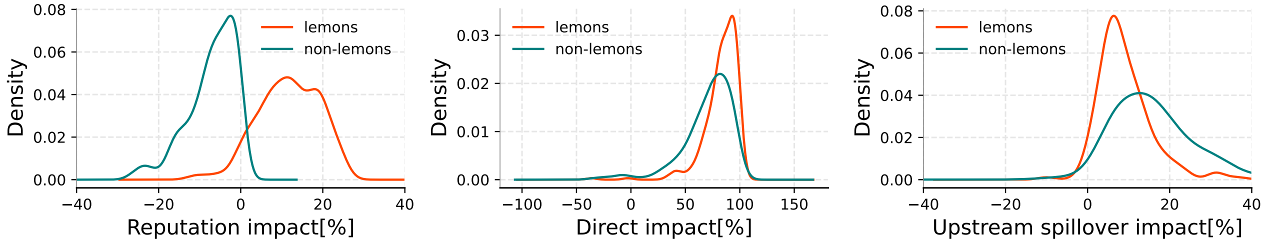
[48] According to Bloomberg NEF's annual battery price survey, EV battery prices fell by 6.3% per quarter from 2013 to 2018. Source: https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/

[49] Multiple media and industry reports document that the battery is the costliest vehicle component for—ranging from more than 40% to around 60% of the total components cost. Our estimates fall into this range.

[50] This is from the calibration that a 10% increase in EV sales leads to a 1% decrease in battery costs.

[51] In the full-information scenario, consumers have perfect information about lemons and fire probabilities, and there is no reputation externality. Mathematically, we change the variable *lemonshare* to 0 for nonlemons and to 1 for lemons. I change the EV fire externality variable $\mathbb{1}(fire)_{c,t-1}$ to 0. Consumers could still have some ex post loss from EV fires, but there is no across-firm reputation externality.

Figure 7: Decomposition of subsidy impact



Note: This figure reports results from the profit decomposition in Equation 13. We report firms' profits from electric vehicle models only.

reports the impact of the subsidy on firm–quarter-level profits through the three channels. The impacts are in percentages, with the denominators being the actual profits, which are detailed on the left-hand side of Equation 13. The impacts of all three channels are substantial and heterogeneous. The reputation impact is, in general, positive for lemons because consumers would not buy lemons if they knew the cars had poor experience quality, as in the full-information counterfactual. The impact on nonlemons is, in general, negative because some GV consumers would have bought a nonlemon in the full-information counterfactuals where they know EVs are not that bad. Some signs are opposite because of the substitutions and because nonlemons can also catch fire. The direct impact can be as large as 100%. This is because some cars' consumer prices are equal to or even lower than their marginal costs. Thus, without a subsidy, no consumers would buy them. Lemons benefit slightly more than nonlemons from the direct impact because the estimated price sensitivity α is high, as explained in Section 4.1. Figure A.11a plots how nonlemons and lemons' average profits change as α changes. When α is smaller, nonlemons could benefit more than lemons from the subsidy. In a large range close to our estimated α, lemons benefit more than nonlemons. The upstream spillover channel has a large impact on profit changes because battery costs decreased by almost half. The impact on lemons is smaller mainly because lemon cars usually have a lower driving range.

Dynamic parameters We set the discount factor β to be 0.85, and Table 9 reports the estimated cost parameters.[52] The average industry-level entry cost stands at 261.8 million RMB (40.3 million USD). This is significantly higher than the market-level cost, which averages 20.7 million RMB (3.18 million USD). Γs represents the industry-level sunk cost in Equation 8. Γ_2 indicates that GV firms have technological advantages. Γ_2 indicates that lemons have a significantly lower entry cost than high-quality firms. Notice that lemons have a much lower activation cost than GV firms. This can explain why, despite their technological advantages, most well-known GV firms did not enter until 2017. γs represents the market-level sunk cost in Equation 7. GV firms have a lower average entry cost because they sell GVs in most provinces. Furthermore, this cost does not depend on firm–market

[52] Recall that the scrap value is set to 0.

distance for GVs because $\gamma_2 + \gamma_3$ is close to 0. New EV firms need to pay a higher market-level entry fixed cost (FC). The results stem from a data pattern where some firms with GV experience enter more than 5 provinces each year, whereas most EV-only firms enter approximately 2 provinces annually. The estimation results match several publicly listed firms' annual reports.[53] The model can match a set of national-level and market-level moments well. Appendix B.6 reports more model fit discussions.

Table 9: Entry cost estimation results (10 million RMB)

			GV advantage		Lemon		Distance (100 km)				ϵ	
Ind.-level	Γ_0	26.179	Γ_1	-3.750	Γ_2	-1.924					ρ	3.242
		(3.573)		(1.191)		(0.110)						(1.232)
Mkt.-level	γ_0	2.073	γ_1	-1.250			γ_2	0.031	γ_3	-0.024	ρ	0.182
		(0.010)		(0.021)				(0.007)		(0.005)		(0.027)

Notes: This table reports estimates of Equations 7 and 8.

6 Policy Evaluation

We begin by comparing the observed scenario with a no-subsidy counterfactual to understand the policy impact. We then decompose the subsidy's impact by simulating the policy under several counterfactuals that disentangle these three economic forces: the direct impact, the reputation impact, and the upstream spillover impact. Last, Section 6.3 delves further into the impact of lemon firms, addressing both the consequences of their presence and the reasons that subsidies attract them.

6.1 Welfare definition

We calculate welfare from 2012 to 2022 to capture the long-term subsidy impact. Total welfare consists of consumer welfare, the emission externality, firm profit, firm investment spending, and government subsidy spending. We include subsidy spending with a parameter $\lambda = 1$ to represent the cost of public funds. Section B.5 explains the simulation method. Equation 14 explains consumer welfare, and the rest of the terms are standard, with details in Equations B.16–B.19.

We follow the consumer welfare calculation framework of Allcott (2013), Train (2015), and Barahona et al. (2020). In this framework, consumers hold misperceptions, and their ex ante expected utility at the time of purchase differs from their experienced utility. Let $u_{i,oj,ct}$ denote the monetized

[53] For example, both SAIC and BAIC disclosed to the media that the cost of building a factory is 1,000 million. This aligns with our estimations, even though firms tend to overreport their investments and round to whole numbers. Source: https://www.sohu.com/a/167856508_391226

ex post utility of consumer i buying model o from firm j in city c period t.

$$
\begin{aligned}
CW_{mt} &= \sum_{oj \in O_{mt}} \sum_{c \in C_m} \int_i Pr_{i,oj,ct} \cdot u_{i,oj,ct} di \\
&= \sum_{oj \in O_{mt}} \sum_{c \in C_m} \int_i Pr_{i,oj,ct} \left[\underbrace{\frac{1}{\alpha_i} \cdot (\delta_{i,oj,ct} + \theta_i {q^e}_{jct} - \alpha_i (p_{ojt} - s_{ojct}))}_{\text{ex ante utility } u_{i,oj,ct}} + \underbrace{\frac{\theta_i}{\alpha_i} \cdot (q_j - {q^e}_{jct})}_{\text{experience quality}} \right] di
\end{aligned}
, \quad (14)
$$

where the probability of choosing product oj for consumer i, $Pr_{i,oj,ct}$, is a function of the consumer's ex ante utility, which is based on the current reputation ${q^e}_{jct}$. This equation includes one more term than consumer ex ante choice utility: experience quality for EVs in Equation 14. The vector q_j consists of three elements: the firm's lemon status, a dummy variable for EV firms in the city, and a dummy for firms involved in fires, similar to q^e_{jct} as defined in Equation 4. This vector represents the actual quality of firm j. For the lemon status, we assign a value of 1 to lemons and 0 to nonlemons. The difference between this and the lemon share variable captures the choice distortion due to incomplete information. The EV fire dummy is set to 0 for all firms not involved in fires, indicating that the reputation externality affects only the choice probabilities and not the ex post utilities.

To account for the long-term impact of the subsidy, we assume that the subsidy stops in 2019, as the government originally announced. We designate 2019–2022 as the post-subsidy period and 2012–2018 as the subsidy period. Given that the reputation externality diminishes over time and to avoid potential overestimation of its impact, we assume no reputation externality during the post-subsidy period.

6.2 Quantification of the subsidy's overall impact and the three channels

The net impact of the subsidy is nearly 0 (-0.94 billion RMB). Table 10 reports the impact, taking into consideration firm price, market-level entry, and industry-level entry responses. The static welfare impact is -27.16 billion RMB, indicating that the welfare gain does not offset government spending. This finding is consistent with the previous literature that focuses on the consumer side (Guo and Xiao (2022)), which also identifies a negative welfare impact from the Chinese EV subsidy. Studies of the US, Canada, and EU electric vehicle market (Sheldon and Dua (2019), Harvey (2020), Thorne and Hughes (2019)), abstracting from firm entry responses, also find that a subsidy is not cost-effective.

Both the market-level and industry-level entry responses enhance the subsidy's benefits. The subsidy increases EV sales by 83%, leading to a 39.74 billion RMB increase in consumer surplus and an emissions reduction of 3.37 billion RMB, according to Table 10.[54] This promotes the entry of 57% of lemon firms and 49% of nonlemon firms. Without the subsidy, firms would, on average, enter

[54] Our estimate is larger than the result of Li et al. (2022), who find that the subsidy contributes to more than half of the EV sales in China. Their paper does not consider firm-side responses.

Table 10: Welfare impact of the subsidy (billion RMB)

	Simulated Reality	No subsidy baseline		
		(i) Price response	(ii) Mkt.-level entry	(iii) Ind.-level entry
		(diff)	(diff)	(diff)
Consumer surplus	4,106.26	14.87	25.52	**39.74**
EV profit	32.74	22.23	24.28	**32.74**
GV profit	631.21	-10.59	-11.60	**-12.02**
Investment	10.17	–	1.41	**3.15**
Emission reduction	-421.48	3.00	3.27	**3.37**
Subsidy spending	56.67	–	–	–
Total welfare	4,290.69	-27.16	-14.19	**-0.94**

Notes: This table provides average outcomes from 50 simulations. The first column displays the simulated reality results. The next three columns contrast this simulated reality with a no-subsidy baseline, accounting for the price response, market-level entry response, and industry-level entry responses, respectively. The numbers in these three columns indicate the impact of these responses.

three fewer provinces. The total benefit of the subsidy is 55.73 billion RMB against a cost of 56.7 billion RMB, resulting in a nearly zero net welfare impact. For detailed sales and firm numbers, see Table A.9.

Why is the net impact zero? We look into the three channels. To estimate the impact of each channel, we simulate scenarios in which a specific channel is deactivated. We find a net loss of -11.37 billion RMB from the direct channel and a further -6.13 billion RMB loss from the reputation channel. Moreover, the upstream spillover channel contributes large welfare gains.

Direct channel We calculate the direct impact by running a counterfactual scenario in which the subsidy is removed while the battery and EV marginal costs continue to decrease as in reality and the impact of reputation factors on consumer choice is as in reality. Column (i) in Table 11 presents the impact through the direct channel, with the first panel presenting the welfare differences and the second panel highlighting key outcomes. The direct channel generates a benefit of 45.30 billion RMB and government spending of 56.67 billion RMB, resulting in a negative net impact.

The direct impact of the subsidy is to bring consumer prices closer to vehicles' marginal cost and emissions reduction benefits.[55] The subsidy itself, along with the direct channel–induced entry of approximately ten new firms and two more provinces per firm, substantially reduces this gap. The gap decreases from 80 thousand RMB (31%) to an average of nearly zero within the subsidy period. These reductions serve as the primary driver for increased EV sales (78.2% of EV sales and 90.1% of emissions reduction[56]) and address the underadoption of EVs due to market power and environmental

[55] Emissions reduction is computed as the difference in emissions with and without the EV model, reflecting the improvement over the environmental impact of the cars that it replaces.

[56] The difference between emissions reduction and EV sales comes from hybrid models. These models are less subsidy

externalities.

Although decreasing markups can be welfare improving, some consumer prices are lower than their marginal costs and environmental benefits. This can result in deadweight loss DWL.[57] Furthermore, because vehicles are heterogeneous, the choice distortion caused by subsidies can lead to negative welfare even when markups are slightly positive.[58] Therefore, the benefit fails to offset its expenditure, making the net impact negative.

Finally, the subsidy's direct benefit in the post period arises from entry and enhanced competition. Nonetheless, these post-subsidy improvements offset the loss during the subsidy period only modestly, with just a 7 thousand RMB change in markup and a 9% increase in sales attributable to the direct channel. Thus, the losses during the subsidy period dominate the overall net impact, suggesting that the subsidy should better balance the static losses and the dynamic gains. Figure A.7 illustrates the changes in the gap between consumer prices and vehicle marginal costs and emissions reduction across years.

Reputation channel To assess the reputation channel's impact, we evaluate a full-information counterfactual by replacing $Pr_{i,oj,ct}$ in Equation 14 (and in Equations-B.16–B.19 for other welfare components) with $Pr^{fullinfo}_{i,oj,ct}$. This represents the probability of consumers purchasing model o from firm j if there were no reputation externalities and consumers had full information about product quality.[59] Firm strategies (σ^*_m, σ^*_I) and the state variable distribution $\widehat{F}_{mt}(\bar{s}_m|\sigma^*_m, \sigma^*_I)$ adjust accordingly.

Column (ii) of Table 11 presents the impact through the reputation channel. The reputation impact reduces the subsidy benefit by 6.13 billion RMB, which is 10.8% of the total subsidy benefit. The reputation losses lead to market shrinkage as expected. EV sales are 4.5% higher without the reputation channel. Lemon firms are more elastic at the market-level entry margin. Without the reputation channel and the consumer choice distortion caused by misinformation, lemon firms would enter only half the number of provinces that they actually do. Entry and expansion of nonlemon firms would see a modest increase. The reputation loss accounts for only 4.3% of the total benefit when we consider only the static losses from consumer ex post welfare losses, choice distortion, and firm profit

sensitive, and we account for them in the EV sales. However, they contribute little to emissions reduction.

[57] Barwick et al. (2023) also find that over half of BEV models had WTP and environmental benefits smaller than their marginal costs, resulting in only a few welfare-improving BEV models.

[58] A simple example illustrates the impact of such choice distortion. Suppose that there are two goods with consumer utility 100 and 90, respectively, giving a consumer surplus of $CS_0 = log(e^{100} + e^{90})$. If we give a subsidy of 10 to the higher-value good that the consumer would have bought, the welfare gain is $log(e^{100+10} + e^{90}) - CS_0 = 9.9 \approx 10 \times 1$, which is almost equal to the expenditure. Here 1 is the probability of purchasing the higher-value goods. However, if we subsidize the lower-value good, the welfare gain is $log(e^{100} + e^{90+10}) - CS_0 = 0.69 < 10 \times 0.5$. Here 0.5 is the probability of purchasing the lower-value goods. In this case, the welfare gain is considerably smaller than the expenditure because of choice distortion.

[59] We force the consumer reputation parameter to 0 for noninvolved firms in EV fires and replace the historical lemon share variable with 1 for lemon firms and 0 for nonlemon firms.

distortions. However, the firm entry responses highlight the adverse selection, deterring high-quality entry in approximately 11 firm–markets (9.2%), amplifying the reputation loss to 10.8%. Table A.11 reports more information about the interaction between entry and reputation losses.

Table 11: Decomposition: Welfare impact of the three channels

	Subsidy impact	Counterfactuals (i) No direct	(ii) No reputation	(iii) No upstream spil.
Welfare (billion RMB)		(diff)	(diff)	(diff)
Consumer surplus	39.74	30.46	-3.36	17.11
EV profit	25.13	22.96	-2.17	16.27
GV profit	-12.02	-10.91	0.27	-7.45
Investment	3.15	2.07	0.05	0.97
Emission reduction	3.37	3.09	-0.23	1.87
Total benefit	55.74	45.3	-6.13	27.65
Subsidy spending	56.67	56.67	-1.97	14.92
Total welfare	-0.94	-11.37	-4.16	12.88
Key outcomes				
Social markup [%]	-0.07	**0.31**	-0.08	0.04
[1,000 RMB]	3.74	**80.49**	3.26	18.05
MC [1,000 RMB] (static)	136.97	136.97	136.96	**170.25**
(eqm)	136.97	141.09	136.05	**173.79**
Lemon share 2015	39.92	17.19	32.05	37.05
2018	13.65	11.66	9.85	12.14

Notes: This table reports average results from 50 simulations. The first panel presents welfare metrics. The initial column reports the difference between the simulated reality and no-subsidy scenario. The following three columns show the differences between the simulated reality and the results from deactivating one channel. Thus, the numbers represent the impact of the direct, upstream spillover, and reputation channels. The summation of the benefits through the three channels is larger than the aggregate impact because we report the partial impacts, and there are positive synergies, especially between the direct and the upstream spillover channels. The second panel reports the equilibrium outcomes of simulated reality and when one channel is deactivated, without taking any differences.

Upstream spillover and sensitivity We calculate the upstream spillover impact by comparing the observed scenario with a counterfactual in which the battery cost decreases at a baseline rate. Based on the main results from our calibration, when we eliminate the causal effect of EV sales on battery cost reduction, battery costs would decrease at a baseline rate of approximately 9% annually, as explained in Section 5.2. The last column of Table 11 reports the results with the baseline battery costs. The upstream spillover channel makes a substantial contribution of 27.65 billion in welfare benefits, accounting for nearly half of the new firm entries and driving 59% of EV sales. This channel contributes the most to the long-term impact, particularly affecting post-subsidy sales by 50%. There are positive synergies between the three channels. Without upstream spillovers, markups would increase slightly due to fewer entrants.

The large impact and synergies of the upstream spillover channel highlight the importance of considering this channel in counterfactual policy analysis. Appendix C.2 presents results on sensitivity and robustness. Even with the most aggressive assumption—that the baseline battery cost reduction rate is approximately 5% per year —the subsidy's benefit only marginally exceeds government spending.[60] A faster cost-decreasing assumption also slightly increases the subsidy's reputation loss, but it remains around 10%.

6.3 Discussion on lemon entrants

The nine identified lemon firms account for 16.5% of the government expenditure (9.25 billion RMB). Two key factors contribute to the inefficiency associated with lemons. First, lemons often exhibit low consumer WTP and an even lower experience utility, eliminating direct channel benefits and generating loss through choice distortion and DWL. Second, lemons generate a reputation externality and cause underadoption of high-quality EVs. In equilibrium, the reputation channel also deters the entry of nonlemon firms into the industry. Section 7.3 discusses when this impact becomes more severe.

Why do subsidies attract lemons? In provinces with high consumer price elasticity, subsidies benefit lemons more than nonlemons. The intuition has been discussed in Section 4.1 and Figure 4. The subsidy incentivizes more price-sensitive consumers to purchase EVs, which primarily benefits less expensive cars. Models from lemon firms usually have lower prices because these cars also have low observed attributes such as driving range and vehicle weight. Table A.8 reports these correlations. To confirm this intuition, we plot the probability of choosing EVs and lemon EVs for consumers with different price sensitivities. Figure A.12a plots these functions for one example province, Hubei, indicating that price-sensitive consumers are more likely to opt for lemon EVs. Consequently, as the subsidy increases, average profits for lemon firms rise more rapidly than those for nonlemons, as demonstrated in Figure A.12b.

Province heterogeneity in attractiveness and entry spillover The reputation impact accounts for 10.8% of the benefit rather than dominating it. In addition, the Chinese EV industry does not exhibit a low-quality low-reputation equilibrium. The containment of this negative impact is largely attributed to province heterogeneity and the industry-level entry margin. While many provinces attract lemons more than nonlemons, some provinces promote nonlemons firms. Zhejiang province is an example of a market with a higher income and a lower price sensitivity, and its subsidy impact is the opposite: the subsidy benefits nonlemons more than lemons. In addition, Zhejiang is more distant

[60] This is supported by the aggressive calibration that a 10% increase in EV sales leads to a 1.5% decrease in the battery cost.

than Hubei from lemon plants. Figure A.13 presents details for Zhejiang province. Finally, two major markets, Beijing and Shanghai, exhibit almost no lemon entrants.

The entry spillover effect across provinces aids the expansion of nonlemon firms. While the industry-level entry margin exhibits low elasticity, the market-level entry margin is notably more elastic. As a result, once a market draws in a newly active firm, further expansions become more feasible, leading to spillover effects across markets. Provinces that attract nonlemon firms can offset the substantial industry-level entry costs for these firms. As nonlemon firms expand into more markets in subsequent years, lemons face increased competition and gradually lose their dominance. Thus, the entry spillover benefits mainly the expansion of nonlemons and limits that of lemon firms. As shown in Table 11, the average lemon share is almost 40% in 2015 and 13% in 2018. Additionally, the subsidy's reduction in 2017 and 2018 played a role in this decline. The provincial heterogeneity, along with the presence of influential cities such as Beijing and Shanghai and the substantial industry-level entry costs, help mitigate the potential escalation of the reputation effect and prevent lemons from dominating the market at a national level.

Policy implications Significant welfare losses arise from both the direct and the reputation channels. We identify four policy implications. First, oversubsidizing decreases the direct impact when generating DWL and choice distortion. Furthermore, it primarily benefits lemons in price-sensitive markets, making it advisable to lower subsidies and improve efficiency. Second, alternative subsidies that more effectively target nonlemon firms can better address the reputational concerns arising from subsidies. Because we observe a negative correlation between lemons and observed attributes (Table A.8), increasing the subsidy stringency based on observed attributes can be an effective screening tool. Third, the optimal policy design hinges on the magnitude of entry costs because entry responses contribute to both the direct channel markup changes and the amplification of the equilibrium reputation impact. Fourth, a regional policy can mitigate reputation losses because lemon attractiveness differs across provinces.

7 Counterfactual Policies

This section discusses alternative policies that can effectively stimulate industry growth while suppressing lemons. The reputation channel decomposition suggests the value of a perfect certification program: 6.13 billion RMB. However, given the difficulty of monitoring every firm's quality, this section relies on market mechanisms to select entrants and balance this trade-off.

We first study the optimal consumer subsidy design. The second part of this section discusses several other policies that can address reputation losses, including investment subsidies and regional policies. The last part of this section reports counterfactuals on other parameter spaces. We find that, in extreme parameter space with high price and reputation sensitivity, it is possible that the reputation channel dominates the impact and that increasing subsidies decreases EV sales.

Throughout the analysis, we keep all other policy conditions the same as in reality.[61] For traceability, we assume that firms do not change the set of models. We endogenize only prices and market structure and consider vehicle attributes, such as driving range, to be exogenous. We assume the cost of public funds $\lambda = 1$. Appendix C.3 discusses alternative values of λ and examines the Pareto frontier between the subsidy benefit and government spending.

7.1 Optimal subsidy design

We study the optimal design of the consumer subsidy by altering the level and stringency of the attribute-based subsidy. These two exercises are done separately; we first solve the optimal level and then solve the optimal stringency at the optimal level.[62] We find that the optimal level is determined mainly by the direct and the upstream spillover channels. The reputation channel pushes slightly for a more conservative level because subsidies attract more lemons in the estimated parameter space. It is mainly the reputation channel that determines the optimal stringency. The alternative stringency exercises assume that the attribute-based subsidy follows a two-part structure $T + t \cdot Drivingrange$. As lemons are correlated with low observed characteristics (Table A.8), increasing t can effectively differentiate lemons' and nonlemons' profits and screen lemons.

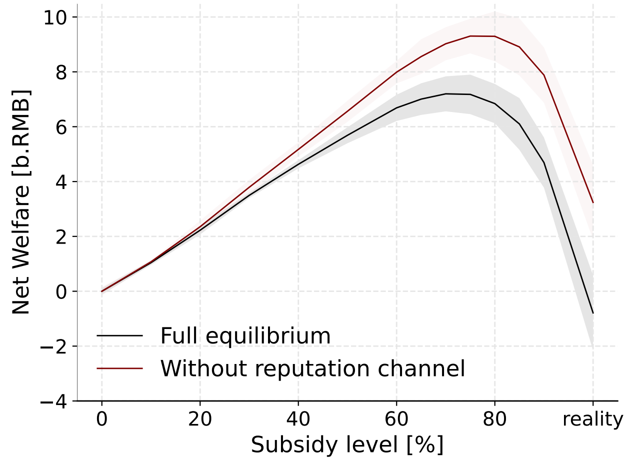
Optimal subsidy level In the counterfactual simulations, we set subsidies to 10%, 20%, ..., and 90% of the current policy. Figure 8 presents the net welfare impacts of these counterfactual subsidy scenarios, defined as the difference between welfare gains and subsidy expenditures. The welfare-maximizing subsidy level is found to be 70% of the current policy (gray curve in Figure 8), significantly improving policy efficiency from nearly 0 to 7.35 billion RMB (1.11 billion USD). The detailed changes in each welfare component can be found in Appendix Figure A.8. Table 12 summarizes the key outcomes for the scenarios with no subsidy, a 50% subsidy, the optimal level (70%), and the observed policy.

The direct channel yields the inverted U-shaped welfare impact. This pattern reflects the trade-off between the static welfare losses, arising from choice distortion and DWL, and the dynamic gains achieved as more entrants reduce the post-subsidy markups. Initially, the subsidy enhances welfare by addressing the underadoption caused by the environmental externality and market power. However,

[61] Other conditions include the timing of introducing local subsidies, the timing of expanding the subsidy to nationwide, the ratio between local and central subsidies, EV plate benefits, GV plate restrictions, and the number of charging stations.

[62] Due to computational limitations, we do not solve the two dimensions together. Welfare is much more sensitive to level changes than to stringency changes. This implies that, after these two steps, we are not too far from a two-dimensional optimum, which can be a result of several more iterations. Furthermore, we want to focus on the welfare implications of these two policy aspects instead of solving for the two-dimensional optimum.

Figure 8: Alternative subsidy: Net welfare impact



Notes: This figure reports the welfare impact for different subsidy levels. The left panel reports net welfare impacts, defined as the difference between welfare gains and subsidy expenditures. The black curve represents the full equilibrium outcome, and the red curve shows the results without the reputation channel. Shaded areas represent the standard deviations of 50 simulations. Detailed welfare components are reported in Figure A.8.

as subsidy levels increase further, additional subsidies may introduce more choice distortion and DWL than the post-subsidy benefits brought by new entrants. Increasing from the optimal to the observed level introduces large choice distortion and DWL. Table 12 shows that the average subsidy–period markup is approximately 13% at the optimal subsidy level and is 0 in the simulated reality. However, the marginal benefit from moving from the optimal level to the observed level is limited. Comparing the last two columns of Table 12, we see that the post-subsidy EV adoption increases by only 2.5%, changing from 188 to 201 thousand EVs per year. The industry-level entry margin is little affected. The market-level entry margin has a larger elasticity, but most marginal entrants are lemons: the number of provinces per lemon firm entered increased from 4 to 7.8. The upstream spillover channel adds some subsidy marginal gains, and the average marginal cost can decrease by 6% with a move from the optimal level to the observed level.

The optimal subsidy level results in a 12% decrease in reputation loss. It reduces lemon firms by 32% and nonlemon firms by only 13%. The last panel of Table 12 provides measures for the reputation channel.[63] While the static impact of these lemons is relatively modest, in the equilibrium, the impact is almost doubled. The consumer surplus losses are amplified to approximately 1 million. This leads to a more significant negative spillover to nonlemon firms. The reputation spillover, defined as the reduction in nonlemon firms' profits, is approximately 1.1–1.9 times as large as the static impact. Ignoring the reputation impact would lead us to set the optimal level to approximately 75%–80%, as shown by the red curve in Figure 8. This would lead to 5.25–7.93 billion RMB more subsidy spending

[63]This ex post loss considers only consumers who purchased lemon EVs. Aggregate differences between ex post and ex ante consumer welfare remain small since nonlemon purchasers experience higher ex post utility. In the final welfare measure, the reputation losses are due mainly to misinformation choice distortion.

(9%–13%) and 0.30 billion RMB (0.5%) lower net subsidy benefits.

Optimal subsidy stringency In the alternative stringency exercises, we set the subsidy levels to 70% of the current level. We assume that the subsidy takes a two-part structure based on driving range: $T + t \times DrivingRange$.[64] [65] To neutralize the policy level, we simulate outcomes with different policy stringencies t while keeping the subsidy for models with an average driving range unchanged.[66] Figure 9 presents the net welfare impacts of the counterfactual subsidy scenarios. Figure A.9 reports each welfare component, and Table 13 summarizes key outcomes for a flat subsidy, the optimal stringency, and an overstrict policy.

Welfare is maximized at 10k RMB per 100 km (1.3k USD per 100 km). Ignoring the reputation channel would result in a lower optimum, decreasing social welfare by 137.07 million RMB (20.77 million USD). This difference highlights the role of subsidy stringency. It not only guides driving range standards but also acts as a screening mechanism, effectively filtering out lemons.

Altering subsidy stringency t reflects the trade-off between costly growth and a higher reputation, and the optimal stringency is determined mainly by the reputation channel. Increasing stringency essentially substitutes low-driving-range EVs with those with a higher driving range, consequently prompting price-sensitive consumers to revert to GVs. This can make expensive cars benefit more from the subsidy and differentiate lemons' and nonlemons' profit. Figure A.14 detailed this effect by plotting lemons' and nonlemons' profits as subsidy stringency changes. When subsidy stringency increased by 1k RMB/100 km, the difference between lemons' and nonlemons' profits increased by approximately 4.5% in 2015 and approximately 2.1% in 2017. This change was more significant in 2015 because the correlation between lemons and driving range was slightly larger in 2015 (-0.43) than in 2017 (-0.34).

It is worth noting that the average profits of nonlemon firms almost do not vary by stringency. Because nonlemon firms also have low-driving-range models, increased stringency has two impacts on nonlemon firms: First, firms with low product attributes profit less and enter less. Second, higher stringency eliminates the reputation externality, prompting nonlemon firms to enter more. Thus, the aggregate impact on nonlemon firms' entry decisions is minimal. These findings suggest that increasing subsidy stringency can effectively differentiate lemons.

The optimal stringency can suppress 39% of the lemon firms in 2015. Table 13 provides the number of firms and their expansion decisions. The last panel of Table 13 reports detailed reputation losses. Compared to a flat subsidy, the optimal stringency reduces reputation losses for consumers by 0.04 billion RMB and decreases the reputation externality generated by lemons by 0.01 billion RMB. The

[64] In reality, the function is nonlinear, as shown in Figure A.10a.

[65] We keep the step-function design, and the alternative stringency changes only the subsidy values for the original thresholds.

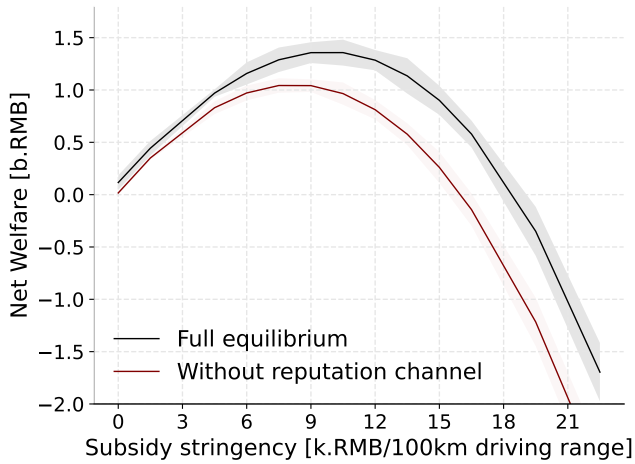
[66] The exact counterfactual subsidy has different levels across years, as it does in reality. Figure A.10a plots the details.

Table 12: Alternative subsidy levels: Welfare and main equilibrium outcomes

	Alternative levels of subsidy			Sim. Reality
	0	50	70	100
Welfare (billion RMB)				
Consumer surplus	–	9.87	17.47	39.74
EV profit	7.61	13.81	18.60	32.74
GV profit	–	-3.23	-5.61	-12.02
Investment	7.02	7.86	8.82	10.17
Emission reduction	–	0.83	1.48	3.37
Subsidy spending	–	7.85	16.98	56.67
Total welfare	–	5.69	7.27	-0.94
Sales in 1,000				
EVs	311.28	633.20	912.48	1,883.46
GVs ·	–	-150.11	-273.00	-660.67
Post-subsidy EVs	151.36	172.02	188.49	201.70
Firms and markets				
a. Industry-level entry margin				
Lemon firms 2015	1.67	2.98	3.99	5.03
2018	5.49	6.53	6.84	7.20
Nonlemons 2015	4.73	6.04	7.88	9.50
2018	20.79	27.41	32.63	35.15
b. Market-level entry margin				
# prov. lemons 2015	0.40	1.40	4.00	7.80
lemons 2018	7.29	8.00	8.29	9.43
nonlemons 2015	1.57	2.00	2.43	3.50
nonlemons 2018	5.52	6.39	6.75	7.48
Social markup and MC				
Markup [%]	0.31	0.20	0.13	-0.07
Markup [1,000 RMB]	85.64	46.83	30.42	4.30
MC [1,000 RMB]	155.26	147.95	144.81	137.73
Reputation Impact (billion RMB)				
One-period impact				
CS ex post loss	–	-0.17	-0.32	-0.85
CS misinfo distortion	–	-0.09	-0.17	-0.42
Spillover	–	-0.40	-0.76	-1.27
Equilibrium impact				
CS loss	–	-0.48	-1.07	-2.44
Spillover	–	-0.44	-1.45	-2.17
Spillover [%]	–	-5.54	-6.61	-7.32
Environmental benefit	–	-0.05	-0.11	-0.23

Notes: This table compares the equilibrium outcome when the subsidy changes from 0 to the observed level. These findings are the average results from 50 simulations. The markup is defined by the difference between the consumer price and the vehicle marginal cost. The sign differences are due to the skewness of the RMB measure. The reputation impact without subsidy is not zero; we report the difference between other scenarios from the no-subsidy scenario to emphasize the subsidy's impact. Table A.9 column (4) reports the levels of the no-subsidy counterfactual. The one-period reputation impact is smaller than the findings in the reduced-form section because we average across markets and periods. Table **??** reports more details on the firm entry responses in the reputation channel.

Figure 9: Alternative subsidy stringency: Net welfare impact



Notes: This figure illustrates the welfare impact of different subsidy stringencies. The left panel shows net welfare impacts, calculated as the difference between welfare gains and subsidy expenditure. The black curve represents the full equilibrium outcome, while the red curve depicts results without considering the reputation channel. Shaded areas indicate the standard deviations from 50 simulations. Figure A.9 reports all welfare components.

equilibrium impact on consumer welfare and firm profits is amplified to 0.52 billion and 0.51 billion RMB, respectively. When a flat policy is applied, a lower reputation leads to market shrinkage, causing a decrease in environmental benefits of 180 million RMB. The optimal policy reduces this loss to 120 million RMB.

A flat subsidy cannot discriminate lemons from high-quality firms and leaves lemons with more room for speculation. However, a stricter policy increases the average subsidy per vehicle, thereby making the transition from GVs to EVs more expensive. Figure A.9 illustrates that the subsidy expenditure increases rapidly as stringency intensifies. The direct channel and the upstream spillover channel exert minimal influence on the optimal stringency level, as we neutralize the subsidy design when altering the stringency. Consequently, altering the stringency t results in negligible changes in aggregate sales. Therefore, the direct channel (mainly reflected by the average markup) and upstream spillover (mainly reflected in the vehicle marginal costs) have little impact. As detailed in Table 13, total sales, marginal cost, and average markup are almost unaffected.

7.2 Other policies

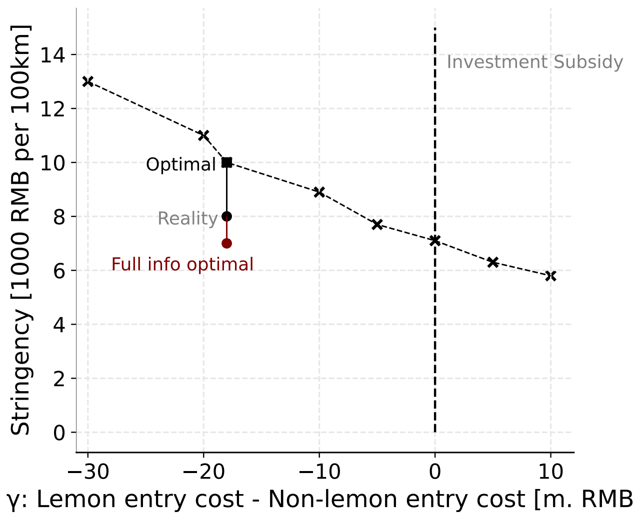
Stringency and entry cost Because increasing subsidy stringency is expensive, we explore investment subsidies that address the entry cost friction and mitigate the reputation impact. Section 5.2 shows the large estimated difference in industry-level entry costs for lemons and nonlemons. Figure 10 reports the optimal stringency when the difference between lemons' and nonlemons' entry costs varies. A lower entry cost for lemons necessitates a higher subsidy stringency. The optimal value converges toward the optimal stringency without the reputation channel because the difference in entry costs

Table 13: Alternative subsidy stringencies: Welfare and main equilibrium outcomes

	Subsidy Stringency (k RMB/100 km)		
	0	10 (Optimal)	18
Welfare (billion RMB)			
Consumer surplus	–	-0.77	2.12
EV profit	23.00	22.39	24.14
GV profit	–	0.13	-0.81
Investment	11.19	11.18	11.24
Emission reduction	–	-0.07	0.13
Subsidy spending	35.43	33.43	38.89
Total welfare	–	0.68	-0.89
Sales in 1,000			
EVs	1,029.97	955.43	1,015.67
GVs	–	19.03	-17.94
Post-subsidy EVs	150.69	149.57	155.30
Firms and markets			
a. Industry-level entry margin			
Lemon firms 2015	5.13	3.07	2.56
2018	7.26	7.17	7.01
Nonlemons 2015	7.47	7.74	7.84
2018	34.39	34.30	34.43
b. Market-level entry margin			
# prov. lemons 2015	5.00	4.80	4.40
lemons 2018	8.29	8.14	8.14
nonlemons 2015	2.09	2.29	2.36
nonlemons 2018	6.55	6.59	6.66
Social Markup and MC			
Markup [%]	-0.04	-0.01	0.02
Markup [1,000 RMB]	10.25	9.80	7.90
MC [1,000 RMB]	140.89	141.40	141.37
Reputation Impact (billion RMB)			
One-period impact			
CS ex post loss	-0.49	-0.38	-0.31
misinfo distortion	-0.25	-0.21	-0.17
Spillover	-0.60	-0.61	-0.63
Equilibrium impact			
CS loss	-1.57	-1.05	-0.65
Spillover	-1.72	-1.23	-0.86
Environmental benefit	-0.18	-0.10	-0.06

Notes: This table compares the equilibrium outcome when the subsidy stringency changes. These findings are the average results from 50 simulations. The markup is defined by the difference between the consumer price and the vehicle marginal cost. The sign differences are due to the skewness of the RMB measure. The one-period reputation impact is smaller than the findings in the reduced-form section because we average across markets and periods. Table **??** reports more details on the firm entry responses in the reputation channel.

Figure 10: Required stringency for different levels of entry cost



Notes: This figure plots the optimal stringency for different parameter values Γ_2 in Equation 7.

between lemons and nonlemons increases. This sheds light on the policy design of investment subsidies. The part on the right of the estimated Γ can be interpreted as a penalty on lemon firms or an entry subsidy for top-quality firms. As shown in Figure 9, increasing stringency is costly, and an investment subsidy for top-quality firms or a penalty on lemons can reduce the necessary stringency and save government expenditures.

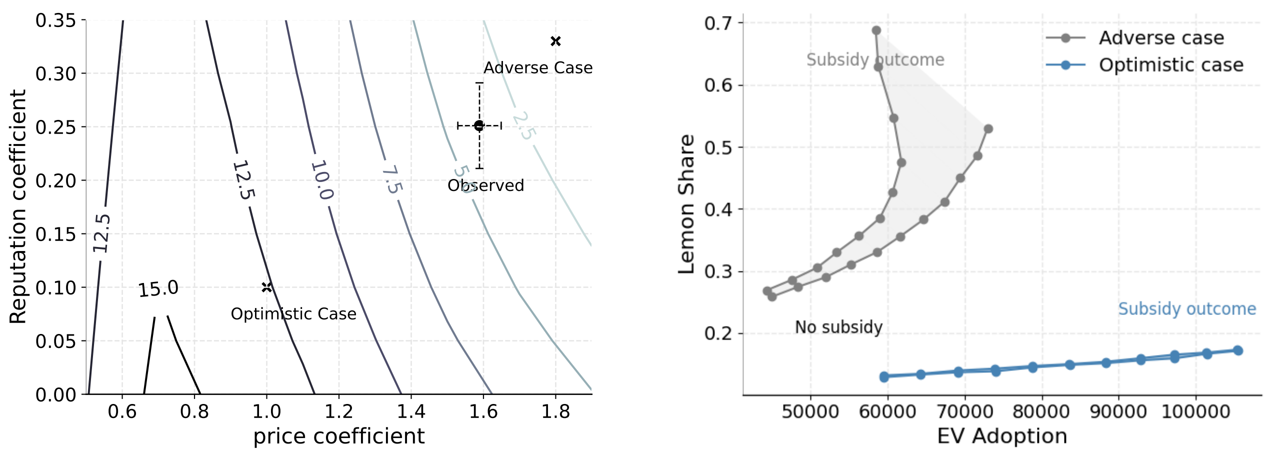
Restrict subsidy in certain provinces Section 6.3 suggests that some provinces exhibit more severe lemon problems than others, and there is cross-province entry spillover because of industry-level entry margins. Once a province attracts lemons into the industry, subsequent expansion decisions for lemons become cheaper and more elastic. Motivated by these findings, we simulate counterfactual policies that curtail subsidies in certain provinces. We run simulations for a counterfactual policy that delayed subsidies in four selected provinces with high price sensitivity and lemon attractiveness.[67] The results suggest that this can reduce the reputation impact from -10.8% to -7.9% and save 5.2 billion RMB (10.5%) in government expenditures. Additionally, the number of nonlemon firms in these provinces in 2018 dropped by only 3.2%, thanks to the cross-province entry spillovers. While the proposed policy offers potential benefits, it may also introduce equity concerns among different provinces. The exploration of these equity implications is beyond the primary focus of this paper.

[67] The four provinces are Hebei, Hubei, Shandong, and Sichuan. Their average lemon shares in 2015 were larger than 50%.

7.3 Determinants of impact and sensitivity

We find that the reputation channel reduces 10.8% of the subsidy benefit in the Chinese EV market. This impact could be more severe in other market environments. This section discusses the key primitives of the policy impact—consumer prices sensitivity, reputation sensitivity, and firm entry cost—and discusses under what market conditions policymakers should consider the reputation impact and plan for a more conservative and stricter policy. We also show that, in the adverse parameter space, the reputation channel can dominate the subsidy's impact and increasing subsidies can decrease EV sales.

Figure 11: Welfare impact of the subsidy



(a) Impact of price and reputation coefficients

(b) Equilibrium path as subsidy increases

Notes: These figures display the results for counterfactual parameters. In Figure 11b, the dots represent two equilibrium outcomes—the lemon share and EV adoption—as subsidies increase from 0 (on the left) to the observed level (on the top/right). In the optimistic case (depicted in blue), an increasing subsidy leads to higher EV adoption with only a slight increase in the share of lemons. In the adverse case, multiple equilibria are observed. In the worst equilibrium (the left boundary), an increased subsidy can actually result in decreased adoption.

We simulate equilibrium outcomes with data from one example province (Hubei) and change the key primitives. Figure 11 illustrates the influence of consumer price and reputation sensitivities on welfare, with examples of adverse and optimistic cases. Increasing the price coefficients yields a nonmonotonic impact. This is driven mainly by the direct channel, as the consumer price elasticity determines the benefit of smaller markups and the size of DWL. A subsidy in a less price-sensitive environment can generate little impact because consumers are inelastic. However, with large price coefficients, the subsidy generates DWL. Increasing price sensitivity also increases reputation loss. Section 6 has already pointed out that subsidies attract lemons more when consumer price sensitivity is large. Figure A.11a shows the average profits of lemons and nonlemons as the price coefficients vary and evidences this.

In markets with a higher reputation sensitivity, the subsidy leads to higher welfare losses due to the reputation channel. The isocurves being denser at the top suggests this. Whether negative quality signals from lemons have a long-term impact depends on both consumer reputation sensitivity and firm entry costs. A "no-amplification region" exists when the reputation parameter is small. In this case, the reputation impact remains small even if the subsidy favors lemons as long as the reputation externality is insufficient to alter nonlemon firms' entry decisions. Moreover, consumers eventually forget the negative quality signals from lemons in later periods. In the observed parameter space, the equilibrium spillover impact is double the static impact. A higher entry cost friction enhances nonlemon firms' sensitivity to profit reduction, thereby amplifying the equilibrium reputation spillover. Figure A.11b depicts nonlemons' profits varying with consumer reputation sensitivity and the no-amplification region.

The reputation impact can outweigh the direct benefit when consumer price sensitivity and reputation sensitivity are both large. We pick adverse and optimistic cases based on Figure 11a and plot the subsidy impact in these two cases in Figure 11b. The dots represent two equilibrium outcomes—the lemon share and EV adoption—as the subsidies increase from 0 (left) to the observed level (top/right). In the optimistic case (blue), an increasing subsidy would lead to higher EV adoption and a lightly increasing share of lemons. Conversely, in the adverse case (gray), increasing subsidies may not necessarily increase adoption, as indicated by the gray curves. The left boundary of the gray area represents the worst equilibrium, while the right boundary represents the best equilibrium. In the worst equilibrium, a higher subsidy could decrease EV adoption, demonstrating that the reputation impact outweighs the direct benefit. This highlights the risk of a low-reputation low-quality low-adoption equilibrium in the adverse market environment.

Summary and policy implications In environments with a high price elasticity, the direct channel's trade-off calls for a conservative policy, while reputation concerns lead to an even more conservative policy and a higher subsidy stringency. This is due to the relative ease of incentivizing adoption in such environments, but consumers primarily choose cheaper cars and lemons. A higher entry cost amplifies the necessity of subsidies and improves the efficiency of the direct channel, but it worsens the reputation concern. In extreme cases, the reputation impact can be dominant. In environments with a lower price elasticity, we require a higher subsidy level, and increasing subsidy benefits nonlemons more. In this case, subsidy stringency is less necessary. Lowering stringency can also save subsidy expenditures and stimulate faster growth. Table A.13 displays the impact of subsidies in various market environments and summarizes the above discussion.

8 Conclusion

Many countries are implementing green industrial policies. This paper develops a framework for optimal subsidy design, considering the direct, upstream spillover, and reputation channels. We evaluate the observed subsidy design of the Chinese electric vehicle market, which is among the most successful green industrial policies in the world yet also faces significant criticism. We find a nearly zero net welfare impact, low efficiency, and significant reputation losses. Our model suggests that, in the optimal subsidy design, it is mainly the direct channel and the upstream spillover channel that determine the optimal subsidy level. The reputation channel necessitates a more conservative subsidy level because the subsidy attracts lemons more than nonlemons. The optimal stringency is determined mainly by the reputation channel. These results offer new evidence supporting the use of attribute-based subsidies, highlighting its role as a screening mechanism that suppresses lemons and the associated reputation loss.

When do subsidies attract lemons? In what environment would the reputation concern be more relevant? This paper establishes the relationship between consumer subsidy and lemon entrants through consumer price elasticity, and it explains how to subsidize industry growth in markets with lemons. The starting point is the imperfectly observed quality heterogeneity of early-generation products. We build a model to explain how government policies, such as consumer subsidies, alter different types of firms' incentives, influence reputation, and shape industry structure dynamics. We highlight the importance of reputation concerns in subsidy design and identify several effective strategies to mitigate lemons and their reputation externality. These findings can be extended to other green industrial policies.

References

Aghion, P., J. Cai, M. Dewatripont, L. Du, A. Harrison, and P. Legros (2015). Industrial policy and competition. *American economic journal: macroeconomics 7*(4), 1–32.

Aguirregabiria, V. and P. Mira (2002). Swapping the nested fixed point algorithm: A class of estimators for discrete markov decision models. *Econometrica 70*(4), 1519–1543.

Allcott, H. (2013). The welfare effects of misperceived product costs: Data and calibrations from the automobile market. *American Economic Journal: Economic Policy 5*(3), 30–66.

Bachmann, R., G. Ehrlich, Y. Fan, D. Ruzic, and B. Leard (2023). Firms and collective reputation: a study of the volkswagen emissions scandal. *Journal of the European Economic Association 21*(2), 484–525.

Bai, J., L. Gazze, and Y. Wang (2021). Collective reputation in trade: Evidence from the chinese dairy industry. *The Review of Economics and Statistics*, 1–45.

Bajari, P., C. L. Benkard, and J. Levin (2007). Estimating dynamic models of imperfect competition. *Econometrica 75*(5), 1331–1370.

Barahona, N., C. Otero, S. Otero, and J. Kim (2020). Equilibrium effects of food labeling policies. *Available at SSRN 3698473*.

Barwick, P. J., M. Kalouptsidi, and N. B. Zahur (2023). Industrial policy implementation: Empirical evidence from china's shipbuilding industry.

Barwick, P. J., H.-s. Kwon, and S. Li (2023). Attribute-based subsidies and market power: an application to electric vehicles.

Benkard, C. L., P. Jeziorski, and G. Y. Weintraub (2015). Oblivious equilibrium for concentrated industries. *The RAND Journal of Economics 46*(4), 671–708.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile Prices in Market Equilibrium. *Econometrica 63*(4), 841.

Berry, S., J. Levinsohn, and A. Pakes (2004). Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market. *Journal of Political Economy 112*(1), 68–105.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott (2017). Lemon technologies and adoption: measurement, theory and evidence from agricultural markets in uganda. *The Quarterly Journal of Economics 132*(3), 1055–1100.

Castriota, S. and M. Delmastro (2015). The economics of collective reputation: Evidence from the wine industry. *American Journal of Agricultural Economics 97*(2), 469–489.

Ching, A. T. (2010). Consumer learning and heterogeneity: Dynamics of demand for prescription drugs after patent expiration. *International Journal of Industrial Organization 28*(6), 619–638.

De Groote, O. and F. Verboven (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review 109*(6), 2137–72.

Gerarden, T. D. (2023). Demanding innovation: The impact of consumer subsidies on solar panel production costs. *Management Science*.

Guo, X. and J. Xiao (2022). Welfare analysis of the subsidies in the chinese electric vehicle industry. *Journal of Industrial Economics*.

Hansen, J. D., C. Jensen, and E. S. Madsen (2003). The establishment of the danish windmill industry—was it worthwhile? *Review of World Economics 139*, 324–347.

Harrison, A. and A. Rodríguez-Clare (2010). Trade, foreign investment, and industrial policy for developing countries. *Handbook of development economics 5*, 4039–4214.

Harvey, L. D. (2020). Rethinking electric vehicle subsidies, rediscovering energy efficiency. *Energy policy 146*, 111760.

Head, K. (1994). Infant industry protection in the steel rail industry. *Journal of International Economics 37*(3-4), 141–165.

Heutel, G. and E. Muehlegger (2015). Consumer learning and hybrid vehicle adoption. *Environmental and resource economics 62*(1), 125–161.

Holland, S. P., E. T. Mansur, and A. J. Yates (2021). The electric vehicle transition and the economics of banning gasoline vehicles. *American Economic Journal: Economic Policy 13*(3), 316–44.

Itskhoki, O. and B. Moll (2019). Optimal development policies with financial frictions. *Econometrica 87*(1), 139–173.

Kwon, H.-s. (2023). Subsidies versus tradable credits for electric vehicles: The role of market power in the credit market.

Lane, N. (2018). Manufacturing revolutions-industrial policy and networks in south korea. In *Journal of economic history*, Volume 78, pp. 629–629.

Levin, J. (2009). The dynamics of collective reputation. *The BE Journal of Theoretical Economics 9*(1), 0000102202193517041548.

Li, J. (2017). Compatibility and investment in the us electric vehicle market. *Job Market Paper 23*.

Li, S., L. Tong, J. Xing, and Y. Zhou (2017). The market for electric vehicles: indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists 4*(1), 89–133.

Li, S., X. Zhu, Y. Ma, F. Zhang, and H. Zhou (2022). The role of government in the market for electric vehicles: Evidence from china. *Journal of Policy Analysis and Management 41*(2), 450–485.

Liu, E. (2019). Industrial policies in production networks. *The Quarterly Journal of Economics 134*(4), 1883–1948.

Luzio, E. and S. Greenstein (1995). Measuring the performance of a protected infant industry: the case of brazilian microcomputers. *The Review of Economics and Statistics*, 622–633.

Murray, B. C., M. L. Cropper, F. C. de la Chesnaye, and J. M. Reilly (2014). How effective are us renewable energy subsidies in cutting greenhouse gases? *American Economic Review 104*(5), 569–74.

Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica 69*(2), 307–342.

Novan, K. (2015). Valuing the wind: renewable energy policies and air pollution avoided. *American Economic Journal: Economic Policy 7*(3), 291–326.

Nykvist, B. and M. Nilsson (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature climate change 5*(4), 329–332.

Sheldon, T. L. and R. Dua (2019). Measuring the cost-effectiveness of electric vehicle subsidies. *Energy Economics 84*, 104545.

Shiferaw, B., T. Kebede, M. Kassie, and M. Fisher (2015). Market imperfections, access to information and technology adoption in uganda: Challenges of overcoming multiple constraints. *Agricultural economics 46*(4), 475–488.

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy 13*(4), 393–432.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica 79*(1), 159–209.

Thorne, Z. and L. Hughes (2019). Evaluating the effectiveness of electric vehicle subsidies in canada. *Procedia Computer Science 155*, 519–526.

Tirole, J. (1996). A theory of collective reputations (with applications to the persistence of corruption and to firm quality). *The Review of Economic Studies 63*(1), 1–22.

Train, K. (2015). Welfare calculations in discrete choice models when anticipated and experienced attributes differ: A guide with examples. *Journal of choice modelling 16*, 15–22.

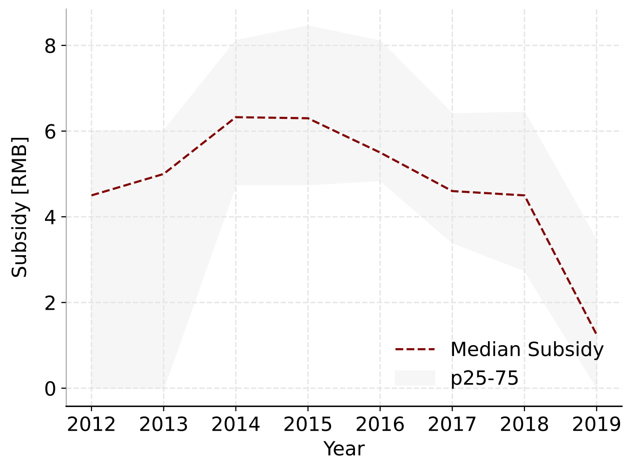
Xing, J., B. Leard, and S. Li (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management 107*, 102432.

Ziegler, M. S. and J. E. Trancik (2021). Re-examining rates of lithium-ion battery technology improvement and cost decline. *Energy & Environmental Science 14*(4), 1635–1651.

Appendices

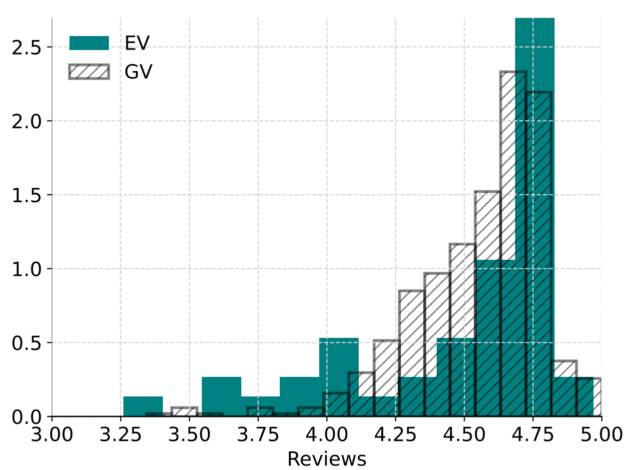
A Additional Figures and Tables

Figure A.1: Average subsidy rate by year [%]



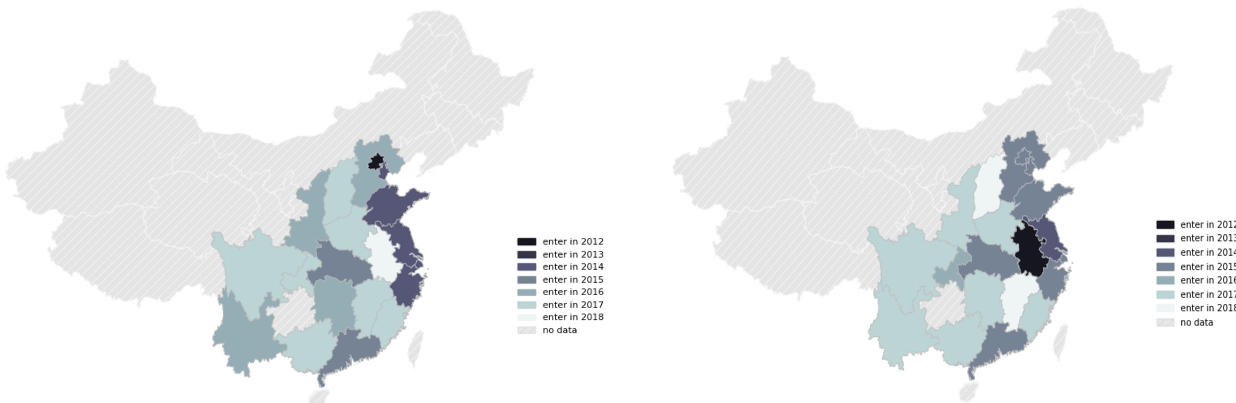
Notes: This figure displays the total subsidy amount by year, including local and central subsidies. As subsidies vary by both model and city, we present the mean, 25th percentile, and 75th percentile of the subsidy. Figure 1 reports the average subsidy rate over time, defined by dividing the total subsidy received for a model by the price of that model.

Figure A.2: Distribution of car quality review scores



Note: This figure plots the distribution of average firm review scores from the Autohome platform.

Figure A.3: Firm expansion path examples



(a) Expansion path of BAIC New Energy (from Beijing)

(b) Expansion path of Chery (from Anhui)

The figure depicts the expansion paths of two example firms. Gray regions are provinces with no data available. A darker color indicates that the firm expands to the market earlier. Panel (a) shows a firm from Beijing that expands roughly from north to south. Panel (b) shows a firm that expands from Anhui (in the center of China) and enters from the east and center to the west and periphery regions. This firm enters Beijing in the third year after becoming active. Firms from the north would enter Beijing much earlier because Beijing is one of the largest EV markets.

Figure A.4: Quarterly city-level policies from 2015 to 2018

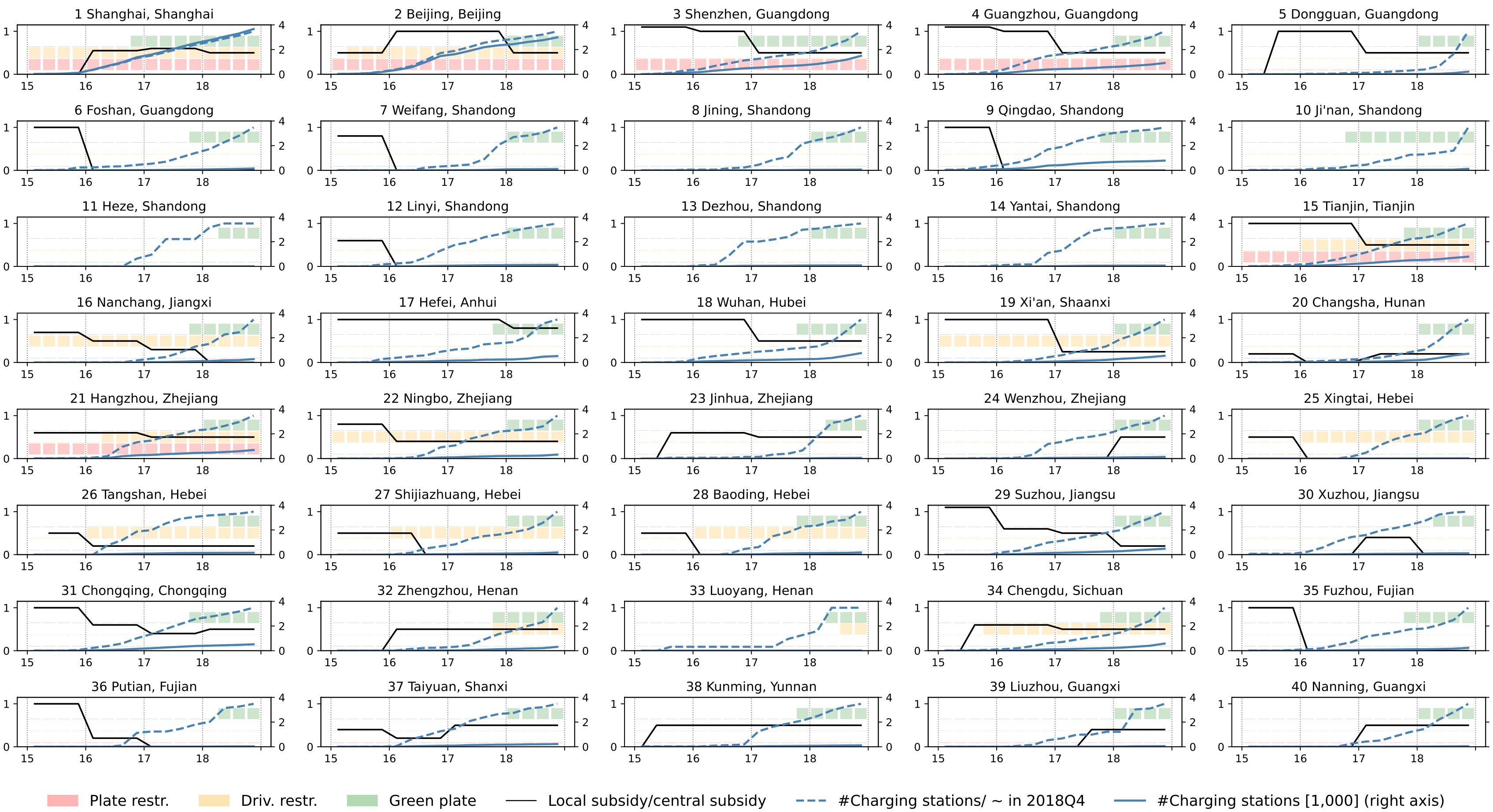
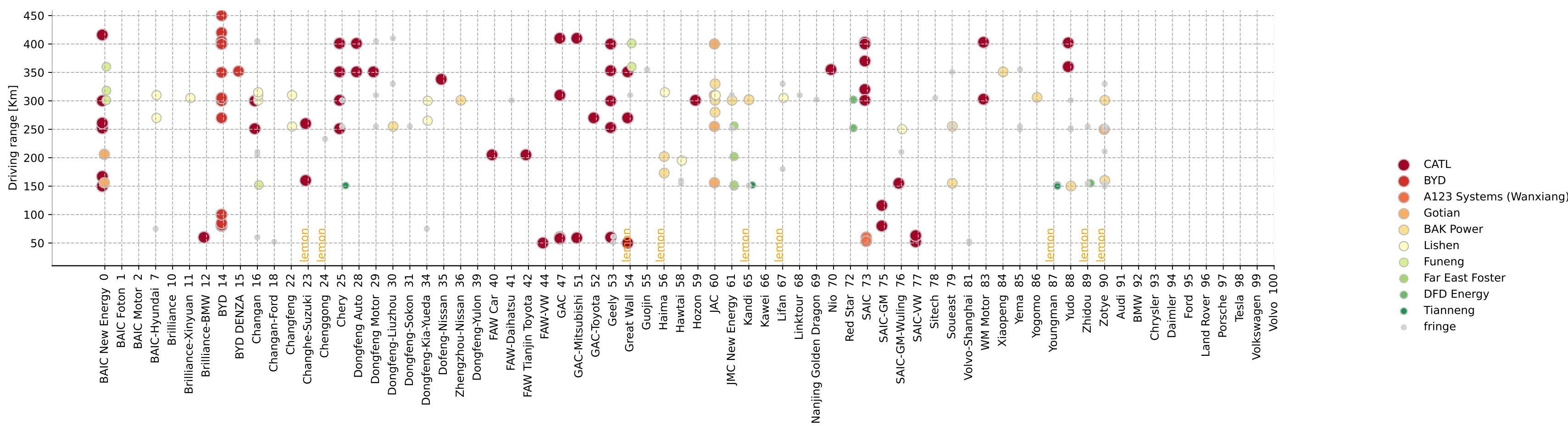
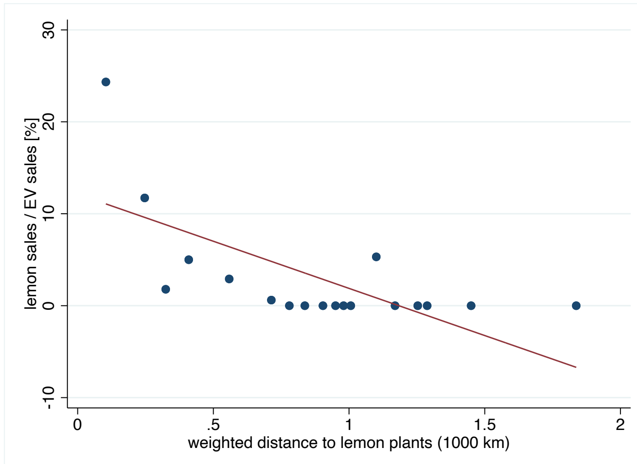


Figure A.5: Relationship between EV firms and upstream battery firms



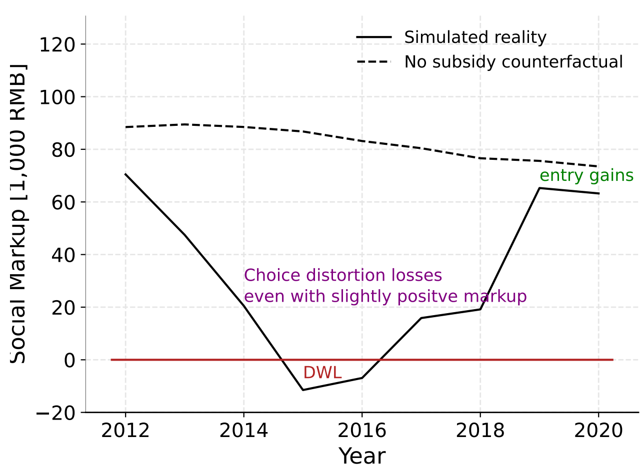
This figure reports the relationship between EV manufacturers and battery suppliers. There are no clear differences between the suppliers of lemon firms and non-lemon firms. This evidence further supports that lemons are EV manufacturers instead of battery suppliers.

Figure A.6: Relationship between lemon share and distance to lemon firms



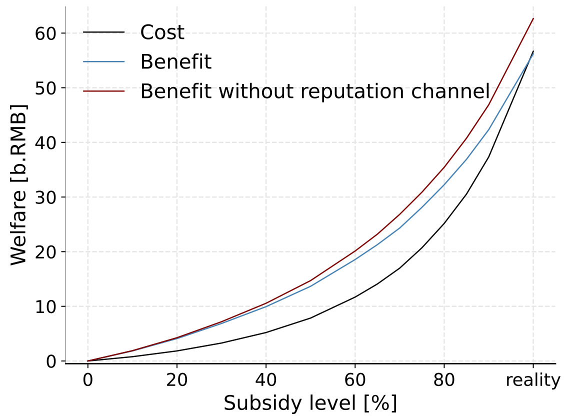
Note: City-level distance to lemon plants and local lemon share.

Figure A.7: Direct channel impact: Social markup



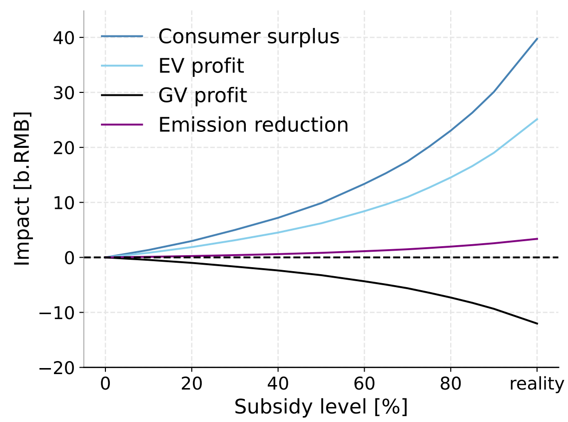
Notes: This figure reports the changes in average social markup, defined by the difference between consumer prices and vehicle marginal costs and emissions reduction. This reflects the gains and losses from the direct channel.

Figure A.8: Alternative subsidy level



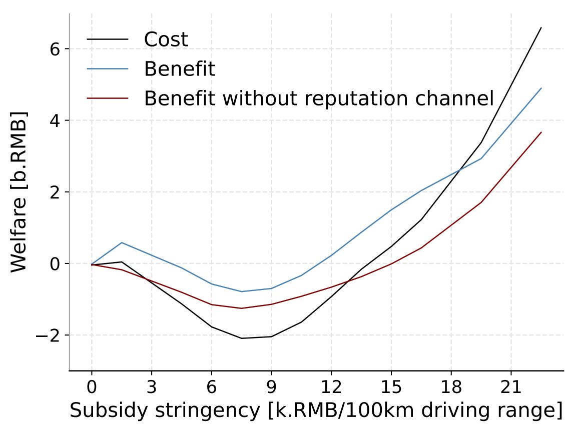
(a) Benefit and government expenditure

(b) Benefit components



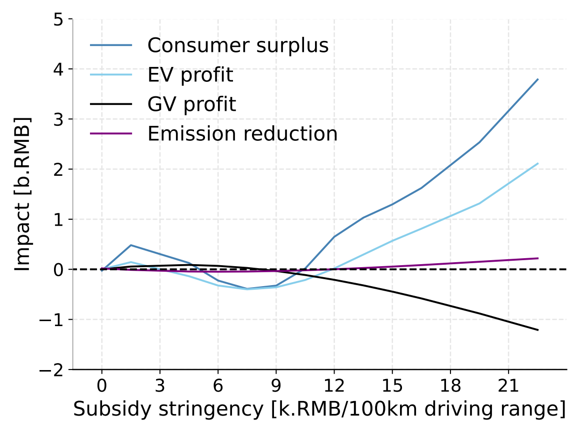
Notes: These figures report the welfare impact for different subsidy levels. The left panel depicts the policy-induced welfare gains (represented by the blue and the red curves) and the total subsidy expenditure (denoted by the black curve). Costs without the reputation channel exhibit a slight deviation from the costs in the full equilibrium, as represented by the black curve in Panel (b). Because this difference is small, we have elected to omit that particular curve from this figure. The right panel depicts changes in the welfare benefit components. The aggregate impact is reported in Figure 8.

Figure A.9: Alternative subsidy stringency



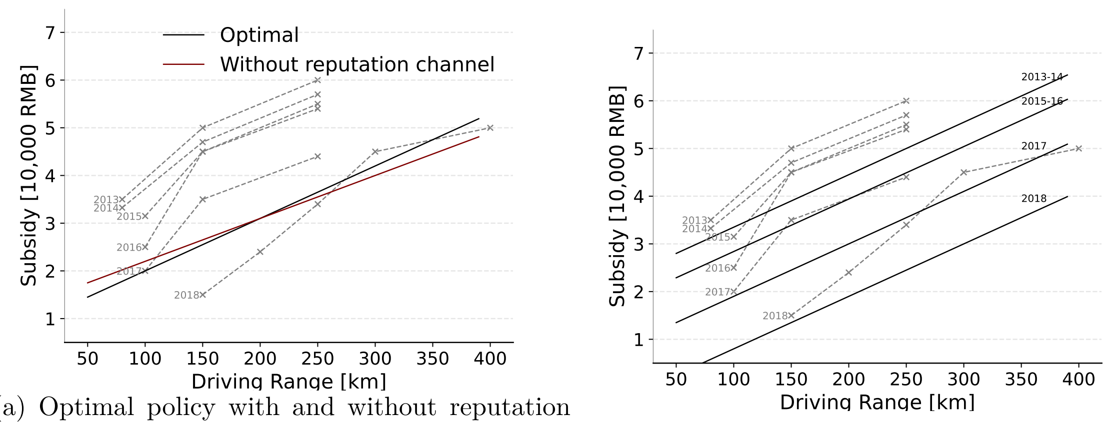
(a) Benefit and government expenditure

(b) Benefit components



Notes: These figures report the welfare impact for different subsidy stringencies. The left panel depicts the policy-induced welfare gains (represented by the blue and the red curves) and the total subsidy expenditure (denoted by the black curve). Costs without the reputation channel exhibit a slight deviation from the costs in the full equilibrium, as represented by the black curve in Panel (b). Because this difference is small, we have elected to omit that particular curve from this figure. The right panel depicts changes in the welfare benefit components. The aggregate impact is reported in Figure 9.

Figure A.10: Optimal policy vs. reality

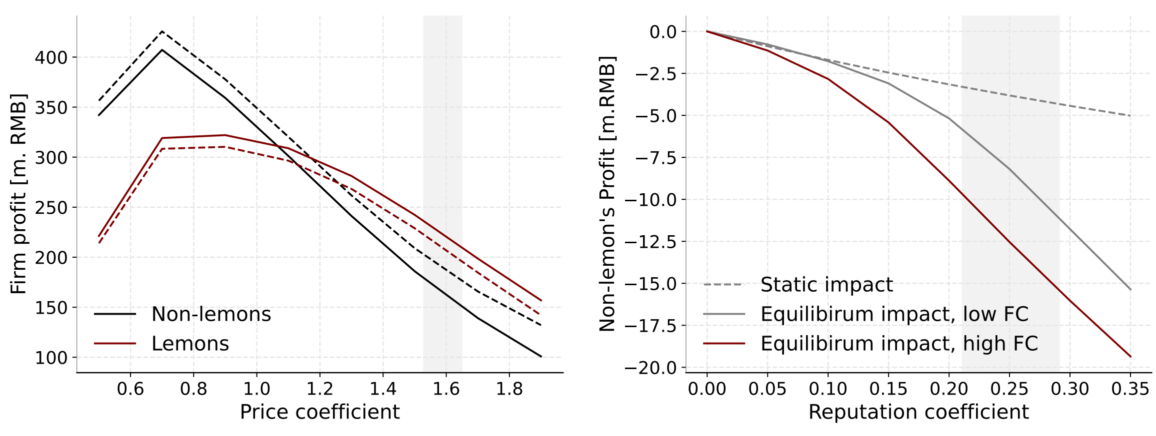


(a) Optimal policy with and without reputation channel

(b) Detailed optimal policy

Notes: The exact counterfactual subsidy has different levels across years, as in reality. We omit this in Figure A.10a to emphasize the stringency changes. Figure A.10b reports the optimal policy design year by year.

Figure A.11: Impact of subsidy on consumer choice and firm profit

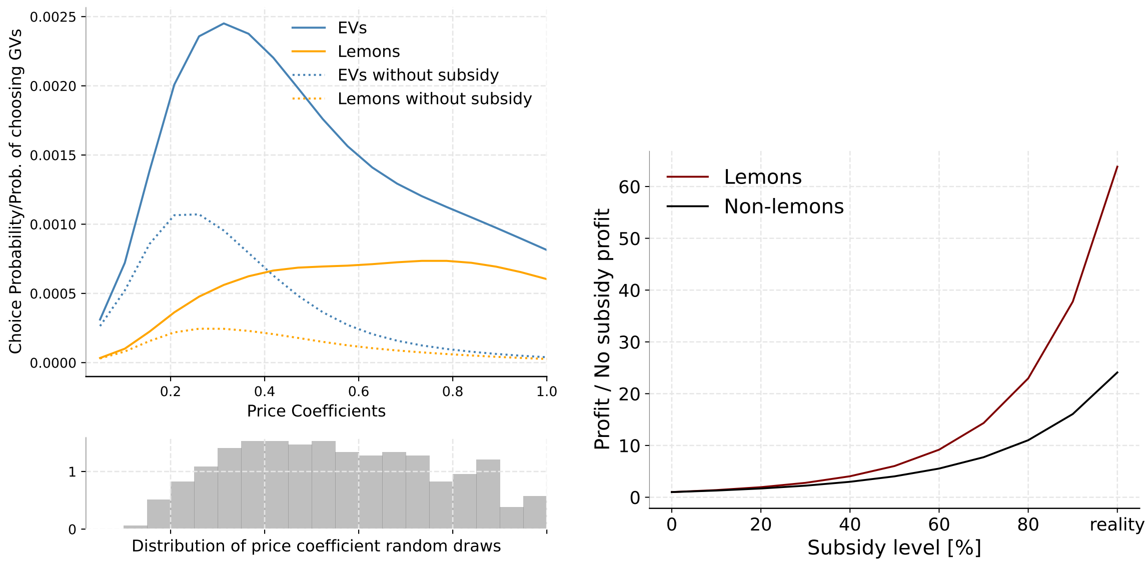


(a) Static profit changes and price coefficients

(b) Reputation spillover and entry amplification

Notes: These figures explain the impact of the consumer taste parameters—price sensitivity and reputation sensitivity—on firm profits. Figures A.11a and A.11b depict firm profit changes. The gray area represents the 95% confidence interval of the estimated price coefficients (collective reputation coefficients). Figure A.11a reports the average province-level profit for lemons (red) and nonlemons (black). Dashed lines represent profits in a full-information scenario, and solid lines represent the observed average profits. Figure A.11b reports firm profit changes as the reputation coefficient increases.

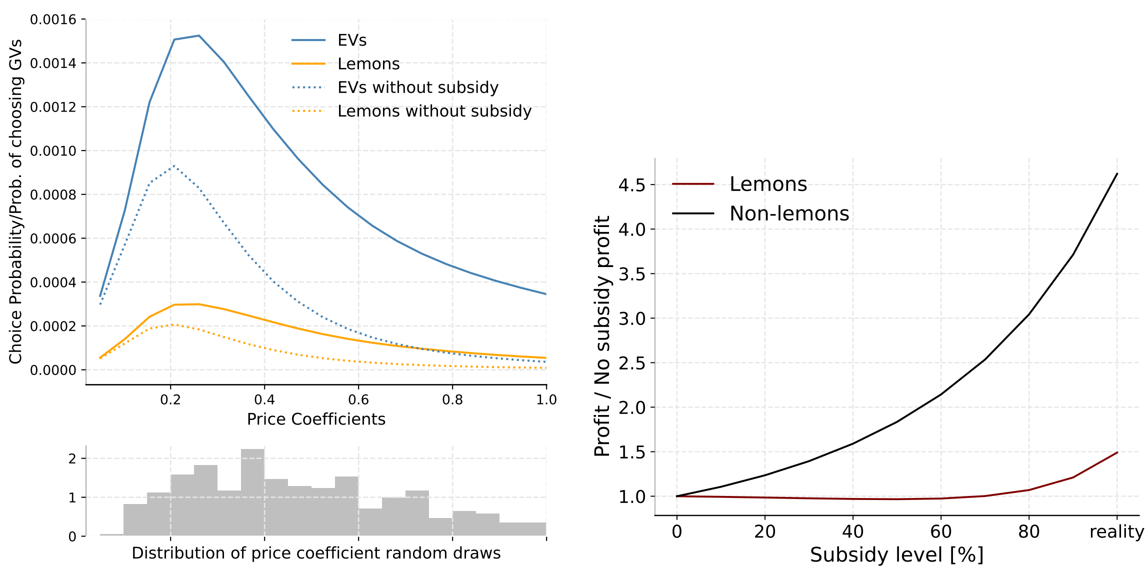
Figure A.12: Example of subsidy impact on lemons and nonlemons: Hubei province



(a) Consumer choice probability (b) Firm profits as subsidy increases

Notes: Hubei province has 8 observed nonlemon firms and 5 lemon firms. Consumer price sensitivity is higher in Hubei than in Jiangsu (Figure A.13) due to the differences in income.

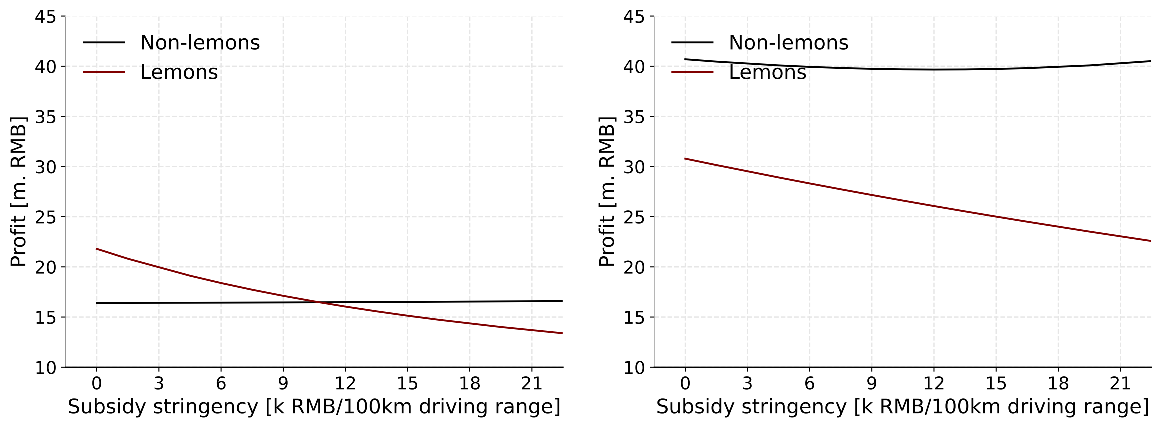
Figure A.13: Example of subsidy impact on lemons and nonlemons: Zhejiang province



(a) Consumer choice probability (b) Firm profits as subsidy increases

Notes: Zhejiang province has 13 observed nonlemon firms and 3 lemon firms. Consumer price sensitivity is lower in Jiangsu than in Hubei (Figure A.12) due to the differences in income.

Figure A.14: Impact of subsidy stringency on lemons and nonlemons' profits



(a) 2015 (b) 2017

Table A.1: Variable notation

Variable	Explanation
Sub- or superscript	
$c \in C$	C: set of cities
$m \in M$	M: set of provinces or markets.[68]
i	index for consumers
$j \in J$	firm j from the set of all firms J
$o \in O_{jt}$	O_{jt} set of models of firm j in period t
Variables	
$s_m = (str_m, \widetilde{q^e}_m)$	$(\{\mathbb{1}_{jm}\}_{j\in D}, n^h, n^l)$ market state variables including market structure and beliefs
$s_I = (str_I)$	$(\{\mathbb{1}(active)_j\}_{j\in D}, nact^h, nact^l)$ industry state variable
D_{ojct}	residual demand
s_{ojt}	$= s^l_{ojct} + s^c_{ojt}$ local subsidy + central subsidy
q^{ev}_{ojt}	vehicle unobserved quality
q^e_{ct}	includes 2 reputation variables $= [lemonshare_{c,t-1}, \mathbb{1}(fire)_{c,t-1}]$
$\widetilde{q^e}_{ct}$	scalar, market-specific EV collective reputation measure, the above vector · coefficients
Other common variables	vehicle price and characteristics p, x ...
Functions	
$\mathbb{E}\pi_{jmt}(s_m, s_I \mid \sigma_I)$	
$V^1_{jmt}(s_m, s_I \mid \sigma_m, \sigma_I)$	market-level value for firm j in market m and period t. $\mathcal{S}^m \times \mathcal{S}^I \longrightarrow \mathbb{R}$
$V^0_{jmt}(s_m, s_I \mid \sigma_m, \sigma_I)$	1 for incumbent and 0 for potential entrant
$V^{pa}_{jt}(s_I \mid \sigma_{mkt}, \sigma_I)$	industry value for nonactive firm j in period t. $\mathcal{S}^I \longrightarrow \mathbb{R}$
$v_{jt}(a = 1, s_I \mid \sigma_{mkt}, \sigma_I)$	choice-specific value for active firm j in period t if staying in the industry
σ_{jmt}	$\mathcal{S}^m \times \mathcal{S}^I \times \mathcal{E} \longrightarrow \{0, 1\}$.
	market-level entry strategy for firm j in market m and period t
$\{\sigma^{act}_{jt}, \sigma^{ext}_{jt}, \sigma^p_{jt}\}$	$\mathcal{S}^I \times \mathcal{E} \longrightarrow \{0, 1\} \times \{0, 1\} \times \mathbb{R}$
	industry-level entry strategy for firm j in period t
σ_j	all strategies for firm j
σ_m	all market-level strategies for market m (all period all firm)
σ_{mkt}	all market-level strategies (for all market-period-firm)
σ_I	all industry-level strategies for all firms j
$F(s'_m \mid s_m, s_I; \sigma_m, \sigma_I)$	market state transition probability given all firms' strategy for market m (σ_m)
	and industry strategy that determines potential entrants (σ_I)
$\widetilde{F}(s'_m \mid s_I; \sigma_m, \sigma_I)$	oblivious belief about market m's next-period state conditional on today's industry state
$G(s'_I \mid s_I; \sigma_I)$	industry state transition probability given all firms' industry-level strategy σ_I

Table A.2: Parameter notation

	Parameter	Explanation
Consumer Utility	β, θ, α, σ	consumer preference parameters, defined in Equation 3
	ξ, δ	idiosyncratic shock, FEs, and mean utility, defined in Equation 3
Firm Revenue	ω, η	defined in Equation B.14
Firm Entry Cost	γ, Γ, ρ	defined in Equations 7 and 8
	The above parameters usually have sub- or superscript	
Constant	β	discount factor when used without sub- or superscript
	γ	Euler constant when used without sub- or superscript
	ν	exit scrap value in Equation B.6
	λ	cost of public funds in counterfactual defined in Equation B.20

Table A.3: Relationship between lemon share and the IVs: Central subsidy × firm–market distance

	(1)	(2)	(3)	(4)
	lemonshare	*lemonshare*	*lemonshare*	*lemonshare*
Central S × distance^{-1}	0.584**	0.789***	0.763***	0.756***
	(0.266)	(0.255)	(0.257)	(0.267)
Inc 2020	0.207	0.000	0.000	0.000
	(1.517)	(.)	(.)	(.)
Bachelor 2020	-0.683**	0.000	0.000	0.000
	(0.311)	(.)	(.)	(.)
N	640.000	640.000	640.000	640.000
period FE	Yes	Yes	Yes	Yes
city FE		Yes	Yes	Yes
province–year FE	Yes	Yes	Yes	Yes
city–quarter FE				Yes
province–quarter FE			Yes	Yes

Table A.4: First stage of lemon share variable

	(1)	(2)
	$lemonshare_{t-1}$	$lemonshare_{t-1}$
$\text{centrals}_{t-1} \times \text{Inv. distance}_{jc}$	0.151***	0.110***
	(0.021)	(0.025)
nodriverstr	-2.952*	-0.294
	(1.591)	(1.488)
greenplate	1.683***	1.948***
	(0.649)	(0.645)
Subsidy	-0.000	0.259
	(0.388)	(0.392)
Motor power		2.449
		(1.478)
Driving range		1.647
		(2.285)
N	19,448	19,448
Joint-F on excluded IVs	97.131	215.064
Underidentification stat	298.967	328.575
Weak identification stat	44.430	73.456

Note: $lemonshare_{t-1}$ is rescaled to a 10% level. Standard errors are clustered at the city level. $*p < 0.10; **p < 0.05; ***p < 0.01$.

Table A.5: Impact of historical lemon share on EV sales

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
$lemonshare_{t-1}$	0.002	-0.052***	0.016	-0.057***
	(0.003)	(0.016)	(0.095)	(0.019)
No drive rstr.	0.273**	0.276*	0.224**	0.263**
	(0.171)	(0.172)	(0.113)	(0.132)
Green plate	0.169	0.189*	0.172*	0.164*
	(0.141)	(0.135)	(0.112)	(0.109)
Subsidy	-0.166***	-0.176***		
	(0.019)	(0.021)		
Price			-0.189***	-0.189***
			(0.022)	(0.021)
Motor power			0.525***	0.449***
			(0.210)	(0.204)
Driving range			0.021	0.037
			(032)	(0.40)
N	19,448	19,448	19,448	19,448
$adj.R^2$	0.261	-0.339	0.291	-0.160
Lemon IVs		Y		Y
Price IVs			Y	Y
Joint-F on excluded IVs		97.131		215.064
Underidentification stat		298.967		328.575
Weak identification stat		44.430		73.456
Model–period	Yes	Yes		
Firm–fuel type–period			Yes	Yes
City–fuel type, province–firm, province–year	Yes	Yes	Yes	Yes

Notes: This table supplements Table 5. $lemonshare_{t-1}$ is rescaled to a 10% level. Columns (1) and (2) report OLS and 2SLS results from Equation 2. Columns (3) and (4) relax the model–period FEs and includes firm–fuel type–period FEs instead. x_{ojt} are vehicle attributes, including motor power and driving range. p_{ojt} is the price for model o from firm j. The rest of the variables and fixed effects are the same. Standard errors are clustered at the city level. $*p < 0.10; **p < 0.05; ***p < 0.01$.

Table A.6: Robustness check: Impact of lemon share on EV sales

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
$lemonshare_{t-1}$	-0.039***	-0.058***	-0.052***	-0.031***	-0.047**	-0.057***
	(0.014)	(0.018)	(0.016)	(0.009)	(0.012)	(0.019)
No drive rstr.	0.188**	0.124**	0.276*	0.291***	0.147*	0.263**
	(0.094)	(0.061)	(0.172)	(0.107)	(0.097)	(0.132)
Green plate	0.173*	0.201**	0.189*	0.138*	0.154*	0.164*
	(0.115)	(0.100)	(0.135)	(0.092)	(0.097)	(0.109)
Subsidy	-0.164***	-0.171***	-0.176***			
	(0.016)	(0.015)	(0.021)			
Price				-0.193***	-0.190***	-0.189***
				(0.016)	(0.016)	(0.021)
Motor power				0.633***	0.424***	0.449***
				(0.140)	(0.142)	(0.146)
Driving range				0.038	0.018	0.037
				(0.041)	(0.041)	(0.040)
$adjR^2$	-0.235	-0.342	-0.339	-0.262	-0.181	-0.160
N	19,448	19,448	19,448	19,448	19,448	19,448
model–period	Yes	Yes	Yes			
firm–fuel type–period				Yes	Yes	Yes
city–fuel type	Yes	Yes	Yes	Yes	Yes	Yes
province–year		Yes	Yes		Yes	Yes
province–firm	Yes		Yes	Yes		Yes
Joint-F on excluded IVs	84.923	119.660	97.131	272.235	248.942	215.064
Underidentification stat	89.660	256.544	298.967	145.338	261.373	328.575
Weak identification stat	13.079	37.981	44.430	21.305	58.080	73.456

Note: $lemonshare_{t-1}$ is rescaled to a 10% level. Standard errors are clustered at the city level. $*p < 0.10; **p < 0.05; ***p < 0.01$.

Table A.7: Impact of reputation factors on potential buyers' probability of purchasing an EV

	(1)	(2)	(3)	(4)	(5)	(6)
Impact of friends' experiences						
Friends' experience	0.114***					
	(0.005)					
Battery issues		-0.036**				
		(0.017)				
Engine issues			-0.037*			
			(0.021)			
Other quality issues				-0.023		
				(0.016)		
Impact of lemons						
Friends' EV brand = lemon					-0.057**	
					(0.025)	
Heard of lemon brands					0.026***	
					(0.009)	
Impact of EV fires						
Local EV fire						-0.083***
						(0.017)
Aware of any EV fire						-0.064***
						(0.009)
R^2	0.250	0.030	0.028	0.029	0.152	0.068
N	738	676	672	637	248	752
Inc grp, age grp, city FEs	Y	Y	Y	Y	Y	Y

Note: $*p < 0.10; **p < 0.05; ***p < 0.01$

Table A.8: Correlation between lemons, prices, and observed attributes

	MSRP	Driving range
2012	-0.49	-0.07
2013	-0.52	-0.01
2014	-0.43	-0.29
2015	-0.51	-0.43
2016	-0.32	-0.38
2017	-0.22	-0.34
2018	-0.24	-0.30

Notes: The correlation between driving range and lemon status is lower in earlier years because there was little variation in driving range given technology limitations.

Table A.9: Subsidy impact: Vehicle sales and number of firms

	Simulated Reality	No subsidy baseline (i) Price response	(ii) Mkt.-level entry	(iii) Ind.-level entry
Sales in 1,000				
EVs	1,883.46	425.15	336.07	311.28
GVs	–	604.65	648.66	660.67
Post-subsidy EVs	201.70	203.75	159.85	151.36
Firms and markets				
a. Industry-level entry margin				
Lemon firms 2015	5.03	–	–	1.67
2018	7.20	–	–	5.49
Nonlemons 2015	9.50	–	–	4.73
2018	35.15	–	–	20.79
b. Market-level entry margin				
# prov. lemons 2015	5.80	–	1.20	0.40
lemons 2018	9.43	–	6.89	7.29
nonlemons 2015	3.50	–	1.50	1.57
nonlemons 2018	7.48	–	4.89	5.52
Markup and MC				
Markup [%]	-0.07	0.30	0.31	0.31
Markup [1,000 RMB]	4.30	77.49	83.26	85.64
MC [1,000 RMB]	137.73	148.62	152.05	155.26

Notes: This table reports average results from 50 simulations. The markup is defined by the difference between the consumer price and the vehicle marginal cost. The sign differences are due to the skewness of the RMB measure.

Table A.10: Decomposition: Vehicle sales and the number of firms

	Subsidy impact	Counterfactuals (i) No direct	(ii) No reputation	(iii) No upstream spil.
Sales in 1,000				
EVs	1,883.46	408.42	1,951.60	768.59
GVs	-660.67	-33.57	-637.11	-197.04
Post-subsidy EVs	201.70	192.75	213.34	105.29
Firms and markets				
a. Industry-level entry margin				
Lemon firms 2015	5.03	1.67	5.07	1.91
2018	7.20	5.49	6.92	5.02
Nonlemons 2015	9.50	6.70	9.73	6.50
2018	35.15	28.79	35.18	26.28
b. Market-level entry margin				
# prov. lemons 2015	7.80	2.27	5.17	3.40
lemons 2018	9.43	7.43	4.43	6.86
nonlemons 2015	3.50	1.71	3.79	2.15
nonlemons 2018	7.48	5.75	8.27	6.42

Notes: This table reports average results from 50 simulations. The first panel presents welfare metrics. The initial column reports the difference between the simulated reality and no-subsidy scenarios. The following three columns show the differences between the simulated reality and the results from deactivating one channel. Thus, the numbers represent the impact of each channel. The sum of the benefits through the three channels is larger than the aggregate impact because we report the partial impacts, and there are positive synergies, especially between the monetary impact and the upstream spillover. Subsequent panels report equilibrium outcomes of the simulated reality and when one channel is deactivated, without taking any differences.

Table A.11: Entry responses and reputation impact

	Reality	No-subsidy baseline (i) Price response	(ii) Mkt.-level entry	(iii) Ind.-level entry
Reputation Impact (billion RMB)				
One-period impact				
CS ex post loss*	-0.98	-0.45	-0.30	-0.13
CS misinfo distortion	-2.70	-2.46	-2.38	-2.29
Spillover	-1.93	-1.32	-1.06	-0.66
Equilibrium impact				
CS loss	-31.03	–	-29.08	-27.67
Spillover	-2.58	–	-0.86	-0.41
Spillover [%]	-7.32	–	-5.54	-4.74
Environmental benefit	-1.32	-2.81	-2.87	-2.92

Notes: This table explains how entry amplifies the reputation channel. The differences between column one and the following columns exhibit the impact of entry on reputation losses.

Table A.12: Impact decomposition: The three channels

	Subsidy impact	Counterfactuals (i) No direct	(ii) No reputation	(iii) No upstream spil.
Variables Reflect Direct Impact				
Markup [%]	-0.07	**0.31**	-0.08	0.04
Markup [1,000 RMB]	3.74	**80.49**	3.26	18.05
Variable Reflects Upstream spillover impact				
MC [1,000 RMB] (static)	136.97	136.97	136.96	**170.25**
MC [1,000 RMB] (eqm)	136.97	141.09	136.05	**173.79**
Reputation Impact (billion RMB)				
One-period impact				
CS ex post loss	**-0.85**	-0.17	–	-0.45
misinfo distortion	**-0.42**	-0.21	–	-0.25
Spillover	**-1.27**	-0.66	–	-1.93
Equilibrium impact				
CS loss	**-3.36**	-1.21	–	-1.26
Spillover	**-2.17**	-0.35	–	-0.78
Spillover [%]	**-7.32**	-3.19	–	-4.47
Emission benefit	**-0.23**	-1.76	–	-2.98

Notes: This table explains the impact of each channel. The differences between column one and the highlighted numbers are the first-order impacts of each channel, and the gray parts are synergies between the channels.

Table A.13: Determinants of subsidy impact

(a) Subsidy Impact Scenarios

		Price coef. α L	H
θ	L	optimistic	low efficiency
	H	reput. spillover	adverse case

(b) Impact of of a higher entry cost

		Price coef. α L	H
θ	L	–	higher direct benefit
	H	amplify reput. spl.	a worse adverse case

Note: The table lists the subsidy impacts in different market environments.

B Model Solution Method and Estimation Details

B.1 More equations and choice probabilities

Section 4.2 reports the main equations. This section lists all detailed equations. Firm profits and pricing follow the standard approach in the literature. The demand of each model is:

$$d_{ojct}(p_o, p_{-o\in O_{jt}}, p^*_{-j}) = mktsize_{ct} \cdot \int_i \frac{exp(u_{i,oj,ct})])}{\sum_{o'\in O_{ct}} exp(u_{i,o',ct})} di. \tag{B.1}$$

A firm's optimal price is

$$p_{ojt} = mc_{ojt} + \Delta_t^{-1} \cdot \sum_c d_{ojct}, \tag{B.2}$$

where the (oj, o') element of Δ is given by

$$\Delta_{oj,o'} = \begin{cases} \dfrac{\partial d_{ojt}}{\partial p_{ojt}} & \text{if } o' = o, \\ \dfrac{\partial d_{o'jt}}{\partial p_{ojt}} & \text{if } o' \in O_{jt}, \\ 0 & \text{otherwise.} \end{cases} \tag{B.3}$$

In the finite-period dynamic model, we assume that the last period repeats forever. The last period's value of firm j in market m is a function of market m's current oblivious market structure s_m and firm j's belief about equilibrium prices conditional on current industry structure s_I and all firms' industry-level pricing strategy σ^{ind}.

$$V^1_{jmT}(s_m, s_I|\sigma^{ind}) = \frac{1}{1-\beta} E\pi_{jmt}(s_m, s_I|\sigma^{ind}), \tag{B.4}$$

$$V^0_{jmT,s_I}(s_m, s_I) = 0. \tag{B.5}$$

The optimization problem for an active firm j is

$$\max \begin{cases} \beta \sum_m \iint_S \Big[& V^1_{jmt'}(s'_m, s'_I|\sigma_m, \sigma_I) P^{\mathbb{1}jm}_{t'}(s_m, s_I|\sigma_{jm}) + \\ & V^0_{jmt'}(s'_m, s'_I|\sigma^m, \sigma_I) \left(1 - P^{\mathbb{1}jm}_{t'}(s_m, s_I|\sigma_{jm})\right) \Big] d\widetilde{F}(s'_m|s_I; \sigma_m, \sigma_I) dG(s'_I|s_I) + \epsilon^{ext}_{jt}(1) \\ \\ \beta \nu^{scrap} + & \epsilon^{ext}_{jt}(0) \end{cases}, \tag{B.6}$$

where $P_{t'}^{\mathbb{1}jm}(s_m, s_I|\sigma_{jmt})$ is the probability of firm j being incumbent in market m in the next period, given its optimal strategy in market m, σ_{jm}. $\widetilde{F}(s'_m|s_I;\sigma_m,\sigma_I)$ is the oblivious belief on next period t' market states s'_m conditional on today's industry state s_I. It is oblivious because it is not conditional on today's market-specific state s_m.

Firms' action probabilities in equilibrium are as follows. Denote the value of staying active $v_{jt}(a = 1, s_I;\sigma_{mkt},\sigma_I)$ (the first line of Equation 12 except for β and $\epsilon_{jt}^{act}(1)$) and the value of staying inactive $v_{jt}(a = 0, s_I;\sigma_{mkt},\sigma_I)$ (the second line of equation 12 except for $\epsilon_{jt}^{act}(0)$). The conditional choice probability of firm j entering the industry is given by Equation B.7. Denote the value of entering a market $v_{jmt}(ent = 1, s_I, s_{mt};\sigma_{mkt},\sigma_I)$ (the first line of Equation 11 except for the β, $\varepsilon_{jmt}(1)$, and the fixed costs), and the value of potential entrants $v_{jmt}(ent = 0, s_I, s_{mt};\sigma_{mkt},\sigma_I)$ (the second line of Equation 11). The conditional choice probability of firm j entering market m is given by Equation B.8.

$$P_t^j(act|s_I;\sigma_{mkt},\sigma_I) = \frac{exp(\frac{-\overline{FC}_j + \beta v_{jt}(a=1,s_I;\sigma_{mkt},\sigma_I)}{\rho})}{exp(\frac{-\overline{FC}_j + \beta v_{jt}(a=1,s_I;\sigma_{mkt},\sigma_I)}{\rho}) + exp(\frac{\beta v_{jt}(a=0,s_I;\sigma_{mkt},\sigma_I)}{\rho})} \tag{B.7}$$

$$P_t^{jm}(ent|s_I,s_m;\sigma_{mkt},\sigma_I) = \frac{exp(\frac{-\overline{FC}_j + \beta v_{jt}(ent=1,s_I;\sigma_{mkt},\sigma_I)}{\rho})}{exp(\frac{-\overline{FC}_j + \beta v_{jt}(ent=1,s_I;\sigma_{mkt},\sigma_I)}{\rho}) + exp(\frac{\beta v_{jmt}(ent=0,s_I,s_{mt};\sigma_{mkt},\sigma_I)}{\rho})}. \tag{B.8}$$

Denote the continuation value of staying active $v_{jt}(a = 1, s_I;\sigma_{mkt},\sigma_I)$ (the first line of Equation B.6 except for β and $\epsilon_{jt}^{ext}(1)$). The conditional choice probability of exiting the industry is

$$P_t^j(ext|s_I;\sigma_{mkt},\sigma_I) = \frac{exp(\frac{\beta v_{jt}(a=1,s_I;\sigma_{mkt},\sigma_I)}{\rho})}{exp(\frac{\beta v_{jt}(a=1,s_I;\sigma_{mkt},\sigma_I)}{\rho}) + exp(\frac{\beta\nu^{scrap}}{\rho})}. \tag{B.9}$$

The maximized pseudo-likelihood procedure iterates over steps 3–8 for each guess of parameters. The pseudo-likelihood function for market-level entry and industry-level actions are:

$$ll(\gamma 0,\gamma_1,\gamma_2,\gamma_3,\Gamma) = \sum_j\sum_m\sum_t logP_{mt}^j(ent|s_{mt},s_{It};\gamma 0,\gamma_1,\gamma_2,\gamma_3)\cdot(1-\mathbb{1}_{jmt}), \tag{B.10}$$

$$ll(\Gamma_0,\Gamma_1,\Gamma_2,\gamma) = \sum_j\sum_t logP_t^j(act|s_{It};\Gamma,\widehat{\gamma})\cdot(1-\mathbb{1}_{jt}^a) + logP_t^j(ext|s_{It};\Gamma,\widehat{\gamma})\cdot\mathbb{1}_{jt}^{ext}. \tag{B.11}$$

Note that there is no market-level exit choice, so Equation B.10 includes only the likelihood of entering the market when a firm has not entered, $\mathbb{1}_{jmt} = 0$.

B.2 Solution method

We propose a nested-loop method to solve the equilibrium iteratively. Figure 6 in Section 4.2 explains the idea. In this section, we formalize the solution method step by step. It is initialized with oblivious strategy $\widetilde{\sigma}_I$ and $\widetilde{\sigma}_m, \forall m \in M$ (line 1-3). Then, it computes the industry state transition conditional on industry activation and exit strategy $(\sigma^{act}, \sigma^{ext})$ (line 5). This gives the distribution of the number of potential entrants to each market in each period. The next step calculates expected profits for each market mt conditional on industry-level pricing strategy σ^p, for every possible market state s_m (line 6). Lines 5 and 6 provide beliefs on profits and the number of potential entrants for each market, and then the algorithm goes to the inner loop (lines 7–13).

Algorithm 1 Nested-loop method

1: $\sigma_I \leftarrow \tilde{\sigma}_I$
2: $\sigma_m \leftarrow \tilde{\sigma}_m$, for all m
3: $\Delta^I \leftarrow 100$, $\Delta^m \leftarrow 100$,
4: **repeat**
5: compute $G(s_I'|s_I; \sigma^{act}, \sigma^{ext}), \forall t = 0, 1, ..., T-1$
6: compute $E\pi_{jmt}(s_m, s_I; \sigma^p)$ for all m, t, j, s_m, s_I
7: **for** $m = 1, 2..., M$ **do**
8: solve entry dynamics for market m by backward induction
9: **for** $t = T-1, T-2, ...1, 0$ **do**
10: get $\sigma^*_{jmt}, \forall j \in D$ by solving FXP of entry game with $|D| + 2$ players [69]
11: choose σ^*_{jmt} to maximize $V^0_{jmt}(s_m, s^I_t | \sigma_{jmt}, \sigma^D, \sigma_I)$ as in equation 11, $\forall j \in J \setminus D$
12: **end for**
13: **end for**
14: choose $\sigma^{ext*}_{jt}, \sigma^{act*}_{jt}$ to maximize equation B.6 and 12 , $\forall j \in J$, for $t = [T-1, T-2, ..., 1, 0]$
15: choose σ^{p*}_{jt} to maximize equation B.12, $\forall j \in J, t \in [0, 1, ..., T-1]$
16: $\Delta^I = ||ccp(\sigma_I) - ccp(\sigma^*_I)||_{p*}$, $\Delta^m = ||ccp(\sigma_m) - ccp(\sigma^*_m)||_{p*}$
17: $\sigma_I \leftarrow \sigma^*_I$
18: $\sigma_m \leftarrow \sigma^*_m$, for all m
19: **until** $\Delta^I < \varepsilon$, $\Delta^m < \varepsilon, \forall m$

As explained above, conditional on industry strategy and industry state, markets are independent. Thus, we solve each market's dynamics independently by backward induction. For each market m

[69] The $|D| + 2$ players are all dominant firms, n^h representative high-quality fringe firms and n^l representative low-quality fringe firms. We assume dominant firms ignore fringe firms' heterogeneity when considering off-equilibrium path responses. Thus, this is a game with $|D| + 2$ instead of $|D| + n^h + n^l$ players.

period t, we solve the dominant firm's strategy using fixed point (FXP) as in classic 1-period entry games (line 10). [70] [71] We then solve fringe firms' entry strategies using σ^*_{jmt} considering their location, cost, and profit heterogeneity (line 11). The algorithm allows firms to have different strategies, so the strategy has a subscript j. From lines 7 to 13, the inner loop gives optimal market-level strategies $\sigma_m = \{\sigma_{jmt}\}_{j\in J, t=0,1,2,\ldots,T-1}$, for all m, conditional on all firms' playing industry strategy σ_I and the associated transition G and expected revenue $E\pi$.

The algorithm then goes back to the outer loop and calculates the optimal activation and exit strategy (line 14). Since market-level strategies σ^*_m from the inner loop define the value for each market (V^1_{jmt}, V^0_{jmt}), we now can add all markets' values to evaluate exit or activation decisions, as explained in Equations B.6 and 12. Both optimization problems are solved by backward induction from the last period $T-1$. The industry-level pricing strategy is solved by maximizing expected profits conditional on $(\sigma^*_m, \sigma^{ext*}, \sigma^{act*})$ (line 15). We assume that firms form expectations on where each firm is based on their strategies $(\sigma^*_m, \sigma^{ext*}, \sigma^{act*})$ and maximize profit given this expected market structure, as explained in Equation B.12. Lines 14, 15 and 5, 6 are the outer loop of the algorithm that iterates industry strategies, conditional on the market-level strategies σ_m given by the inner loop.

Finally, the algorithm computes differences in conditional choice probabilities between updated strategies (σ^*_m, σ^*_I) and last-iteration strategies (σ_m, σ_I) (line 16). $||\cdot||_{p*}$ is a probability-weighted norm that adds up the CCP differences in each state with weights equal to the probability of the state happening. The probability is defined by updated firm strategies (σ^*_m, σ^*_I). If the differences are larger than model tolerance ε_1 and ε_2, the algorithm updates strategies (line 17–18) and goes on to the next iteration.

B.3 Approximation method

Approximate per-period profit Line 15 in Algorithm 1 lets the firm choose prices. The firm's profits are firm–year-specific functions of the full station variable, as is its pricing strategy. In the dynamic game, we assume that firms maximize price based on oblivious state variables $\{s_m, s_I\}$. Note that this approximation does not affect firm marginal cost estimation, in which we assume that firms set prices with perfect information on the exact market structure. This simplification applies only to the entry cost estimation.

We first reduce the per-period profit from a function of full state variables to partially oblivious

[70] The FXP includes all dominant firms, n^h representative high-quality fringe firm and n^l representative low-quality fringe firms. Fringe firms' location, cost, and profit heterogeneities cannot be considered because the state variables do not track where each fringe firm is. In addition, we have assumed that firms do not track fringe rivals' identities. These heterogeneities are considered in line 12 of the algorithm because the model keeps track of all firms' identities and exploits these variations.

[71] The solution method needs to include representative fringe firms in the fixed point to capture the differences in fringe firms' strategies and the associated state transition probability when a dominant firm deviates. Thus, the algorithm can better approximate the difference between on-path and off-path strategies.

state variables (s_m, s_I). Firm j choose prices $\{p_{oj}\}_{o\in O_{jt}}$ to maximize its expected profit conditional of the oblivious state variables:

$$\max_{\sigma_j^p} \sum_m \sum_{s_m} \sum_{str^f} \underbrace{\sum_{c\in C_m} \pi_{ct}(\sigma_j^p, \sigma_{-j,t}^p, str_{ct}^f, \widetilde{q}_{ct}^e)}_{\text{profit of province } m \text{ given full state } str_{ct}^f} \quad \widehat{F}(str_{ct}^f | s_{mt}) \widetilde{F}(s_{mt}|s_{It}; \sigma_m, \sigma_I). \tag{B.12}$$

Firms set national prices, so Equation B.12 sums over markets m. For each market (province) m, if the firm tracked full state variables with fringe rivals' identities, then it is able to know the exact profit of this province defined in Equation 5, which is the middle part in Equation B.12. Because firms track only the oblivious state variable, they form expectations on the exact market structure str_{ct}^f conditional on oblivious state variation s_{mt} and obtain $\widehat{F}(str_{ct}^f|s_{mt})$. Furthermore, as national strategies depend only on industry state variables, we further integrate over $\widetilde{F}(s_m|s_I;\sigma_m,\sigma_I)$, which is firms' oblivious beliefs on market m's state based on equilibrium strategies (σ_m, σ_I) and current industry structure s_I, and $\widehat{F}(str_{ct}^f|s_{mt})$ is the simulated distribution of full market structure str^f with fringe identities conditional on the oblivious state variable s_m. Note that firms do not use strategies of other markets $\sigma_{m'}$ or the state of other markets $s_{m'}$ while forming this expectation, thanks to the small market assumption.

Given the optimal pricing strategy, define the expected profit for firm j in market m period t as:

$$E\pi_{jmt}(s_m, s_I|\sigma^{ind}) = E\Big[\sum_{c\in C_m} \pi_{ct}(\sigma^{p*}, str_{ct}, \widetilde{q}_{ct}^e)\Big| s_m, s_I; \sigma^{ind}\Big] \tag{B.13}$$

$$= \underbrace{\omega_0 \cdot \mathbb{1}(s_I)}_{\text{national impact}} - \underbrace{\omega_1 \cdot \mathbb{1}(str_{mt}^D) - \omega_2 \cdot log(n_{mt}^h + n_{mt}^l + 1)}_{\text{competition}} - \underbrace{\eta \cdot \widetilde{q^e}_{mt}}_{\text{reputation}}, \tag{B.14}$$

$$\widetilde{q^e}_{mt} = \hat{\theta}_1 lemonshare_{m,t-1} + \hat{\theta}_2 \mathbb{1}(fire)_{m,t-1}. \tag{B.15}$$

All parameters in Equation (B.14) are firm–market–period specific. Super/subscripts (j, m, t) are dropped to simplify notation.

The first term represents the impact of national industry state s_I on the profit in market m through the firm pricing strategy. As explained above, prices are at the national level, so other markets' structures can affect market m's profit, and the small market assumption reduces this interdependence to operate only through industry structure s_I. The second term represents competition within market (m, t), where ω_0 is a vector and each element represents the mean impact of the market-dominant firms' state on firm j's payoff. ω_1 is a scalar that captures the impact of one more fringe firm on firm j's profit; note that the impact is firm–market–period specific. The third term represents the impact of reputation, and $\widetilde{q^e}_{mt}$ is a reputation measure at the province–quarter level. Equation B.15 is almost the same as Equation 4 but defined at the province level. To obtain the parameters in Equation B.14, we simulate all possible market structures with different combinations of fringe firms and then regress the profits onto oblivious state variables s_{mt}.

A firm j's per-period payoff from market t equals $E\pi^j_{mt}(s_m, s_I) + \varepsilon^{\pi}_{jmt}$, the expected profits conditional on state variables and an error term. $\varepsilon^{\pi}_{jmt} = \pi(\{s_{ct}\}_{c\in C}) - E\pi(s_m, s_I)$. We assume this is mean 0 and i.i.d. across firm–market and over time. Note that firms observe the realization of the error term after making time t's decisions, so $\varepsilon^{j,\pi}_{mt}$ does not affect firms' strategies. Therefore, we do not need to impose any distributional assumption on it.

To determine the profits from entering earlier than firms actually did, I introduce a fictitious set of models for periods preceding the firm's actual activation. This set is created through an extrapolation based on the distribution of model characteristics at time t and the firm j's characteristic position in the observed periods. The foundational assumption here is that the optimal choice of model characteristics by firms remains consistent.

Approximate state variable evolutions State variables include the market structure and market collective reputation. Market structure transition comes from firms' beliefs on rivals' strategies. Market-level EV collective reputation is a weighted summation of historical lemon sales and historical fires. These should be functions of the full state variables because accurate sales are affected by every firm's identity. We reduce this to functions of partially oblivious state variables using regressions. Consumer perceptions are also functions of the state variables.

B.4 Estimation method

We estimate the dynamic entry model separately. Estimation of the dynamic model involves steps similar to the solution method with fewer iterations. In the spirit of Bajari et al. (2007), we utilize the data as much as possible to approximate the outer loop strategies, which avoids the costly outer loop calculation. We set the initial guess of industry structure transition probability G equal to the observed number of active firms in each period and the initial guess of firms' pricing strategies equal to observed prices. We then solve the inner loop and update the outer loop strategies once to correct for the poorly estimated exit and activation CCP and pricing strategies due to lack of data. This idea comes from Aguirregabiria and Mira (2002).[72]

The following line numbers refer to Algorithm 1. The detailed estimation steps are:

1. Calculate $G_t(s'_I|s_I)$, for $t = 0, 1, ..., T$ using the activation and exit CCP from the data (line 4).

2. Compute $E\pi_{jmt}(s_m|p)$ with observed prices p (line 5):

[72] The algorithm usually converges within five iterations of the outer loop. The inner loop's beliefs on transitions G and profits $E\pi$, which are associated with outer loop strategies, update very little after two iterations, although the outer loop strategies can update.

- The following lines explain how to approximate the per-period profits function $E\pi_{jmt}(s_m|p)$ and reduce it from a function of the full state variables to oblivious state variables.

1. Simulate all possible market structures with different combinations of firms.
2. Calculate market-level (province-level) profits $\pi_{jmt} = \sum_{c \in m} \pi_{ict}$ for each of the simulated market structures, assuming prices equal to the observed prices.
3. Approximate π_{jmt} with oblivious market state variables $s_{mt} = (\mathbb{1}_{jmt}, \forall j \in D, n^h, n^l)$ following Appendix B.
4. Obtain expected profits $E\pi_{jmt}(s_m|p)$ as a function of oblivious state variables s_m.

3. Guess the dynamic parameters (γ, Γ, ρ).

4. Solve the inner loop, as explained in lines 7–13, and obtain market-level entry strategy σ_{jmt}.

5. Go over the outer loop once to improve firms' beliefs on industry strategies.

   - Update industry strategies σ_I as explained in lines 14–15.
   - Update industry state transition probability G (line 4) and repeat step 2 with updated prices to calculate $E\pi_{jmt}(s_m|\sigma^p)$ (line 5).

6. Solve the inner loop again as explained in lines 7–13, and obtain market-level entry strategies σ_{jmt} and conditional choice probabilities.

7. Solve the outer loop activation and exit strategies $(\sigma^{act}, \sigma^{ext})$ and obtain conditional choice probabilities.

8. Evaluate the parameters using a pseudo-likelihood estimator with the above 2 sets of choice probabilities.

B.5 Welfare simulation method

The total welfare includes consumer welfare (defined in Equation 14), emission externality, firm profit, firm investment spending, and government subsidy spending from 2012 to 2022.[73] In each market denoted as m, these welfare components (except from consumer welfare) are listed in Equation B.16-

[73] We note that, while the subsidy program officially commenced in 2009, our analysis takes into account only subsidy spending and welfare gains beginning in 2012 due to data limitations. As detailed in Section 2, both subsidy spending and industry growth were negligible before 2012.

B.19 and are functions of the market state $\overline{s}_m$.

$$EE_{mt} = \sum_{oj \in O_{mt}} \sum_{c \in C_m} \int_i Pr_{i,oj,ct} \cdot emission_{oj} di, \tag{B.16}$$

$$FP_{mt} = \sum_{oj \in O_{mt}} \sum_{c \in C_m} \int_i Pr_{i,oj,ct} \cdot (p_{ojt} - mc_{ojt}) di, \tag{B.17}$$

$$FI_m = \mathbb{1}_{jm} \cdot FC_{jm}, \tag{B.18}$$

$$SS_{mt} = - \sum_{oj \in O_{mt}} \sum_{c \in C_m} \int_i Pr_{i,oj,ct} \cdot s_{ojct} di. \tag{B.19}$$

Note that the full market structure $\overline{s}_m$ differs from the oblivious market structure s_m defined in Section 4.2. The latter includes only the incumbent status of dominant firms and the number of fringe firms, while $\overline{s}_m$ encompasses the incumbent status of all firms. The final welfare, as defined in Equation B.20, is computed as the expected welfare within the counterfactual equilibrium. For each counterfactual, we draw 50 simulations from firms' equilibrium strategy (σ_m^*, σ_I^*) and obtain the simulated probability distribution of $\overline{s}_m$ for each period t, denoted as $\widehat{F}_{m,t}(\overline{s}_m | \sigma_m^*, \sigma_I^*)$. We include subsidy spending with a parameter $\lambda = 1$ to represent the cost of public funds:

$$W = \sum_{t=2012} \beta^t \sum_m \int_{\overline{s}_m} CW_{mt}(\overline{s}_m) - EE_{mt}(\overline{s}_m) + FP_{mt}(\overline{s}_m) - FI_{mt}(\overline{s}_m) - \lambda SS_{mt}(\overline{s}_m) d\widehat{F}_{mt}(\overline{s}_m | \sigma_m^*, \sigma_I^*). \tag{B.20}$$

B.6 Model fit

At the industry level, the model simulation fits the data well. The model can match a set of national-level and market-level moments well. The 2017 number of firms is 31 in the observed data and 33 in the simulated reality, and in 2018, the two numbers are 55 and 47, respectively. Our model can capture most firms' actions at the market level. The observed number of firm–markets in 2017 is 281, and our simulated reality reports an average of 241. The two numbers are 504 and 415 in 2018. Although we cannot capture all the fringe firms' actions, the sales data fit well. The data have 1,605 thousand EV sales from 2015 to 2018, and the simulated reality predicts 1,569 thousand, accounting for 97% of observed EV sales. Ignoring those fringe firms' market-level entry should not affect the estimated welfare results substantially.

C Discussion on Assumptions and Sensitivity

C.1 Discussion on lemons

We define 9 lemon firms in Section 2.3. This section discusses this definition, related assumptions, and simplifications.

We assume that consumers have imperfect information about lemons. We first argue that the accessibility of reviews and quality data was limited for consumers at the time of purchase, given that most of these data are from post-2018. The Car Quality Network platform was established in 2015 and gained popularity over time. Data from after 2018 represent 74% of the total records, with consumers filing, on average, 1.36 years post-purchase. Thus, the 2019 and 2020 records cover a large number of models before 2018. There were only 4,235 EV reviews before 2019, whereas 2019 to 2021 have 30,872 EV reviews, or 87.94% of our total dataset. Furthermore, the EV reviews are limited relative to the GV reviews, covering only 35 out of the 57 EV firms in our sales and notably lacking information on smaller firms. Table C.14 reports the number of reviews by year. Second, the signals that consumers can observe are imperfect. Even though a relationship exists between observed and unobserved quality, among cars in the lower price range, nearly 43% are lemons, while the remainder are nonlemons. Last, the influx of over 50 new firms into the industry adds to the confusion, especially when only 16 of these are recognizable GV brands. Notably, among the lemon firms originating from the GV sector, their EV market shares are higher than those in the GV market. This rapid entry of firms limits consumers' ability to discern the quality of each individual firm.

Table C.14: Number of reviews by year

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
GV	22,186	70,825	101,978	129,205	152,421	128,592	102,115	109,207	39,922	11,833
EV	0	0	217	483	905	488	2,142	4,994	7,902	17,778

A fundamental simplification in our analysis is treating vehicle quality as exogenous, focusing primarily on modeling the entry–exit margin.

First, this means that firms draw their qualities and then decide whether to enter the EV industry. They do not choose among various technologies with different qualities to invest in. While this might be relevant for larger firms, we argue that the majority of smaller firms typically encounter an opportunity, with their primary decision being about market entry rather than technological selection.

Second, we assume that firms do not improve their inherent quality over time, implying that lemon firms cannot evolve into high-quality firms. If lemon firms enter the market, they consistently produce low-quality cars. Several pieces of evidence support this assumption. Data indicate that the review score ranking for each firm remains stable over time.[74] While observed attributes such as driving range have increased, actual assembly and production quality are difficult to enhance. Improvements in these areas require redesigning and upgrading the entire production line, which is almost equivalent to paying the initial entry cost once more.

C.2 Upstream spillover assumptions and sensitivity tests

We calibrate the results with a log-log regression, following Nykvist and Nilsson (2015) and Ziegler and Trancik (2021). Table C.15 reports baseline battery costs without EV sales. The estimated annual battery cost reduction rate is approximately 20%, as shown in the first column. In the main specification, we assume that the baseline battery costs are as in the 5th column.

Table C.15: Estimated and baseline battery cost reduction rate

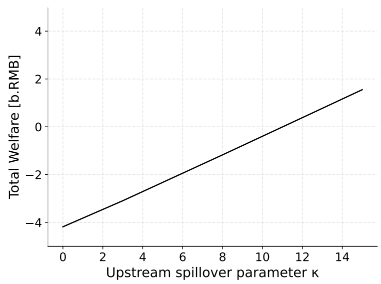
		Reality [$k.RMB/kWh$]		Baseline [$k.RMB/kWh$]		
Year	EV Sales$_{t-1}$ (1,000)	Estimated	Industry report	**Main**	Conservative	Aggressive
2015	47.96	4.15	3.73	6.34	5.17	7.22
2016	161.54	3.24	2.88	5.77	4.39	6.86
2017	267.43	2.64	2.14	5.25	3.73	6.51
2018	448.52	2.15	1.76	4.78	3.17	6.19

We examine sensitivity by varying the impact of EV sales on battery cost, denoted as κ_1. The most conservative assumption is that there is no upstream spillover benefit. This means that κ_1 equals 0 and battery costs decline at the same rate as they do without the subsidy, by approximately 20% annually. Conversely, the most aggressive assumption that we test is $\kappa_1 = 1.5$, implying that the battery cost is reduced by 1.5% for every 10% increase in EV sales. This upper-bound rate for the subsidy's impact through the upstream spillover channel implies a baseline rate that is slower than the pre-2012 trend.

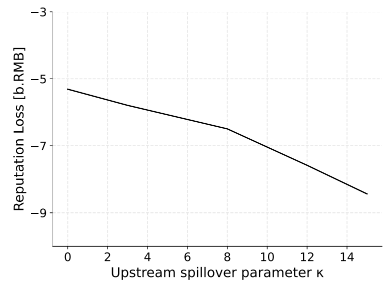
Figure C.15a represents the subsidy's welfare impact when the upstream spillover parameter varies. Figure C.15b and Figure C.15c depict the reputation losses when the upstream spillover parameter varies. A larger upstream spillover parameter increases the subsidy's impact, ranging from -4 to 2 billion RMB. Even with the most aggressive assumption, the subsidy benefit only marginally exceeds government spending. A faster cost decrease also slightly increases reputation loss, but it remains around 10%, as seen in Figure C.15c.

[74] The review score ranking of only one firm, BYD, improved over time. We argue that learning by doing can occur in this industry but is rare. Hence, we decided not to include this in the model.

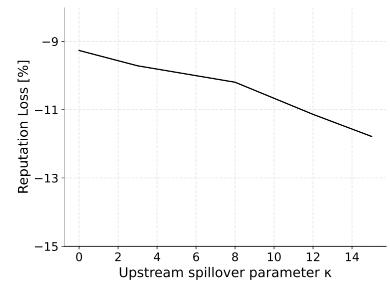
Figure C.15: Sensitivity of welfare results to upstream spillover parameter



(a) Impact on total welfare [b.RMB]



(b) Impact on reputation channel [b.RMB]

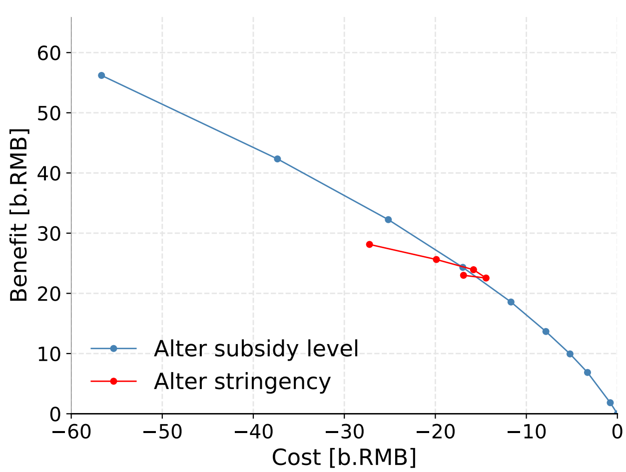


(c) Impact on reputation channel [%]

C.3 More counterfactual policies

Pareto frontier and alternative cost of public funds Figure C.16 plots the welfare outcome of all counterfactual policies that we discussed in the optimal subsidy design. The blue dots represent alternative levels, and the red dots represent alternative stringencies. The blue line makes the Pareto frontier of altering subsidy levels, and the red line shows that improving stringency is Pareto improving, as indicated by the red dots being positioned towards the top right of the blue curve. All the above discussions about efficiency and optimal choice are based on the welfare definition from Equation B.20 and assume the cost of public funds $\lambda = 1$. The optimal subsidy level can differ if the cost of public funds is smaller than one. The observed policy can be rationalized by $\lambda = 0.75$. While we do not solve the optimal level and stringency simultaneously, this figure illustrates the magnitude of the subsidy impact across these two dimensions. Given the relatively modest effect of stringency, we suggest that the 2-dimensional optimal policy closely aligns with the optimal policy in Section 7.1.

Figure C.16: Pareto frontier of counterfactual policies



Notes: This figure plots the Pareto frontier of all the counterfactual policies that we discuss above. The blue dots are outcomes of altering the subsidy level, and the red dots are outcomes of altering the subsidy stringency.