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

Jingyuan Wang[*] Jianwei Xing[†]

Job Market Paper

November 14, 2023

The most recent draft is available here or on my website

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 data from the Chinese EV market 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 lemons. This paper develops a framework for designing green industrial policies, highlighting the critical but often neglected role of the reputation channel.

[*]Department of Economics, Northwestern University. Email address: jingyuanwang@u.northwestern.edu

[†]China Center for Economic Research, National School of Development, Peking University, jerryxing@nsd.pku.edu.cn

[0]We are grateful to Mar Reguant, Robert Porter, Vivek Bhattacharya, and Gaston Illanes for their invaluable mentorship and advice. We thank Jie Bai, Panle Jia Barwick, Meghan Busse, Shengmao Cao, Igal Hendel, Matthew O'Keefe, Alexander Jakobsen, Anran Li, Shanjun Li, Gaston Lopez, Francisco Pareschi, Harry Pei, Willian Rogerson, Benjamin Vatter, Tomas Wilner, and seminar participants at the Northwestern IO workshop, Kellogg strategy seminar, the 2022 NBER innovation bootcamp, 2023 CAERE, the 2023 Columbia University IPWSD workshop, and the 2023 Asian Meeting of the Econometrics Society Conference for helpful comments. We thank Shanjun Li for generously sharing data. We gratefully acknowledge financial support from the Northwestern Graduate Research Grant. All errors are our own.

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 towards residential solar panels. Consumer subsidies are standard policies used by most countries, such as the US, UK, Norway, and China. Ideally, such policies can attain higher welfare by enlarging 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, in 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 performances 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 misperceptions about EV quality are significant adoption barriers.[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 lemons, 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 from 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 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 the optimal design considering three channels, with a particular focus on the reputation impact: (i) the subsidy brings the consumer prices closer to 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) 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 leads 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 the subsidy's impact. 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, attesting to the subsidy's success as an industrial policy. On the other hand, the subsidy incentivized price-sensitive consumers and increased the relative profitability of cheaper cars. This attracted many lemon firms into the market, resulting in a surge of 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 their profits. The government also circulated documents that discussed adverse selections, EV qualities, and consumer trust.[5]

We identify lemon firms in Section 2. Lemons are defined as firms with low unobserved qualities. 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 lemons 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. Results suggest that the experiences of friends who own lemon EVs can negatively impact the perceptions of potential buyers and decrease the probability of them purchasing an EV. This justifies a within-market reputation externality and the city-level lemon share variable. We then validate these two factors. using sales data. We examine the impact of EV fires on uninvolved EV firms using a difference-in-

[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). It is also one important data source for the General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China.

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 lemon share on a city's future adoption of EVs, we find 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 non-lemon 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. A high reputation sensitivity further hurts non-lemons 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. (1995) and Nevo (2001). Assuming 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 non-lemon 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 due to the industry-level entry margin. We use a "nested loop algorithm" to reduce the computational burden caused by this interdependence: the outer loop solves 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. We estimate the entry model using maximum likelihood estimation (MLE). Our analysis reveals that neglecting the industry-level entry results in a 25% underestimation of the subsidy's impact. Failing to consider either margin could lead to biased estimates of 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).[8] 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, and the upstream spillover channel has a large benefit because the reduced battery cost accounts for more than a 20% reduction in the marginal cost of vehicles. The direct channel's loss arises from the deadweight loss (DWL) and choice distortions due to oversubsidizing. The subsidy decreases the gap between consumer prices and social marginal costs[9] 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 non-lemons because of the high estimated price sensitivity, and 57% of the lemon entrants are subsidy-induced.[10] To quantify 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 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 accounting for equilibrium entry responses. In equilibrium, the reputation impact leads to a market shrinkage of 68.1 thousand EVs from 2012 to 2018, which make up 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 will rely on market mechanisms to screen entrants.

[8] We report the discounted values, while the undiscounted expenditure is 90.61 billion RMB, or 13.94 billion USD.

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

[10] This number comes from 50 simulations, so it is not a multiple of 1/9.

Section 7 evaluates optimal subsidy design, focusing on two aspects: the level and stringency of the attribute-based policy. We find that the optimal level is mainly determined by the direct channel, while the reputation channel pushes towards a slightly more conservative level. The optimal subsidy level is found to be 70% of the current policy, which significantly improves policy efficiency from nearly 0 to 7.4 billion RMB (1.14 billion USD). Moving 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 are only increased by 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 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 mainly determined by the reputation channel. Assuming the subsidy takes a two-part structure based on the driving range, we find that increasing the stringency can effectively screen lemons, thanks to the correlation between observed and unobserved quality.[11] Neglecting the reputation channel would yield a smaller 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. 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 non-lemon firms in these provinces in 2018 dropped only by 3.2%, thanks to the across-province entry spillovers. These findings shed light on the timing of expanding the subsidy on a national scale.

In summary, this paper discusses optimal subsidy design in markets with lemons. We establish the relationship between consumer subsidy and lemon entrants through 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 alerts policymakers to these dynamics in their decision-making.

Related literature Our study 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 (2023)), and other renewable energy policies (Murray et al. (2014); Novan (2015)). In evaluating

[11] We assume subsidy takes the form $T + t \cdot \mathit{DrivingRange}$ and alter the stringency t.

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 the 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 found 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 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 mostly focuses 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 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 and these 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).[12] 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.[13] 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 like 1:1 or 1:0.5.

Table 1: Central subsidy criteria: 2013-2018

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

Figure 1 displays the average as well as 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.[14]

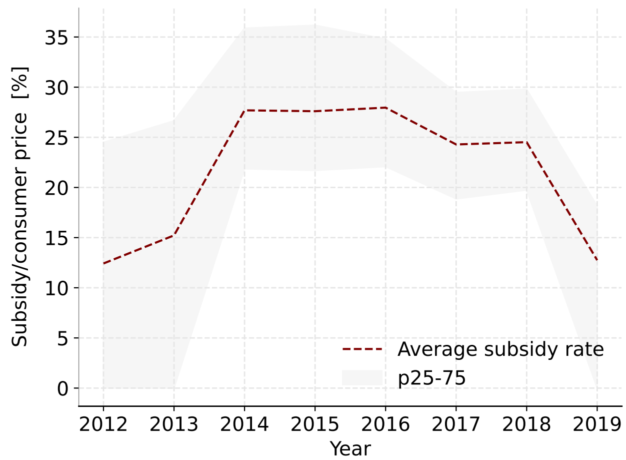
Policies have significant variations across cities and across time variations. This results in large differences in consumer demand and firm entry decisions. Different cities began their subsidy programs at varying times and adjusted their local policies over time. In addition to subsidies, local governments have implemented non-monetary policies. These include driving restrictions for gaso-

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

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

[14] This figure only reports the subsidy statistics for the first quarter of 2019 due to data availability. What's more, 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. The subsidy rate is defined 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.

line vehicles (GVs)[15], plate registration restrictions for GVs[16], and green plate benefits for EVs[17][18]. 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, non-monetary policies, and the 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 mainly based 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, (4) charging station data from the China Electric Vehicle Charging Infrastructure Promotion Alliance.

Demand estimation focuses on the top 40 EV cities spanning 20 provinces from 2015 to 2018.[19] 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 sales almost doubled every year, while GV sales dominated the market in both the number of models and

[15]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.

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

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

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

[19]These 40 cities encompass all the 13 first-round pilot cities and are partially overlapped with the 88 second-round pilot cities.

sales. 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 EVs for GVs. Firms set the manufacturer's suggested retail prices (MSRP) at a national level, and 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 the lowest end even lower than GVs. Also, 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 the averages of annual sales per model, prices, and key vehicle attributes by year. Panel A reports summary statistics for gasoline vehicles and Panel B reports summary statistics for electric vehilces. 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 the review and repair data

Lemons are defined as firms with a 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 non-lemons is their electronic system and platform design. First, the electronic systems of an EV are different from those of a GV, thus lacking 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 a 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 mostly manufactured in the upstream industry, and (ii) vehicles with the same battery supplier can exhibit different qualities.[20]

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.[21] First, we collect consumer reviews on the Autohome platform, China's largest vehicle review platform, from which automakers purchase data and market reports. We get 1,138,945 reviews from 2014-2021, including 32,441 EV reviews. Second, we collect complaints and repair data on the Car Quality Network, which is the largest online complaints filing and repairing platform. It is 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.[22] 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 lemons. The review data only covers 35 EV firms in our sales data, so we supplement it with data from the complaints filing and repair platform. We calculate the complaint rate for each firm and define lemons as firms with a complaint rate higher than the 70 percentile of all EV models (3.0 per 1,000 sales).[23] The two definitions are aligned for the overlapped firms.[24] Combining both definitions, we identify nine "lemon" EV firms, representing 19% of the EV models in our sample. We define lemons at the firm level rather than the model level, as most firms, particularly the lemon ones,

[20]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 non-lemon firms.

[21]We define lemons as firms characterized by low-quality factories, namely those with inferior electronic systems and platforms. It's important to note that there can be variations in car qualities 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 lemons and non-lemon firms.

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

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

[24]For the 29 overlapped firms, 6 are lemons in both definitions, and 23 are non-lemons in both definitions.

operate a single production line. Additionally, the review scores for models within a given firm are largely consistent.

Assumptions and information structure We make the following assumptions to simplify the analysis: (i) whether a firm is a lemon is exogenous; and (ii) firms know their qualities, but government and consumers do not observe their qualities. 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.

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 more strict 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, most of which have only one production line. This makes the entry and exit decision more relevant. What's more, while observed attributes like 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, data indicates that the review score ranking for each firm remains stable over time.[25] Third, while larger firms may have quality choices, they are not on the entry margin and are not lemons. The following background subsection will explain that most EV firms are fringe. Therefore, we abstract away from these decisions and endogenous entry and exit decisions, focusing on the entry selection issue.

Consumers and the government have imperfect information about lemons because electronic systems and platform designs are unobserved. 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. Most reviews are posted after 1.5 years of purchasing and in our study mainly after 2018. Table C.14 reports the number of reviews by year. Appendix C.1 provides more supporting evidence of these assumptions and simplifications.

[25] 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. So we decided not to include this in the model.

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.[26] 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). That represents 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. As per some publicly listed firms' annual reports, industry entry costs can soar to hundreds of millions of RMB.[27] Such substantial initial costs are pivotal when assessing industry trends and the subsidy impact. We manually collect firm plant locations and their entry periods from media reports.[28] For firms that lack media coverage, we designate their entry period as the time preceding any observed sales. Table 3 reports the number of EV firms during the sample period and the number of provinces an EV firm entered by year. The number of electric vehicle firms increased from 6 in 2012 to 55 in 2018.[29] 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 percent of EV firms operate

[26] Low-speed EVs are like scooters and golf carts, with a speed of around 20 30km/h.

[27] BACI reported an expenditure of 1000 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)

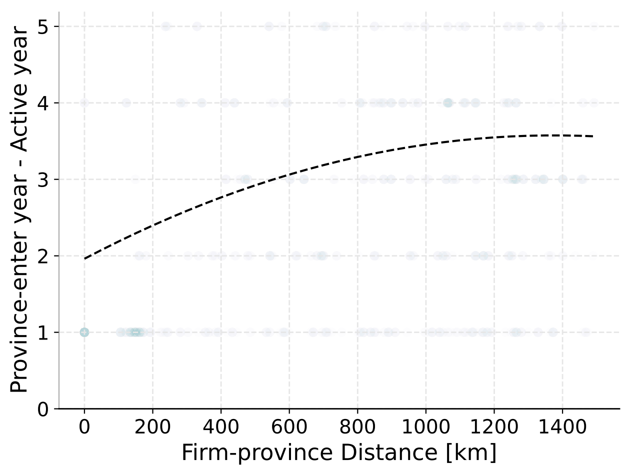
[28] Firms typically announce their plans. In our dataset, the plant completion dates generally align with the commencement of sales.

[29] The number of firms producing gasoline vehicles remains stable at around 60.

in three provinces or fewer, another 25 percent have entered more than ten provinces. The increasing entry and expansion activities are mostly attributed 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 the 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, while 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 provinces had no lemons. In 2018, the average lemon share was 10.3%, and lemons 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 a small market power.

Modeling implications We refer to the two entry steps as "industry-level entry" (or "active") 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 locations are exogenous in our analysis based on the discussion in the firm background. Second, we use distance as a market-level entry cost shifter to rationalize the pattern that firms tend to enter into nearby markets first. Third, we assume there is no constraint in entering multiple provinces in the same year, given that many firms are entering multiple provinces per year.

3 Evidence of the Reputation Externality

We use two reputation factors to capture the reputation spillover—EV fires and 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 from friends' experience, impacts potential buyers' perceptions and decreases the probability that they will purchase an EV. This justifies a within-market reputation externality and the local lemon share variable. Next, we use sales data to examine the reputation externality of EV fires with a difference-in-difference (DID) design that compares the same firms' sales in the event city to sales in other cities. Finally, we test the impact of 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 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 according to 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 limited our sample to potential buyers who do not currently own an EV.

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 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

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 on line					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 observations that already had an EV and observations with answering times less than 2 minutes, we left with around 700 observations. $*p < 0.10; **p < 0.05; ***p < 0.01$

negative even when we control for the variable "aware of any EV fire". Table A.7, which reports results when the dependent variable is changed to the probability of purchasing EVs, 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 the firm-city series where a firm entered earlier than 6 months before the event. Combining all the 35 events, we estimate the following difference-in-difference (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 log of EV sales of firm j, city c, 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 only identify the differences 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 "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.

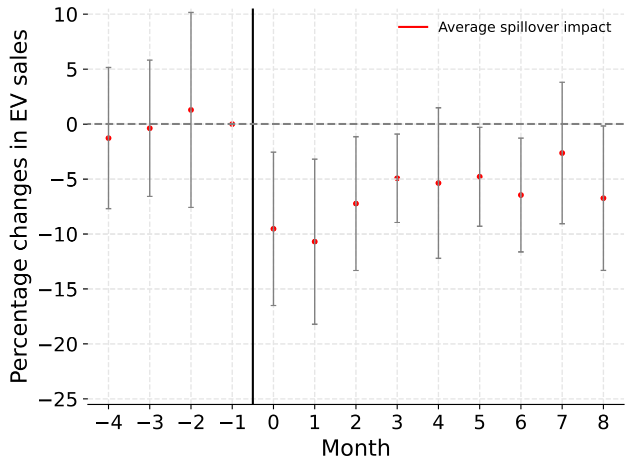
Figure 3 plots the estimates from Equation 1. The coefficient on relative month -1 is normalized to zero. Coefficient β_2^k represents the percentage changes of sales in each period. Two insights can be drawn from the figure. First, there is a significant spillover impact after an EV fire, with sales 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. The consumer survey has suggested that exposure to lemon EVs through friends' experiences decreases 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 and it varies at the city-quarter level..[30] 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,

[30]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 Heutel and Muehlegger (2015), who also find initial sales of low-quality EVs will decrease future adoption rate due to consumer learning.

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.

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 increasing lemon share on future EV adoptions in the same city. s_{ojct} is the city-model-specific subsidy, determined by 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 local unobserved demand factors. Time-invariant preferences are controlled by city-fuel type fixed effects and province-firm fixed effects, which captures local preference towards green products and province-specific preferences for local firms.[31] Province-year FEs control the province-specific unobserved policies or income shocks that vary across years.

We use instrumental variables (IVs) for prices and 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) battery supplier dummy interacted with battery capacity.[32] All these IVs vary by model. The subsidies vary across time, and local subsidies further provide cross-sectional variation. Battery supplies and

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

[32]We categorized the 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.

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 OLS and 2SLS results from Equation 2. Columns (3) and (4) relaxes 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.5 reports full results with all coefficients and more relevant tests on excluded IVs.

capacity are shifters for marginal costs. To deal with the potential endogeneity of the lagged lemon shares 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 results. The OLS results suggest a slightly positive relationship between lemon share and EV sales. City unobserved demand shocks can confound the relationship (e.g., consumers' preference for cheaper cars). IVs help identify the reputation impact of lemon shares, and both columns (2) and (4) suggest a negative impact of historical lemon shares on EV sales. $lemonshare_{t-1}$ is rescaled to a 10% level, and results from column (2) suggest that a 10% increase in lemon share will decrease 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 to 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 subsidy and reputation. We then explain firm responses, the entry selection problem, and the 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 An illustrative model and key primitives

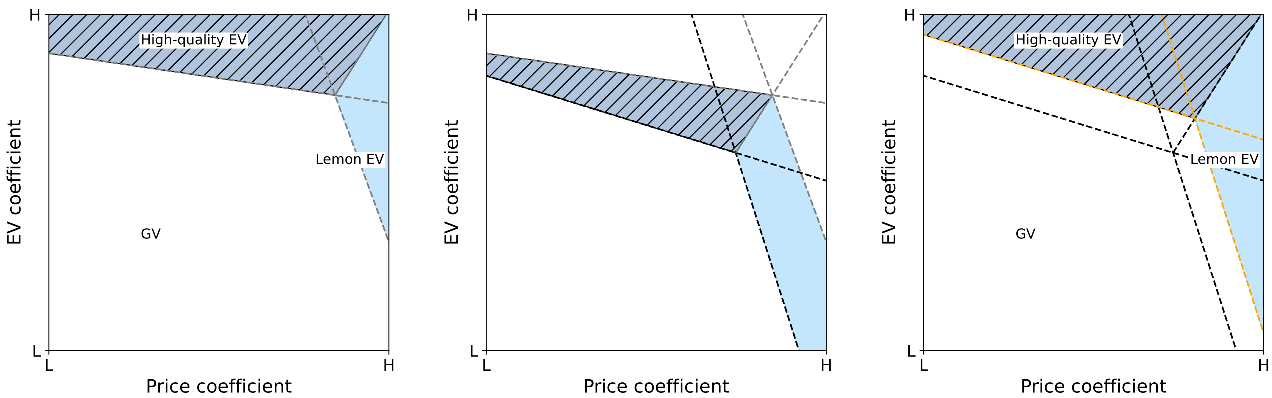
This section uses an illustrative example to explain how the three key primitives—consumer price sensitivity, reputation factor sensitivity, and entry fixed cost—affect the subsidy's impact. We focus on the reputation channel's impact and explain when and why the subsidy attracts lemons.

Consumer price and reputation sensitivities determine the profits that lemons and non-lemons derive from the subsidy, as well as 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 EV 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 firm price and s_j representing subsidy. Consumers exhibit heterogeneous sensitivity to EVs θ_i^0, its reputation θ_i, and heterogeneous price sensitivity α_i. Figure 4 explains consumer choices and shows that subsidy-incentivized high 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 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 for the unobserved quality, such as a lower driving range and a smaller vehicle size. Without loss of generality, we assume 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.

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 (which is the high-quality one), while light blue consumers choose the cheaper EV (which is the lemon). The remaining white consumers choose the GV model. When a subsidy s is introduced, it incentivizes consumers to shift from GVs to EVs. Figure 4b highlights the shifted consumers. High price-sensitive consumers are more inclined to switch, as indicated by the larger

Figure 4: Illustration: subsidy 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.

light blue area compared to the dark blue area. These two areas reveal whether the lemon or non-lemon 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, non-lemon firms benefit more from the subsidy. A decline in EV reputation—due to a rise in lemon share or an occurrence of an EV fire event—causes consumers to switch back to GVs, 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 non-lemons. 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.

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 non-lemons and results in fewer 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, non-lemons 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 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 the last period repeats indefinitely. Figure 5 provides an overview of the model timing. There are a finite number of firms, 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.[33] [34] 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.[35] They first decide whether to become active in the EV industry and, if so, pay the 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 they have entered and their margin costs. Based on city c'

[33] 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.

[34] 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.

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

policies and the EV reputation factors—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.[36]

State variables include the following. Industry state includes industry structure—firms' active statuses—and current battery cost, denoted as ω_t. Each market's state includes market structure and current EV reputation in that market. We assume firms have perfect information on the subsidy policy path and abstract away from potential policy uncertainties. We further assume the subsidy stops in 2019, as originally planned by the government.[37] 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 lemons. 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 non-active GV firms or non-active new EV firms, observe the private information regarding their sunk cost shock ε^a_{jt} and decide whether to activate in the EV industry. Active firms observe shocks on their scrap value ε^{ext}_{jt} 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.
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.

[36]Purchasing an EV from other cities can not get the full subsidy.

[37]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.

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 Normal distribution $\mathcal{N}(0, \sigma_k)$. We include random coefficients for fuel type and 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 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.[38] We further include firm-period fixed effects $\overline{\xi}_{jt}$ to control 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 by 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 variations to assess temporal sensitivity changes. It is possible that consumers develop a better understanding of each firm as time progresses, thereby diminishing the impact of reputation factors. However, reduced-form regressions do not find significant heterogeneity in reputation factor sensitivity across time, probably due to limited variation in the data. We argue this simplification is acceptable

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

because one important reputation factor, $lemonshare_{ct}$, exhibits a significant decline in later years, as detailed in Section 2.[39] Thus, reputation externalities diminish over time, despite our model 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 on more expensive models. Furthermore, by allowing 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.[40] 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 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 the marginal cost takes the following form:

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

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 $\bar{\xi}_j$ and $\bar{\xi}_y$ stand for firm fixed effects and year fixed effects, respectively.

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

[39] In 2014-2015, the lemon share can be as large as 80%. In 2018, most markets have fewer than 5% lemons.

[40] We assume firms do not use dynamic pricing strategies. This stance is supported by two primary pieces of evidence. First, our data indicates 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.

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 decisions ε_{jmt}, for firm active decisions ε^{a}_{jt}, and for exit decisions ε^{ext}_{jt}. These random shocks $\sim$ Type II extreme distribution with variance ρ and mean $\rho\overline{\gamma}$.[41] 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 only registers two industry exits. Because we only observe two exits until 2018, we can not 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 includes (i) demographics and market size changes and (ii) policy changes that shift consumer demand from GVs to EVs. These mainly affect consumer choices, as defined in Equation 3. We take all these conditions as given without estimating the process. State variables include industry structure, battery cost ω_t (referencing Equation 5), market structures, and market-specific EV reputations. We discuss the transitions of 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, active, expansion, and exit decisions.[42] The industry state includes industry structure and battery cost: $s_{It} = (str_{It}, \omega_t)$, where the industry structure $str_{It} = (\{\mathbb{1}(active)_{jt}\}_{j\in\mathcal{D}}, n^h_t, n^l_t)$ includes the three dominant firms' status, number of fringe non-lemons (n^h_t), and number of fringe lemons (n^l_t). Each market's state includes market

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

[42] 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 around 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 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.

structure and EV reputation: $s_{mt} = (str_{mt}, q^e_{mt})$, where the market structure is defined similarly $str_{mt} = (\{\mathbb{1}_{jmt}\}_{j\in\mathcal{D}}, n^h_{mt}, n^l_{mt})$. We further reduce market interdependency. Industry-level actions, including active, exit, and pricing, are only determined by 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 $(\varepsilon_{jmt}, \varepsilon^a_{jt}, \varepsilon^{ext}_{jt})$. A firm's strategy includes active, entry, exit, and pricing decisions. Specifically, $\sigma_{jt}(S_t, \varepsilon_{jt})$ has the following four components:

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

which include market-level entry decisions for all M markets σ^{ent}_{jmt} and three national-level decisions active σ^{act}_{jt}, exit σ^{ext}_{jt}, and pricing σ^p_{jt}. $\sigma^p_{jt}(s_I)$ 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, like 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, we do 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 not others. Section 5.2 shows the large heterogeneity in firm profits and subsidy impact in 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 non-lemons. 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 firms only track the three dominant firms' identities. Also, 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 simplification 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 only track the identities of dominant rival firms and keep track of the number of rival fringe lemon and non-lemon firms (n^h and n^l). Fringe firms affect other firms' profits through the aggregate numbers.*

This assumption reduces the state space from 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 only depend on industry state s_{It}. This assumption restricts the impact of each market $\{s_{mt}\}_{m\in M}$ on industry-level active, 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. Firstly, 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 non-lemons. For industry-level active and exit decisions, firms consider the industry structure and battery costs. When making industry-level pricing decisions, we assume they maximize static profits, as explained earlier. This indicates that the reputation impact and the upstream spillover impact are non-strategic. 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.[43]

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. The reputation factor transition is approximated by calibrating the probability of fires for lemons and non-lemons and simplifying the lemon share definition from the share of sales to a weighted fraction of lemon and non-lemon firms.[44] Appendix B.2 details these approximations.

[43] 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.

[44] We assume the probability of catching fire is 0.002% for lemons and 0.001% for non-lemons. 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 non-lemon firms, for various markets. All fringe firms are uniformly assigned a weight of 1.

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 last-period values for incumbent firms are the continuation value given current states (s_m, s_I) (Equations B.4) and 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 active 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 rivals' entry strategy for market m, self's exit strategy, and rival's entry and exit strategies because all these decisions are made simultaneously, according to the model timing. $E\pi$ captures the self and rivals' pricing strategy in σ_I. Similarly, the net present value of market m to active 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 non-active firm j chooses whether to become active in the EV industry. The Bellman equation for firm j is

$$V^{pa}_{jt}(s_I, \varepsilon_{jt}) = \max \begin{cases} -\overline{FC}_j + \beta \sum_m \iint_S V^0_{jmt'}(s'_m, s'_I|\sigma_m, \sigma_I)d\widetilde{F}(s'_m|s_I; \sigma_m, \sigma_I)dG(s'_I|s_I; \sigma_I) + \epsilon^a_{jt}(1) \\ \beta \int_{s'_I} V^{pa}_{jt'}(s'_I|\sigma_{mkt}, \sigma_I)dG(s'_I|s_I; \sigma_I) + \epsilon^a_{jt}(0) \end{cases} , \tag{12}$$

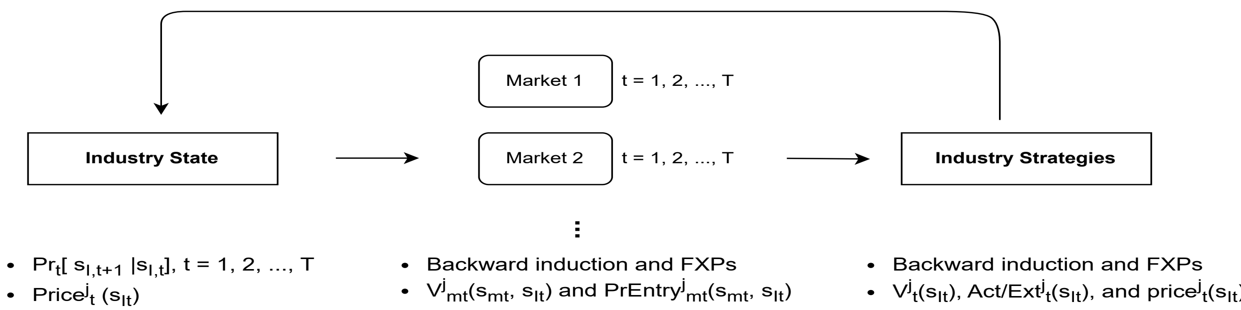
where the last-period value for nonactive firm $V^{pa}_{jT}(s_I) := 0$ for all $j \in J, s_I \in \mathcal{S}^I$. Firms' exit decisions is defined similarly in Equation B.6. Details about the conditional choice probabilities of active, exit, and market-level entry are provided in Appendix B.1.[45]

[45]In Equations 11 and 12, we add a term $-\rho\overline{\gamma}$ to normalize the εs. This compensates for the fact that incumbents do

4.4 Solution method

We use a "nested loop algorithm" to reduce the computational burden caused by the market interdependence. the outer loop solves industry-level entry strategies, while the inner loop solves the entry strategies for each individual market. Figure 6 outlines the "nested loop methods".[46] 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 active, 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



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 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 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 model attributes, including driving range, vehicle weight, and motor power, are

not get a ε every period.

[46] Benkard et al. (2015) introduces 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.

exogenous. We assume 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 IVs for lemon share in a city-period. Section 3 explains IV's exogeneity and relevance and shows first-stage results.

The following variations help identification. First, micro-moments help identify the income coefficients. We use the income-vehicle segment micro-moments from a new buyer survey to identify the price random coefficients.[47] Vehicle segments include compact sedan, sedan, SUV, and MPV. Second, central subsidy changes largely across time, and local subsidy provides cross-sectional variations in prices. Figure A.4 provides detailed variation. Third, the large variation in choice sets across cities and across time helps identify other random coefficients. We assume 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 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 CCP from the data. This idea comes from Aguirregabiria and Mira (2002).[48] 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 function for market-level entry and industry-level actions are detailed in Appendix B.1

Identification is given by the parametric assumptions and relies on rich variation in market-level

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

[48] 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 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 estimation. 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.

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 constant (or outside options).

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. Coefficients on observed vehicle attributes align with intuition. Consistent with reduced form evidence, consumers respond to negative reputation signals, and the effect is significant in both specifications.

We then back out vehicle marginal cost using firms' first-order conditions and the estimated consumer price elasticities.[49] Table 8 reports the marginal cost estimates. Coefficients on observed vehicle attributes align with intuition. The estimated marginal cost for adding 10kg 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 1kWh would cost ¥4,152 in 2015. The battery cost declines by about 20% each year during our sample period, and the marginal cost of battery capacity becomes ¥2,154 per kWh in 2018. Our findings are consistent with the results from Barwick et al. (2023) and industry reports.[50] Batteries account for 57.3% of marginal cost, aligned with industry reports.[51]

In the counterfactual analysis, we extend our model to allow 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). Calibration results suggest that, without EV sales, the baseline battery cost annual reduction rate is 9% in the main specification.[52] Discussion on the calibration and sensitivity tests are in Appendix C.2.

To understand the implications of these demand parameters on firm profits and disentangle the direct monetary impact, the reputation impact, and the battery cost reduction impact, we decompose

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

[50] 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/

[51] Multiple median and industry reports document that battery cost is the largest part of marking a vehicle—ranging from more than 40% to around 60%. Our estimates fall into this range.

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

observed firm profits into three parts, as shown in Equation 13:

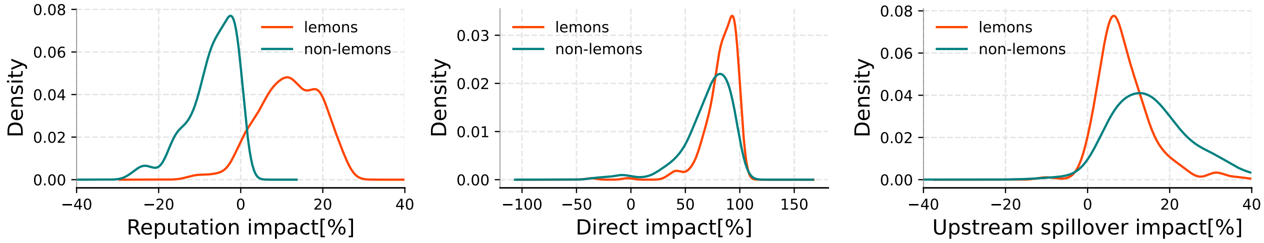
$$\begin{aligned}&\pi_{jt}(s, q^{e*}, mc^*) = \\ &\underbrace{\pi_{jt}(s, q^{e*}, mc^*) - \pi_{jt}(s, 0, mc^*)}_{\text{reputation impact (?)}} + \underbrace{\pi_{jt}(s, 0, mc^*) - \pi_{jt}(0, 0, mc^*)}_{\text{direct impact (+)}} + \underbrace{\pi_{jt}(0, 0, mc^*) - \pi_{jt}(0, 0, mc^0)}_{\text{upstream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

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) full information scenario $\pi_{jt}(s, 0, mc^*)$,[53] (iii) a scenario with full information, no subsidy, but battery cost decreases as in reality $\pi_{jt}(0, 0, mc^*)$, and (iv) the baseline without any government intervention and battery cost decrease 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 market structures the same as in reality to get 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 key primitives α and θ, as explained in Section 4.1. Figure 7 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 wouldn't buy lemons if they knew the cars had poor experience quality in the full information counterfactual. The impact on non-lemons is, in general, negative because some GV consumers would have bought a non-lemon in the full information counterfactuals where they knew EVs are not that bad. Some signs are opposite because of the substitutions and because non-lemons 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 it. Lemons benefit slightly more than non-lemons from the direct impact because the estimated price sensitivity α is high, as explained in Section 4.1. Figure A.11a plots how non-lemons and lemons' average profits change as α changes. When α is smaller, non-lemons could benefit more than lemons from the subsidy. In a large range close to our estimated α, lemons benefit more than non-lemons. 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.

[53] A a full information scenario, consumers have perfect information about lemons and fire probabilities, and there is no reputation externality. Mathematically, I change the variable *lemonshare* to 0 for non-lemons 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,

Figure 7: Decompose subsidy impact



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

Dynamic parameters We set the discount factor β to be 0.85 and table 9 reports the estimated cost parameters.[54] 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 active cost than GV firms. This can explain the fact that, 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 distance for GVs because $\gamma_2 + \gamma_3$ is close to 0. New EV firms need to pay a higher market-level entry FC. The results stem from a data pattern where some firms with gasoline vehicle (GV) experiences enter more than 5 provinces each year, whereas most EV-only firms enter approximately 2 provinces annually. Estimation results match several publicly listed firms' annual reports.[55] 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 (100km)					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.

but there is no across-firm reputation externality.

[54] Recall that the scrap value is set to 0

[55] For example, both SAIC and BAIC disclosed to the media that the cost of building a factory is 1000 million. This aligns with our estimations, even though firms tend to over-report their investments and round to whole numbers. Source:https://www.sohu.com/a/167856508_391226

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. Lastly, Section 6.3 delves further into the impact of lemons, addressing both the consequences of their presence and the reasons 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, 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 Equation 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 experience utility. Let $u_{i,oj,ct}$ denote the monetized 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 consumers' ex-ante utility, which is based on 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 non-lemons. 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 will stop 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 periods. [56]

6.2 Quantify 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 away from firm entry responses, also find subsidy is not cost-effective.

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 price response, market-level entry response, and industry-level entry responses respectively. The numbers in these three columns indicate the impact of these responses.

Both 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 by 3.37 billion RMB, according to Table 10.[57] This promotes the entry of 57% of lemon firms and 49% of non-lemon firms. Without the subsidy, firms would, on average, enter 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.

[56] 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.

[57] Our finding is larger than 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.

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. And 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 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.[58] 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[59]) and address the underadoption of EVs due to market power and environmental externalities.

Although decreasing markup can be welfare-improving, some consumer prices are lower than marginal costs and environmental benefits. This can result in Deadweight Loss (DWL).[60] Furthermore, because vehicles are heterogeneous, the choice distortion caused by subsidies can lead to negative welfare even when markups are slightly positive.[61] 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. But these post-subsidy improvements only offset the loss during the subsidy period modestly, with only 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 the subsidy should better balance the static losses and the dynamic gains. Figure A.7 illustrates the changes in the

[58] Emissions reduction is computed as the difference in emissions with and without the EV model, reflecting the environmental improvement compared to the cars it replaces.

[59] The difference between emissions reduction and EV sales comes from hybrid models. These models are less subsidy-sensitive, and we account for them in the EV sales. But they contribute little in emissions reduction.

[60] Barwick et al. (2023) also found 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.

[61] A simple example illustrates the impact of choice distortion. Suppose 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. But 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.

gap between consumer prices and vehicle marginal costs as well as emissions reduction across years.

Reputation channel To assess the reputation channel's impact, we conduct 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.[62] Firm strategies (σ^*_m, σ^*_I) and the state variable distribution $\widehat{F}_{mt}(\overline{s}_m|\sigma^*_m, \sigma^*_I)$ 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 is 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, lemons would enter only half the provinces compared to actual occurrences. Entry and expansion of non-lemon firms would see a modest increase. The reputation loss only accounts for 4.3% of the total benefit when only considering the static losses from consumer ex-post welfare losses, choice distortion, and firm profit distortions. But firm entry responses highlight the adverse selection, deterring the presence of about 11 firm-markets presence (9.2%), amplifying the reputation loss to 10.8%. Table A.11 reports more information about the interaction between entry and reputation losses.

Upstream spillover and sensitivity We calculate the upstream spillover impact by comparing the observed scenario with a counterfactual in which 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—the baseline battery cost reduction rate is approximately 5% per year —the subsidy's benefit only marginally exceeds government spending.[63]

[62] We enforce the consumer reputation parameter to 0 for non-involved firms in EV fires and replace the historical lemon share variable with 1 for lemon firms and 0 for non-lemon firms.

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

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 simulated reality and no subsidy scenario. The following three columns show 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.

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

cost.

Why do subsidies attract lemons? In provinces with high consumer price elasticity, subsidies benefit lemons more than non-lemons. 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 lemons 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 non-lemons, 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. And 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 non-lemons, some provinces promote non-lemons firms. Province Zhejiang is an example market with a higher income and a lower price sensitivity, and its subsidy impact is the opposite: the subsidy benefits non-lemons more than lemons. Also, Zhejiang is more distant than Hubei from lemon plants. Figure A.13 presents details for Province Zhejiang. Finally, two major markets, Beijing and Shanghai, exhibit almost no lemon entrants.

The entry spillover effect across provinces aids the expansion of non-lemon 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 non-lemon firms can offset the substantial industry-level entry costs for these firms. As non-lemon firms expand into more markets in subsequent years, lemons face increased competition and gradually lose their dominance. Thus, the entry spillover mainly benefits the expansion of non-lemons 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 also played a role in this decline. The provincial heterogeneity, along with the presence of influential cities like 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 more effectively target non-lemon 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.[64] For traceability, we assume firms do not change the set of models. We only endogenize prices and market structure and consider vehicle attributes, such as driving range, as 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.

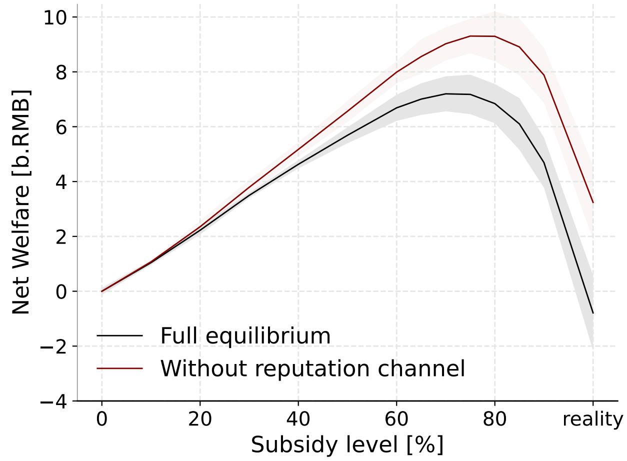
7.1 Optimal subsidy design

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.[65] We find that the optimal level is mainly determined by the direct and the upstream spillover channels. The reputation channel pushes slightly

[64] Other conditions include pivot cities, the ratio between local and central subsidies, EV plate benefits, GV plate restrictions, and the number of charging stations.

[65] 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 optimal, which can be a result of several more iterations. What's more, we want to focus on the welfare implications of these two policy aspects instead of solving for the two-dimensional optimal.

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 results without the reputation channel. Shaded areas represent the standard deviations of 50 simulations. Detailed welfare components are reported in Figure A.8

for a more conservative level because subsidies attract more lemons in the estimated parameter space. The reputation channel mainly determines the optimal stringency. Alternative stringency exercises assume 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 non-lemons' profits and screen lemons.

The Optimal subsidy level In the counterfactual simulations, we set subsidies to 10 percent, 20 percent, ..., and 90 percent 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). Detailed changes in each welfare component can be found in Appendix Figure A.8. Table 12 summarizes key outcomes for 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 static welfare losses, arising from choice distortion and DWL, and the dynamic gains achieved as more entrants reduce post-subsidy markups. Initially, the subsidy enhances welfare by addressing the underadoption caused by environmental externality and market power. But 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 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 only increases by 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% if moving from the optimal level to the observed level.

The optimal subsidy level results in a 12% decrease in reputation loss. It reduces 32% of lemon firms and only 13% of non-lemon firms. The last panel of Table 12 provides measures for the reputation channel.[66] 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 around 1 million. This leads to a more significant negative spillover to non-lemon firms. Reputation spillover, defined as the reduction in non-lemon firms' profits, is about 1.1-1.9 times as large as the static impact. Ignoring the reputation impact would set the optimal level to around 75%-80%, as shown by the red curve in Figure 8. This would lead to around 5.25-7.93 billion RMB more subsidy spending (9%-13%) and around 0.30 billion RMB (0.5%) fewer net subsidy benefits.

The optimal subsidy stringency In the alternative stringency exercises, we set subsidy levels to 70% of the current level. We assume the subsidy takes a two-part structure based on driving range: $T + t \times DrivingRange$.[67] [68] 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.[69] 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, optimal stringency, and an over-strict policy.

Welfare is maximized at 10kRMB per 100km (1.3kUSD per 100km). 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 mainly determined by the reputation channel. Increasing stringency es-

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

[67] In reality, the function is non-linear, as shown in Figure A.10a.

[68] We keep the step-function design, and the alternative stringency only changes the subsidy values for the original thresholds. Other conditions, such as pivot cities, the ratio between local and central subsidies, EV plate benefits, and GV plate restrictions, remain unchanged in all counterfactual analyses.

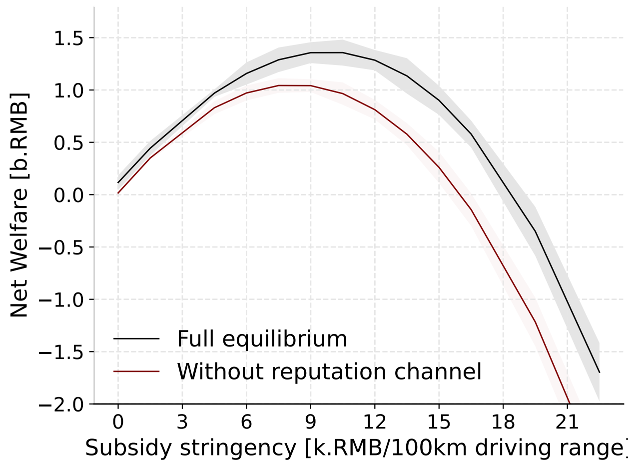
[69] The exact counterfactual subsidy has different levels across years, as it is in reality. Figure A.10a plots the details.

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
Non-lemons 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
non-lemons 2015	1.57	2.00	2.43	3.50
non-lemons 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. 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 reduced-form section findings because we average across markets and periods. Table **??** reports more details on the firm entry responses in the reputation channel.

Figure 9: Alternative stringency of subsidy: 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.

sentially substitutes low-driving range EVs with those of 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 non-lemons profit. Figure A.14 detailed this effect by plotting lemons' and non-lemons' profits as subsidy stringency changes. When subsidy stringency increased by 1kRMB/100km, the difference between lemon profits and peach profits increased by about 4.5% in 2015 and approximately 2.1% in 2017. This change is more significant in 2015 because the correlation between lemons and driving range is slightly larger in 2015 (-0.43) compared to 2017 (-0.34).

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

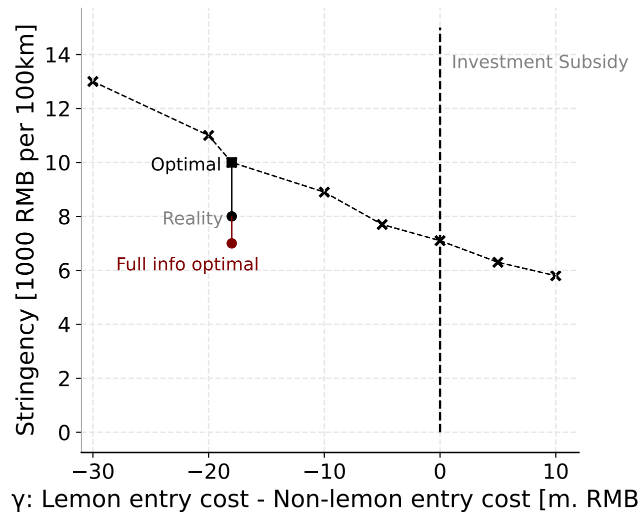
The optimal stringency can suppress 39% of the lemon firms in 2015. Table 13 provides the number of firms and their expansion decisions. The last panel of Table 13 reports detailed reputation losses. Compared to a flat subsidy, optimal stringency reduces reputation losses for consumers by 0.04 billion RMB and decreases reputation externality generated by lemons by 0.01 billion RMB. The 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 by 180 million RMB. The optimal policy reduces this loss to 120 million RMB.

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

	Subsidy Stringency (kRMB/100km)		
	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
Non-lemons 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
non-lemons 2015	2.09	2.29	2.36
non-lemons 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. 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 reduced-form section findings 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.

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 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 the 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 non-lemons. Figure 10 reports the optimal stringency when the difference between lemons' and non-lemons' 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 between lemons and non-lemons 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 an across-province entry spillover due to 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.[70] 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 non-lemon firms in these provinces in 2018 dropped only by 3.2%, thanks to the across-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.

7.3 Determinants of the impact and sensitivity

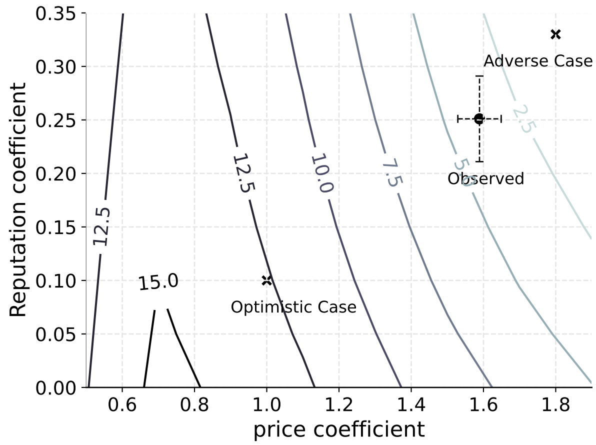
We find that the reputation channel reduces 10.8% of the subsidy benefit in the Chinese EV market. This impact could be more severe in other market environments. This section discusses the key primitives of the policy impact—consumer prices sensitivity, reputation sensitivity, and firm entry cost—and discusses under what market conditions policymakers should consider the reputation impact and plan for a more conservative and strict 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.

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 price coefficients yields a non-monotonic impact. This is mainly driven by the direct channel, as consumer price elasticity determines the benefit of smaller markups and the size of DWL. A subsidy in a low price-sensitive environment can generate little impact because consumers are inelastic. But with large price coefficients, the subsidy generates DWL. Increasing price sensitivity also increases reputation loss. Section 6 already points out that subsidies attract lemons more when consumer price sensitivity is large. Figure A.11a shows the average profits of lemons and non-lemons as price coefficients vary and evident this.

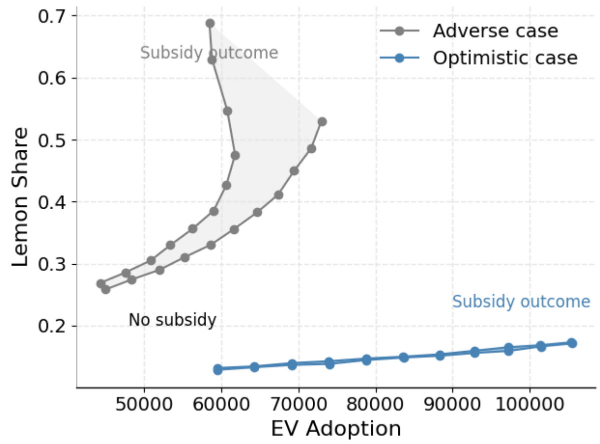
In markets with a higher reputation sensitivity, the subsidy leads to higher welfare losses due to the reputation channel. The iso-curves being denser at the top suggests this. Whether negative quality signals from lemons have a long-term impact depends on both consumer reputation sensitivity and

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

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—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.

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 non-lemon firms' entry decisions. And 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 non-lemon firms' sensitivity to profit reduction, thereby amplifying the equilibrium reputation spillover. Figure A.11b depicts non-lemons' 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—lemon share and EV adoption—as 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. But 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 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 non-lemons 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 which also faces significant criticism. We find a nearly zero net welfare impact, low efficiency, and significant reputation losses. The model suggests that, in designing the optimal subsidy, the direct channel and the upstream spillover channel mainly determine the optimal subsidy level. The reputation channel requests a more conservative subsidy level because the subsidy attracts lemons more than non-lemons. The optimal stringency is mainly determined 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.

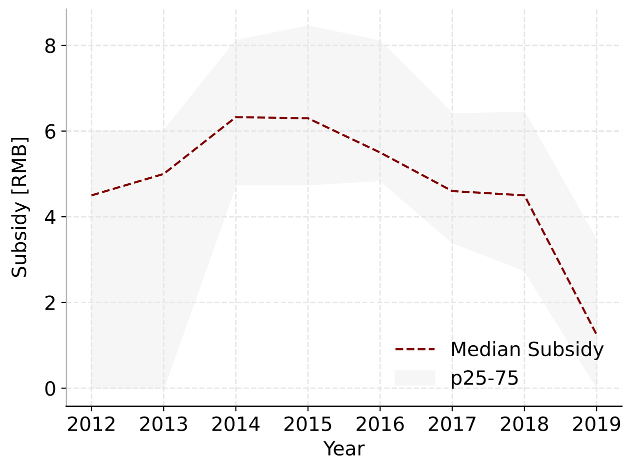
Xing, J., B. Leard, and S. Li (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management 107*, 102432.

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

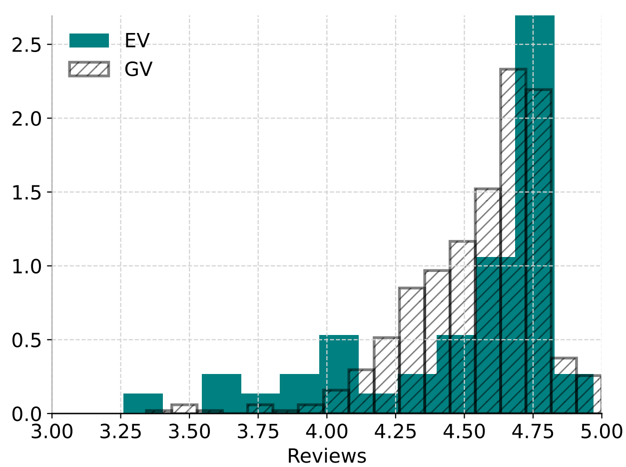
A Additional Figures and Tables

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



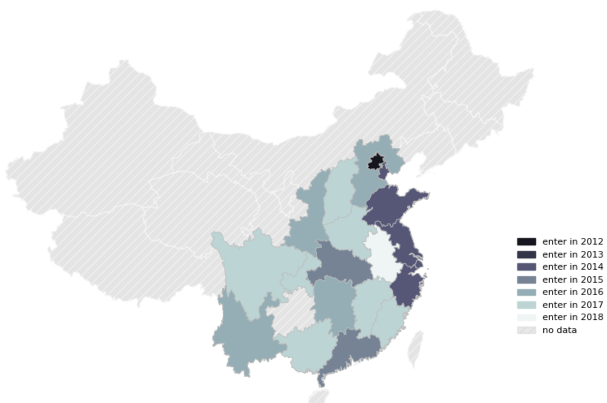
Notes: This figure displays the total subsidy amount by year, including local and central subsidies. As subsidies vary by both model and city, we present the mean, 25th percentile, and 75th percentile of the subsidy. Figure 1 reports the average subsidy rate over time, defined by dividing the total subsidy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

Figure A.2: Distribution of car quality review scores

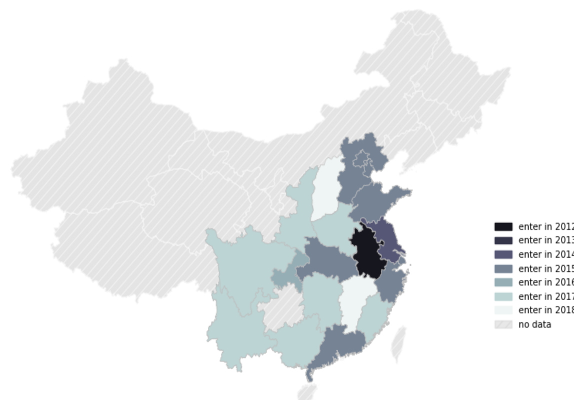


Note: This figure plots the distribution of average firm review scores from Autohome platform.

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) that 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 2015-2018

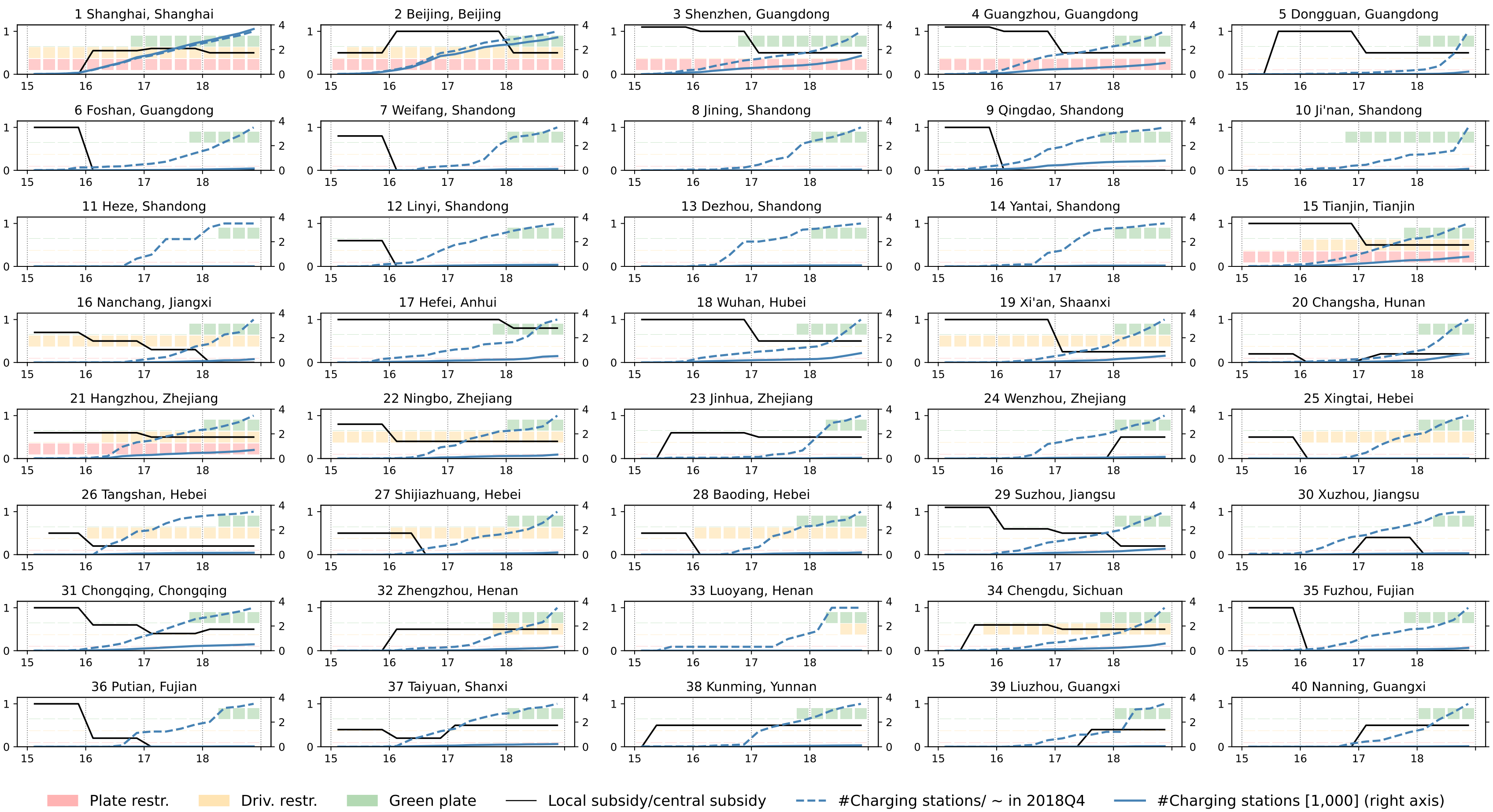
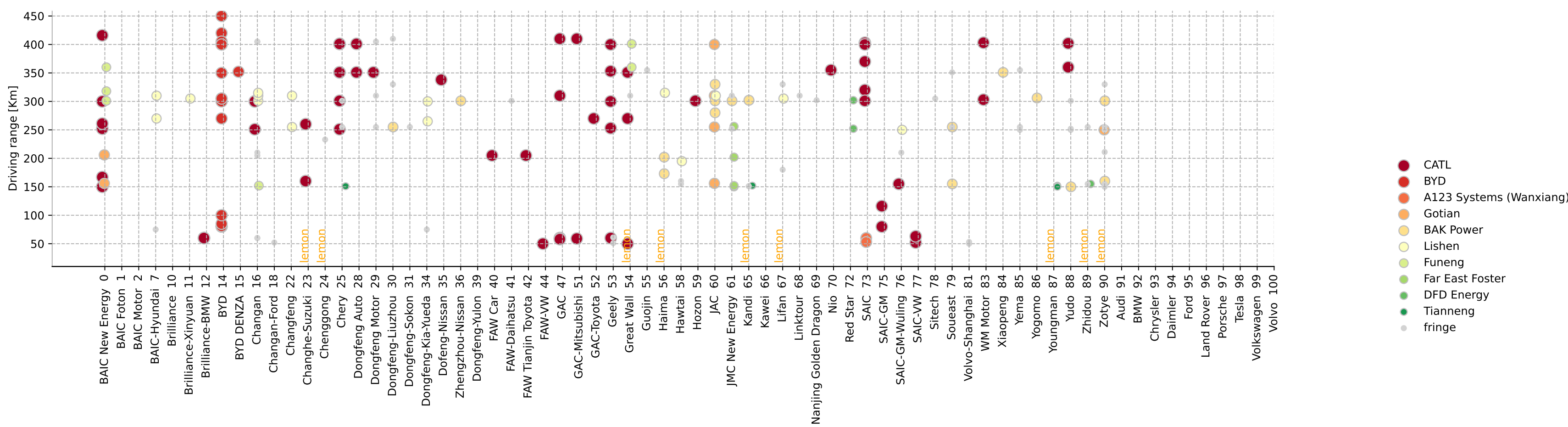
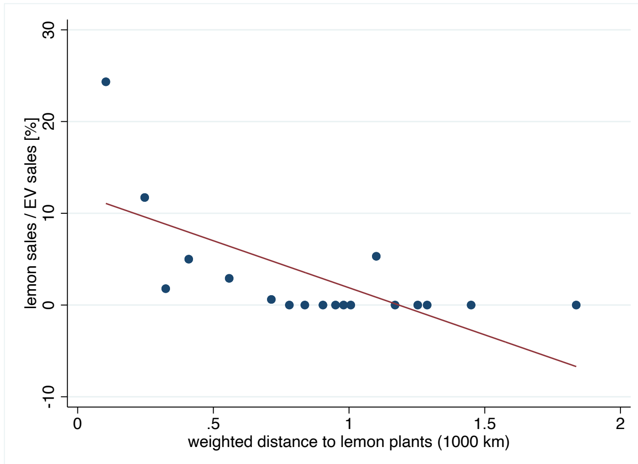


Figure A.5: Relationship between EV firms and upstream battery firms



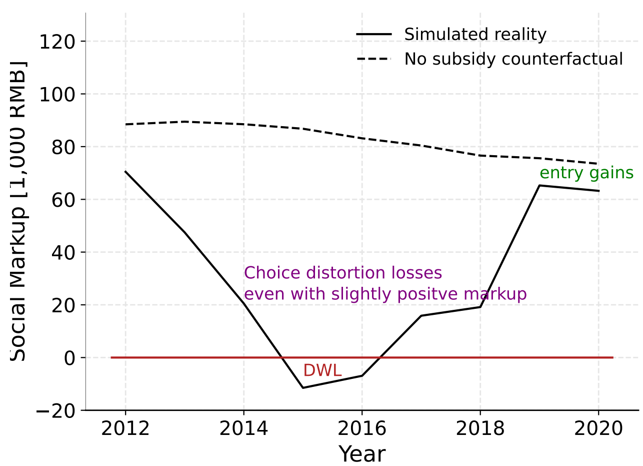
This figure report .... There is no clear pattern of lemon

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



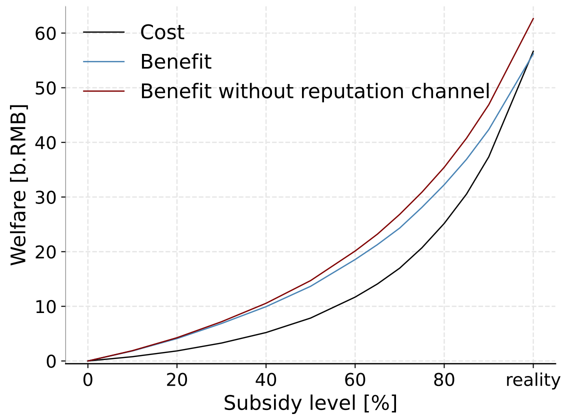
Note: City-level distance to lemon plants and local lemon share

Figure A.7: Direct channel impact: social markup



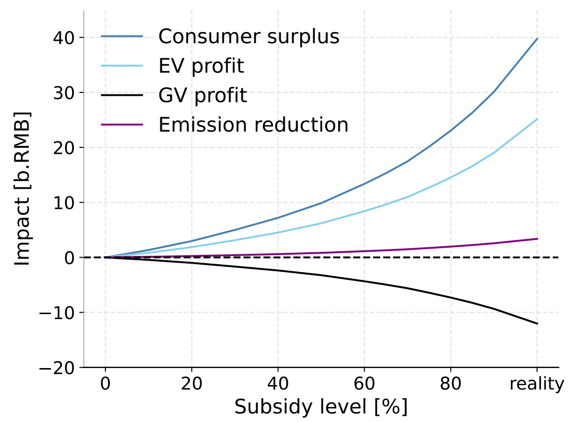
Notes: This figure reports the changes in average social markup, defined by the difference between consumer prices and vehicle marginal costs and emissions reduction. This reflects the gains and losses from the direct channel.

Figure A.8: Alternative level of subsidy



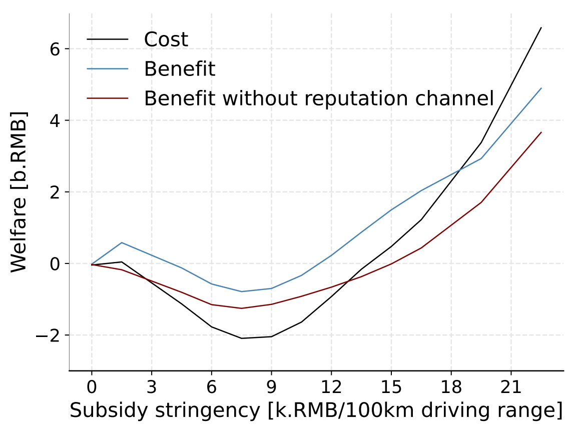
(a) Benefit and Government Expenditure

(b) Benefit Components



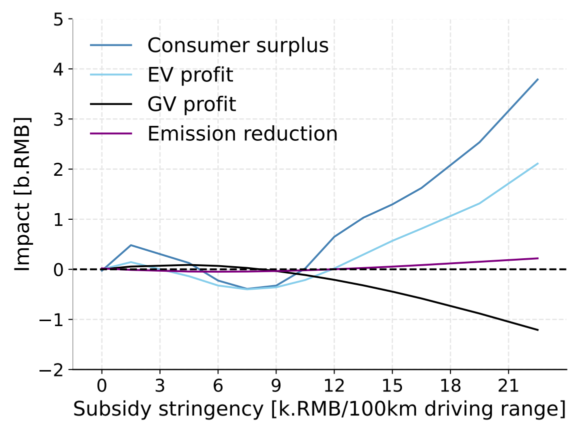
Notes: These figures report the welfare impact for different subsidy levels. The left panel depicts the policy-induced welfare gains (represented by the blue and the red curves) and the total subsidy expenditure (denoted by the black curve). Costs without the reputation channel exhibit a slight deviation 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 welfare benefit components. Aggregate impact is reported in Figure 8

Figure A.9: Alternative stringency of subsidy



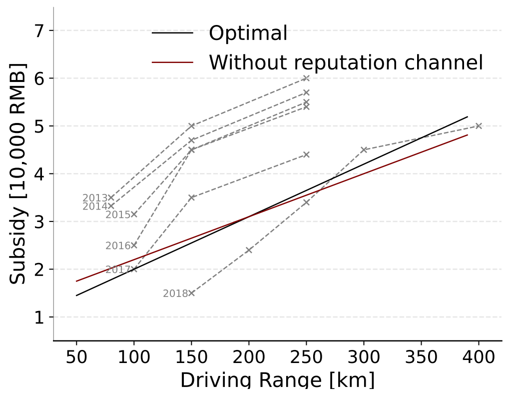
(a) Benefit and Government Expenditure

(b) Benefit Components

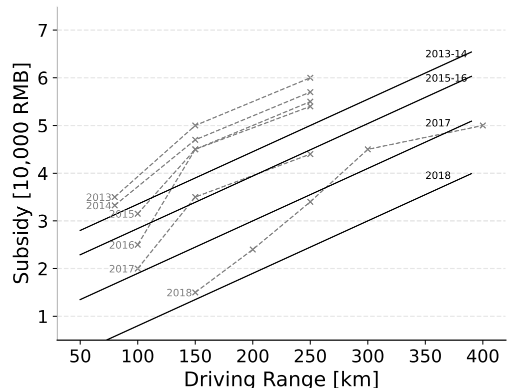


Notes: These figures report the welfare impact for different subsidy stringencies. The left panel depicts the policy-induced welfare gains (represented by the blue and the red curves) and the total subsidy expenditure (denoted by the black curve). Costs without the reputation channel exhibit a slight 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 welfare benefit components. Aggregate impact is reported in Figure 9

Figure A.10: Optimal policy v.s. reality



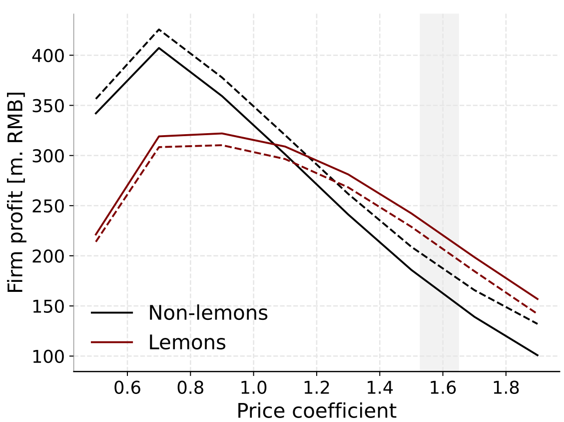
(a) Optimal policy with and without reputation channel



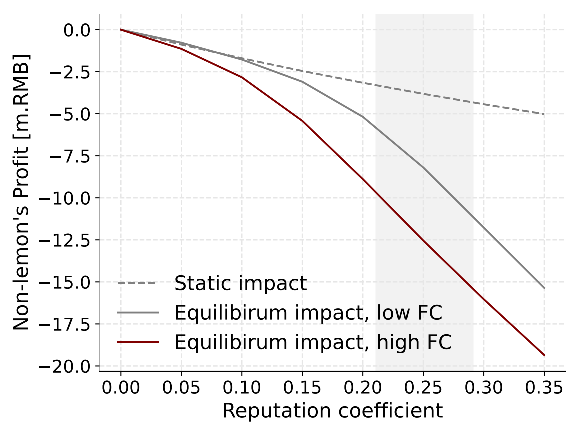
(b) Detailed optimal policy

Notes: The exact counterfactual subsidy has different levels across years, as it is in reality. We omit that 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



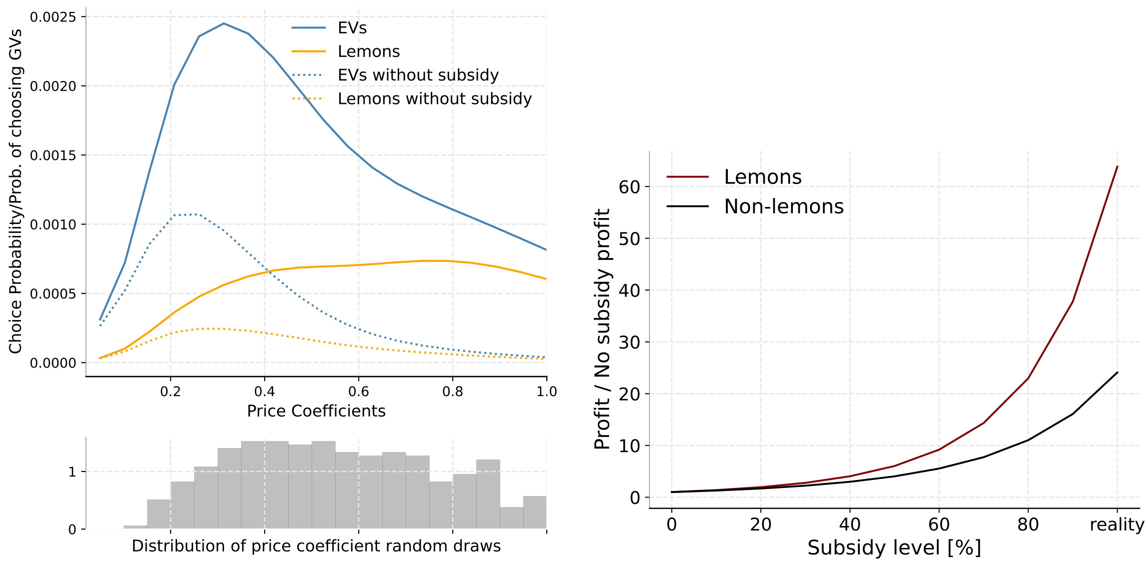
(a) Static profit changes and price coefficients



(b) Reputation spillover and entry amplification

Notes: These figures explain the impact of consumer taste parameters—price sensitivity and reputation sensitivity—on firm profits. Figure A.11a and A.11b depicts firm profit changes. The gray area represents the 95% confidence interval of estimated price coefficients (collective reputation coefficients). Figure A.11a reports the average province-level profit for lemons (red) and non-lemons (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: Impact of subsidy on lemons and non-lemons': Example Province Hubei

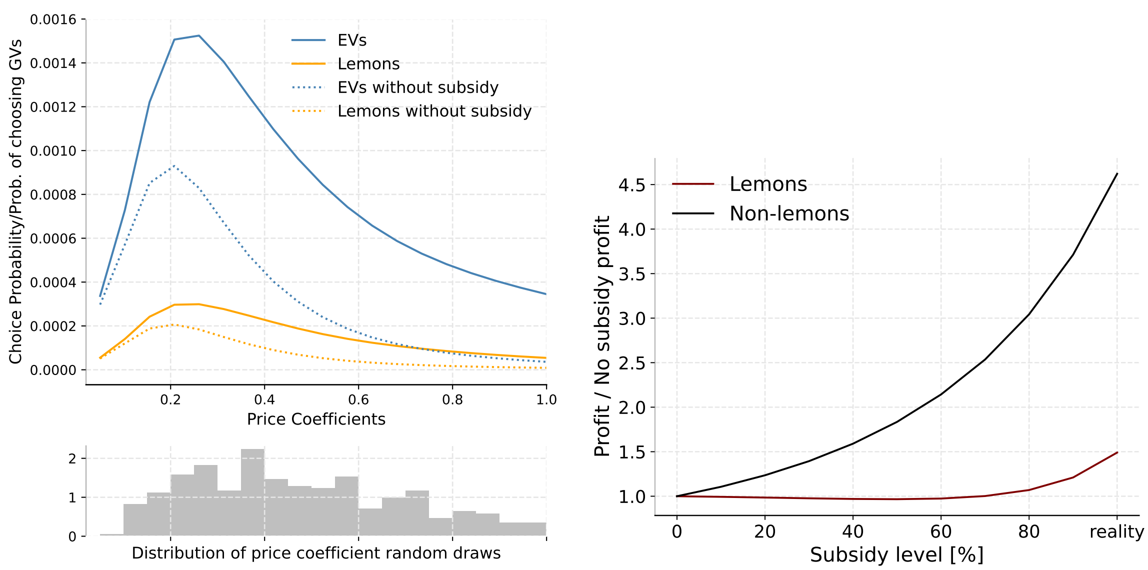


(a) Consumer choice probability

(b) Firm profits as subsidy increase

Notes: Province Hubei has 8 observed non-lemon 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: Impact of subsidy on lemons and non-lemons': Example Province Zhejiang

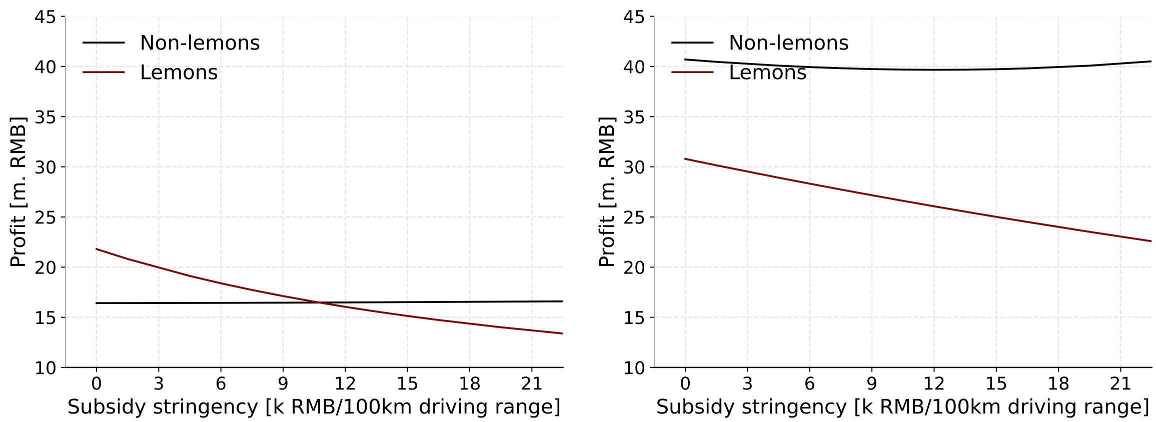


(a) Consumer choice probability

(b) Firm profits as subsidy increase

Notes: Province Zhejiang have 13 observed non-lemon 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 non-lemons' profits



(a) 2015

(b) 2017

Table A.1: Variable notation

Variables	Explanations
Sub- or superscript	
$c \in C$	C: set of cities
$m \in M$	M: set of provinces or markets.[71]
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 include 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 $\cdot$ 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 market m 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 non-active 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 market m 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	Explanations
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 equation 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 $\times$ firm-market distance

	(1)	(2)	(3)	(4)
	lemonshare	*lemonshare*	*lemonshare*	*lemonshare*
Central S $\times$ 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 the lemon share variable

	(1)	(2)
	$lemonshare_{t-1}$	$lemonshare_{t-1}$
centrals$_{t-1}$ $\times$ 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

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

	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	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) relaxes 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 EVs

	(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 lemons is lower in earlier years because due to technology limitations, there was little variation in driving range.

Table A.9: Subsidy impact: vehicle sales and the 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
Non-lemons 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
non-lemons 2015	3.50	–	1.50	1.57
non-lemons 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. 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
Non-lemons 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
non-lemons 2015	3.50	1.71	3.79	2.15
non-lemons 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 simulated reality and no subsidy scenario. The following three columns show differences between the simulated reality and the results from deactivating one channel. Thus the numbers represent the impact of each channels. 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 monetary impact and the upstream spillover. Subsequent panels report equilibrium outcomes of simulated reality and when one channel is deactivated, without taking any differences.

Table A.11: Entry responses and the 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)	(ii)	(iii)
		No direct	No reputation	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 these channels.

Table A.13: Determinants of subsidy impact

(a) Subsidy Impact Scenarios

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

(b) Impact of of a higher entry cost

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

Note: These tables list subsidy impact in different market environments.

B Model solution method and estimation details

B.1 More equations and choice probabilities

Section 4.2 reports main equations. This section lists all detailed equations. Firm profits and pricing follow the standard approach in 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 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 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 only includes the likelihood of entering the market when a firm has not entered, $\mathbb{1}_{jmt} = 0$.

B.2 Solution Method

We propose a "nest 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 industry state transition conditional on industry active 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 Nest 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 [72]
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

[72]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. So 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). [73] [74] 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 optimal active 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 active 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 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 to the next iteration.

B.3 Approximation method

Approximate Per-period profit Line 15 in Algorithm 1 lets the firm choose prices. Firms' profits are firm-year-specific functions of the full station variable, and so is its pricing strategy. In the dynamic game, we assume 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 firms set prices with perfect information on the exact market structure. This simplification only applies to the entry cost estimation.

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

[73] 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. Also, 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.

[74] 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:

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

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 only track the oblivious state variable, they form expecation on the exact market structure str_{ct}^f conditional on oblivious state variation s_{mt} and get $\widehat{F}(str_{ct}^f|s_{mt})$. Furthermore, as national strategies only depend 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, $\widehat{F}(str_{ct}^f|s_{mt})$ 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 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:

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

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

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

All parameters in equation (B.14) are firm-market-period specific. Super/subscript (j,m,t) are dropped to simplify notation.

The first term represents the impact of national industry state s_I on profit in market m through 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 $\tilde{q}^e{}_{mt}$ 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 get 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 they 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 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 firms' identity. We reduce this to functions of partially oblivious state variables using regressions. Consumer perceptions are also functions of 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 active CCP and pricing strategies due to lack of data. This idea comes from Aguirregabiria and Mira (2002).[75]

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 active and exit CCP from the data (line 4).

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

[75] 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 full state variables to oblivious state variables.

1. Simulate all possible market structures with different combinations of firms.
2. Calculate market (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. Get 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 get 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, get market-level entry strategies σ_{jmt} and conditional choice probabilities.

7. Solve the outer loop active and exit strategies $(\sigma^{act}, \sigma^{ext})$ and get 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.[76] In each market denoted as m, these welfare components (except from consumer welfare) are listed in equation B.16-

[76] We note that while the subsidy program officially commenced in 2009, our analysis only takes into account 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, model simulation can fit 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 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-market 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, sales data fits 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 largely.

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 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%, with consumers filing, on average, 1.36 years post-purchase. Thus, the 2019 and 2020 records cover a large amount of models before 2018. There were only 4,235 EV reviews before 2019, whereas 2019 to 2021 account for 30,872 EV reviews, or 87.94% of our total dataset. Furthermore, the EV reviews are relatively limited compared to GVs, and they cover only 35 out of the 57 EV firms in my sales, notably lacking information on smaller firms. Table C.14 reports the number of reviews by year. Secondly, the signals 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 is non-lemons. Lastly, 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 lemons 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.[77] While observed attributes like 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

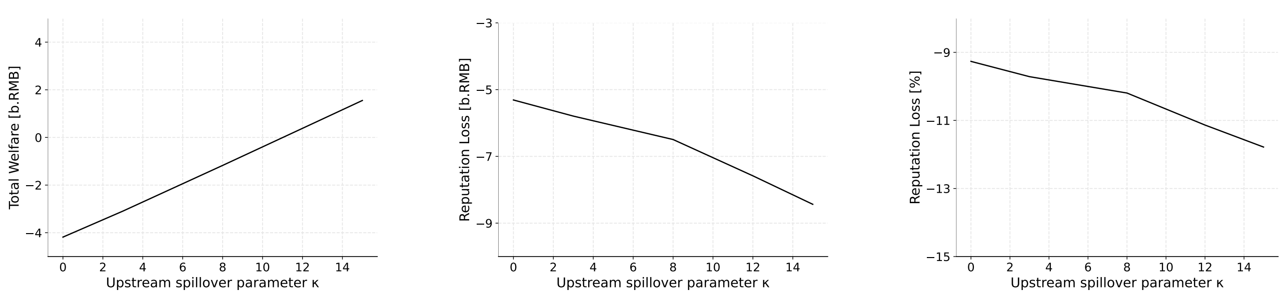
We calibrate the results with a log-log regression following Nykvist and Nilsson (2015) and Ziegler and Trancik (2021). Table C.15 reports baseline battery costs without EV sales. The estimated annual battery cost reduction rate is around 20%, as shown in the first column. In the main specification, we assume 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 to 0, and battery costs reduce at the same rate as without subsidy, about 20% annually. Conversely, the most aggressive assumption we tested for is $\kappa_1 = 1.5$, implying 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.15: Sensitivity of the welfare results to the upstream spillover parameter



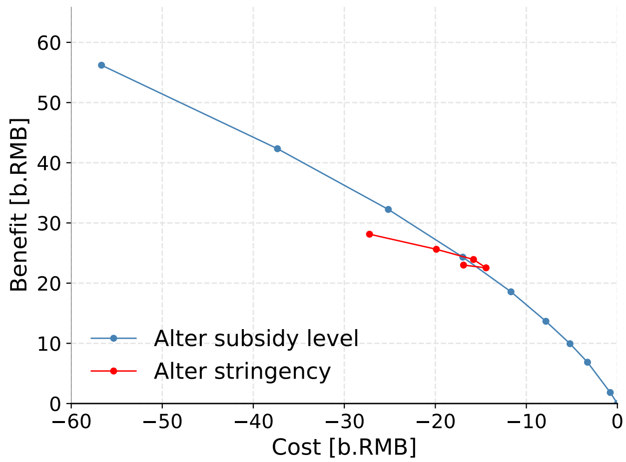
(a) Impact on total welfare [b.RMB]

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

(c) Impact on the reputation channel [%]

[77] 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. So we decided not to include this in the model.

Figure C.16: Pareto frontier of counterfactual policies



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

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, 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.

C.3 More counterfactual policies

Pareto frontier and alternative cost of public funds Figure C.16 plots the welfare outcome of all counterfactual policies 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.