The Tax Incidence and Distributional Effects of Electric Vehicle Subsidies in China

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Abstract

This study investigates the pass-through and distributional effects of electric vehicle (EV) subsidies in China. It evaluates how these effects affect market equilibrium and welfare. Empirical results indicate that EV subsidy pass-through to consumers is more than complete, disproportionately favoring high-income individuals. Additionally, we introduce an equitable subsidy model that prioritizes innovation while being progressive in the sense that it redistributes resources toward low-income households. A surprising finding is that this alternative scheme reduces consumer surplus, as producers exploit its progressive structure, transferring gains. Despite enhancing EV adoption and welfare (excluding externalities), the progressive design of subsidies transfers consumer surplus to producers.

Keywords: subsidy pass-through; regressive subsidy; welfare analysis

JEL Classification: H21, L13, C54, D63

1 Introduction

Automobiles are major contributors to global warming and regional air pollution because of their emissions (Parry et al., 2007; Adamou et al., 2014; Beresteanu and Li, 2011). As the largest carbon emitter and the largest passenger vehicle market, China has introduced many policies, including consumption taxes (Tan et al., 2019) and vehicle quota systems (VQS, Xiao et al., 2017) on fossil-fueled car purchases and subsidies on new-energy vehicles (Hu et al., 2023; Guo and Xiao, 2022), to reduce carbon emissions and mitigate the environmental problems caused by the rapid growth of car ownership in the country.

Subsidies have been widely adopted by many countries to incentivize the substitution of internal combustion engine vehicles (ICEVs) with electric vehicles (EVs), owing to the latter's clean-technology nature (Springel, 2021; Chandra et al., 2010; Guo and Xiao, 2022; Barwick et al., 2023; He et al., 2023). In particular, Li et al. (2022) document that more than half of EV sales can be attributed to consumer subsidies in China. Previous literature (e.g., Li et al., 2018; Guo and Xiao, 2022) suggests that the effectiveness of the subsidies depends on the substitutability between EVs and ICEVs. However, these studies have taken the subsidy scheme as exogenous, and the mechanisms behind the policy effectiveness have not been fully understood (He et al., 2023). In particular, the distributional effects and tax incidence of the subsidies, which play important roles in determining the subsidy effectiveness, have not been fully examined.

Tax incidence and distributional effects are essential in determining the effectiveness of the subsidies for two reasons. First, the incidence, or the pass-through of the subsidies to consumers from their points of view, determines *how much* consumers can get from the total subsidies. Subsidies may only be partially passed through to consumers because manufacturers are able to strategically respond and share a portion of the subsidies. This practice could seriously undermine the effectiveness of the subsidies on EV diffusion. Second, the subsidy distribution over income groups determines *who*, varying in their price sensitivities, can get more subsidies due to policy design. As most current subsidy systems are based on attributes of the vehicles (Barwick et al., 2023), the policy designs favor EVs with high-end features. Such EVs are usually more expensive and thus chosen by high-income consumers, making the system regressive in the sense that it redistributes resources towards high-income households.[1] Since consumers with high incomes are less sensitive to subsidies, the effectiveness of the subsidies is further weakened, challenging the optimality of the current system designs. The pass-through and progressivity of subsidies depend on socioeconomic

[1] In contrast to taxes, the progressivity or regressivity of subsidies is not clearly defined. In this study, we name the progressivity or regressivity of subsidies using the same principles applied to defining the progressivity or regressivity of taxes: If the scheme redistributes resources in favor of high-income households, it is considered regressive. We would like to express our gratitude to an anonymous reviewer and Lucas Davis from the University of California, Berkeley, for comments and suggestions on this definition.

factors such as income and the competition structure of the EV market, making their effects empirical questions.

This paper examines the pass-through and progressivity of the EV subsidies and their equilibrium and welfare implications in the Chinese passenger vehicle market. The Chinese government initiated attribute-based purchase subsidies on EVs in 2010 to promote the adoption of cleaner vehicles. The subsidy scheme grants larger amounts to vehicles with higher maximum travel distance, or driving range, to incentivize the adoption and development of high-tech EVs. We apply a structural model featuring both demand and supply sides of passenger vehicles to analyze the consumers' heterogeneous preferences and manufacturers' competition. Employing the micro-moments BLP identification methods (Berry et al., 1995; Petrin, 2002) and the city-level sales and buyer survey data of passenger vehicles during the years 2016–2019, we estimate the structural model. Further, using the estimated model, we conduct counterfactual analysis to study the pass-through of EV subsidies to consumers and the progressivity of subsidies in income.

Our empirical findings suggest that the EV subsidy scheme is regressive. Also, we find more than complete pass-through of EV subsidies: EV manufacturers pass 121.32% of the subsidies through to their consumers on average in the market for counterfactual analysis. Additionally, in response to different price sensitivities of consumers, the subsidy pass-through also varies across income groups: Consumers in high-income groups can receive higher pass-through, while those in low-income groups get lower pass-through. The finding that pass-through could exceed unity (subsidy overshifting) is not new. Previous literature (e.g., Pless and van Benthem, 2019) has documented pass-through rates as high as over 150%. Weyl and Fabinger (2013) suggest that over-shifting occurs under many familiar models of imperfect competition when demand is sufficiently convex. We provide both theoretical and intuitive explanations for our findings of subsidy overshifting.

Through simulations, we compare the current attribute-based subsidies with alternative subsidies that are based on attributes and also progressive (in income). As the progressive scheme reallocates the subsidy from high-income (less price-sensitive) consumers to low-income (more price-sensitive) consumers, the progressive scheme is expected to be more effective in promoting EV sales. However, our empirical findings are counterintuitive, suggesting that the opposite is true. This is due to manufacturers' strategic decisions on subsidy pass-through in the imperfect competition structure: The progressive scheme drives subsidies to price-sensitive consumers, increasing the overall price sensitivities of the subsidy recipients. Manufacturers do not need to pass as many subsidies as they do with the regressive scheme to get the same demand; consequently, lower subsidy pass-through leads to higher EV prices and lower EV adoption. As pricing decisions are strategic complements, ICEV prices also increase accordingly, driving up overall prices and leading to consumer losses. Intuitively, manufacturers can better exploit their market power with the progressive scheme, which generates a greater distortion, leading to higher welfare loss, compared with the regressive subsidy scheme. This finding also suggests that subsidy pass-through depends on the policy nature of income distribution.

This paper builds on and contributes to the literature in the following ways. First, it is the first study of the subsidy pass-through and its impact on EV adoption in China. Pass-through is an essential factor to be considered in studying the effectiveness of subsidies in imperfect competition. Previous literature on the Chinese EV market (e.g., Guo and Xiao, 2022; Hu et al., 2023; Barwick et al., 2023) has investigated the imperfect competition nature of this market, but insufficient attention has been paid to subsidy pass-through in it. In particular, Guo and Xiao (2022) document preliminary evidence on EV subsidy pass-through, but the driving mechanisms and more importantly the equilibrium and welfare implications of the pass-through were not analyzed. Muehlegger and Rapson (2022) study the subsidy pass-through, leveraging an exogenous variation in large EV subsidies in the US state of California. As individual transaction records are unavailable in the Chinese market, we propose a counterfactual analysis based on structural model estimation to examine the subsidy incidence.

Second, our empirical findings extend the previous works on the progressivity of subsidies and the implications of the distributional effects on policy efficiency. Muehlegger and Rapson (2022) and Borenstein and Davis (2016) suggest that the incentive programs designed to promote the adoption of "clean energy" investments, such as EVs, have gone predominantly to higher-income households in the United States because high-income households are more likely to adopt EVs and thus receive the majority of the incentives.[2] Other studies (Mian and Sufi, 2012; Li et al., 2013; Copeland and Kahn, 2013; Hoekstra et al., 2017) also suggest that incentive programs providing a stimulus toward vehicle ownership may provide it to the households that would have bought a new vehicle anyway, regardless of the subsidy. As households of different incomes have different price elasticities, the cost-effectiveness of subsidies could change significantly over different diffusion stages of innovations such as EVs; therefore, determining the distributional nature of subsidies is essential to discern the effectiveness of the policy. We examine the distributional effects of the EV subsidy and document the empirical evidence on the progressivity nature of the subsidy scheme effective during our sample period. Then, we evaluate its effectiveness in promoting EV adoption by comparing it to simulated progressive schemes and assessing their cost-effectiveness. The proposed progressive subsidy scheme is

[2] Borenstein and Davis (2016) find that the households in the top income quintile have received about 90% of all the tax credits offered to EV buyers.

essentially similar to the tax credit offered to EV consumers in the United States. Such empirical evidence on the impact of subsidy progressivity on the cost-effectiveness of the policy is rare in the literature.

Third, this paper contributes to the scant empirical studies on the relationship between progressivity and incidence of subsidies. Previous research acknowledges that these aspects are important concerns with public policy, including taxes and subsidies (Pless and van Benthem, 2019). However, most of these studies address either pass-through (e.g., Fabra and Reguant, 2014; Sallee, 2011; Ganapati et al., 2020; Kopczuk and Munroe, 2015) or demographic distribution of taxes/subsidies (Chandra et al., 2010; Hoekstra et al., 2017; Mian and Sufi, 2012; Copeland and Kahn, 2013; West, 2004; Jensen and Miller, 2011), while little light has been shed on the link between them. One exception is the study by Stolper (2021), who documents empirical evidence showing that the diesel tax is progressive since the tax pass-through is higher in wealthier regions. This paper provides empirical evidence of their causal relationship from the other direction, supporting the theory proposed by previous literature. Weyl and Fabinger (2013) prove that pass-through depends on both demand and supply elasticities in imperfect competition. Given that consumers are heterogeneous in their price sensitivity, the aggregate demand elasticity should depend on individual price sensitivity and demographic distribution. Therefore, given the income distribution, progressivity could be the *exogenous* reason behind the high pass-through of subsidies: When more subsidies are designed for high-income and low-elasticity consumers, the subsidized consumers' overall price sensitivity is low; consequently, the manufacturers will pass a large portion of the subsidies through to consumers to gain market shares from ICEVs. Our empirical findings support such a relationship between progressivity and pass-through: When the subsidy scheme is redesigned into a system progressive on incomes, the subsidies passed through to consumers become less.

Finally, this paper contributes to the emerging literature on the Chinese EV markets in two ways. First, it applies the micro-moment method proposed by Petrin (2002) to the EV buyer survey data. Previous studies on the Chinese ICEV market (e.g., Li, 2017) have applied the same identification approach, but to the best of our knowledge, no data from surveys on EV buyers have been used to identify the Berry et al. (1995) model with micro-moments. Petrin (2002) finds that the additional information from the micro-moments can significantly reduce the effect of "extreme-tastes" on both model identification and welfare estimation. Using a unique dataset from annual surveys on the EV buyers, we construct the micro-moments in addition to the Berry et al. (1995) moments, which are essential to generate a reliable prediction of counterfactual analysis. Compared with the previous studies on the same market without micro-moments (e.g., Guo and Xiao, 2022), our approach refined the identification of the price coefficient, especially the heterogeneous price sensitivities over different incomes. This is crucial for welfare analysis.

Second, this paper has important policy implications for policymakers in China as well as other countries. Previous studies on this policy (e.g., Guo and Xiao, 2022; Hu et al., 2023) have examined its impact on product adoption and social welfare, assuming the policy structure is exogenous. This paper investigates the mechanism of policy effectiveness by analyzing the pass-through and distributional effects of the policy and, more importantly, endeavors to design a more efficient policy. Through cost-effectiveness analysis, we compare the current regressive EV subsidies to alternative subsidy schemes and find that the current policy is actually more cost-effective because the manufacturers can strategically exploit the other designed progressive subsidies and further distort the price using their market power, resulting in an even lower consumer surplus. As the proposed alternative subsidy scheme is essentially the same as the tax credit program adopted by the United States, our findings imply that the attribute-based EV purchase subsidy could be more cost-effective than the US incentive program. The Chinese EV market is the largest globally, accommodating almost all leading car brands worldwide; therefore, our empirical analysis should be of interest to entrepreneurs and policymakers in many other countries.

The rest of the paper is organized as follows. Section 2 introduces the development of the EV market and the history of EV subsidy policies. Section 3 presents the data for our empirical analysis. Section 4 provides stylized facts about the pass-through and income distribution of EV subsidies. Section 5 specifies the empirical model. Section 6 reports the empirical findings from model estimation and counterfactual analysis. Finally, section 7 concludes the paper.

2 Industry Background and Policy

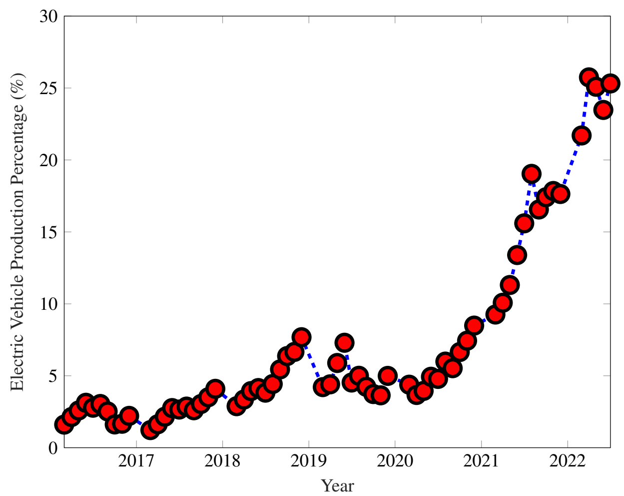
This section first presents the background of China's passenger vehicle industry, focusing on the recent development of EVs. It then discusses the incentive programs targeting the adoption of EVs in China, the United States, and European countries.

2.1 China's Passenger Vehicle Market

China is the largest passenger vehicle production and sales market globally.

The mass-market adoption of passenger vehicles started to take off in China in 2004 because of the continuous decline in vehicle prices and the increase in household incomes. The price drops were primarily driven by cost reductions through learning by doing and by intense competition among both domestic and foreign manufacturers (Li et al., 2015).

Figure 1: EVs as a Share of the Market 2016–2022



Data source: The China National Bureau of Statistics. Note: The figure shows the upward trend of EV output as a share of passenger vehicle market from 2016 to 2022. The red dots are the observed values.

Concurrent with the expansion of the auto industry, the environmental burden of fuel combustion became evident, making it critical for China to develop new energy vehicles. Since 1991, all Five-Year Plans have encouraged EV production. In 2001, China included the research and development of driving systems and motor batteries for pure electric vehicles, hybrid electric vehicles, and fuel cell vehicles into the National High-Tech R&D Program. The government has since then employed incentives to motivate the adoption and production of EVs (Section 2.2.1 introduces these policies in detail). Figure 1 illustrates the growth of China's EVs from 2016 to 2022.

2.2 Policy

This section introduces the current EV subsidy policy in China and then discusses subsidy policies in Europe and the United States. We use European and American policies as alternative incentive programs to the current Chinese subsidy for counterfactual analysis.

2.2.1 China

In 2009, the State Council initiated subsidies on EVs specialized for public services, such as public transportation, rentals, public service, sanitation, and postal services, in 13 cities of China.[3] The subsidies are from two sources and serve different purposes: The central government subsidizes the purchase of EVs, and the local governments subsidize the construction and maintenance of EV-supporting infrastructure. In 2010,

[3]These cities include Beijing, Shanghai, Chongqing, Changchun, Dalian, Hangzhou, Jinan, Wuhan, Shenzhen, Hefei, Changsha, Kunming, and Nanchang.

China started a three-year test of subsidizing individual purchases of EVs in five cities. The selected cities were supposed to offer additional local government subsidies and establish supporting infrastructure, such as charging stations. The subsidized vehicles had to comply with the standards for technical features such as battery mass-energy density and maximum travel distance (range). The central government would cut subventions once a manufacturer's EV sales volume reached 50,000.

The Financial Subsidy Policy for the Promotion and Application of New Energy Vehicles took effect from 2012 until 2020. This national subsidy program aimed to relieve energy and environmental pressure and, more importantly, to develop the auto industry. EVs can be beneficial in protecting the environment by utilizing "cleaner" fuel, which reduces the emission of pollutants. As a consequence, the subsidies contributed to more than half of EV sales between 2015 and 2018 (Li et al., 2022).

The consumer-targeted subsidies are first paid to manufacturers and then passed through to the consumers. Automakers set the manufacturer suggested retail price (MSRP), factoring in the subsidies. After a sale, they collect the subsidy from the government. This payment arrangement leaves the manufacturers an opportunity to take advantage of their market power to skim part of the subsidies, leading to incomplete pass-through.

The subsidy scheme is attribute-based (Barwick et al., 2023), depending on the EVs' ranges: EVs that allow longer travel distances qualify for more subsidies, given that EVs with a higher range are more likely to substitute for ICEVs and contribute more to environment. Table 1 presents the attribute-based incentives on EV purchases from 2013 to 2019. Over time, the range standards increase, while the subsidies decrease significantly for all range levels. For example, during the period of 2013–2015, EVs with ranges of more than 80 kilometers are eligible for subsidies; after June 2019, however, only EVs with ranges of more than 250 kilometers are eligible for subsidies. In terms of subsidy amounts, EVs with ranges over 400 kilometers could receive a subsidy of RMB 60,000 in 2013, while the same vehicles can only be subsidized RMB 18,000 in 2019 (i.e., less than a third of the 2013 level).

The side effect of this attribute-based design is that subsidies go to high-income households because these households are better able to afford high-quality EVs, raising equality concerns. Moreover, high-income consumers are less price-sensitive; therefore, the subsidies could become less cost-effective in promoting EV sales.

Table 1: Subsidies on EVs from the Central Government (in RMB)

	$\leq$ 80 km	$\leq$100 km	$\leq$ 150 km	$\leq$ 200 km	$\leq$ 250 km	$\leq$300 km	$\leq$400 km
January 2013	35,000	35,000	50,000	50,000	60,000	60,000	60,000
January 2014	32,500	32,500	47,500	47,500	57,000	57,000	57,000
January 2015	31,500	31,500	45,000	45,000	54,000	54,000	54,000
January 2016		25,000	45,000	45,000	55,000	55,000	55,000
January 2017		20,000	36,000	36,000	44,000	44,000	44,000
June 2018			15,000	24,000	34,000	45,000	50,000
June 2019					18,000	18,000	25,000

Notes: The table summarizes the subsidies paid by the central government from 2013 to 2019. The first row is the minimum required range for the subsidy; subsidies are not cumulative. The first column is the starting date for the subsidy.

2.2.2 The United States

The United States provides incentives for the adoption of new-energy vehicles through tax credits. Following the Energy Improvement and Extension Act of 2008, the US government granted EV consumers tax credits up to $7,500 based on vehicle weight and battery capacity (Section 205 of the Act). The credit is nonrefundable; it can lower EV buyers' tax bills to zero, but it does not result in a refund. Therefore, high-income households can benefit more from these credits than low-income households. Effective as of January 2023, the policy sets limits on the adjusted gross income that taxpayers can make in order to qualify for the credits. This income cap precludes high-income households from the credits, making the tax credit mechanism a progressive subsidy.

In 2009, the Obama administration passed the American Recovery and Reinvestment Act and granted over US$2.7 billion in subsidies to battery producers and for the development of electric technologies and government EV procurement.

2.2.3 European Nations

European nations also subsidize EV purchases. Table 2 below summarizes the subsidies in Germany, France, the Netherlands, the United Kingdom, and Greece from 2019 to 2021.

Although some of these European nations started to gradually cut subsidies in 2021, most nations have been raising their subsidies on EVs since 2019. This upward trend of EV subsidies is very different from the trend in China.

Another salient feature of these subsidy programs is that most nations grant more subsidies to less-expensive vehicles. As high-income households are more likely to choose expensive cars, the European subsidy programs are designed to be progressive. This approach may explain the high adoption rates in general in

Table 2: Subsidies on EV in Selected European Nations 2019–2021

Country	Price[a]	Subsidy[a]		
		2019	Jan 2020 – May 2020	June 2020 – December 2021
Germany	<40,000	4,000	6,000	9,000
	40,000–65,000	4,000	5,000	7,500
France	<45,000	-	6,000	7,000
	45,000–60,000	-	3,000	3,000
Netherlands	12,000–45,000	-	-	4,000
U.K.	<50,000	3,500	3,000	3,000
Greece			15% of price	

[a] The unit of currency is the pound for the United Kingdom and Euro for the other nations.

European nations (battery EVs and plug-in hybrid EVs accounted for around 18% of new vehicle sales in 2021), compared with the United States (around 5% to 7% of new vehicle sales).

Considering the progressive nature of the European subsidy schemes and the tax credit system in the United States, we design alternative subsidy policies to the current attribute-based subsidies in China for counterfactual analysis and compare their cost-effectiveness.

3 Data

Our data primarily consist of passenger vehicle sales, income distribution of potential buyers and the vehicle buyers' incomes obtained from survey.

3.1 Sales Data

The sales data cover the product-city-level monthly sales of 13 cities in China from 2016 to 2019. The product information is at the trim level, including sales, MSRP, vehicle body type (SUV or sedan), fuel type (gasoline, diesel, electricity, or hybrid), transmission type (auto or manual), weight, power, fuel consumption, length, width, and height. The trim levels for a vehicle refer to different versions of the model. Each trim level has different features, with the higher trim levels offering more equipment. We define a product model as all trim-level model variants with the same model name and specifications of the key features that are no more than 1% higher than those of the base models with the same name.[4] We aggregate the sales over all product variants into the model level, taking the sales-weighted mean of the key features as the measure of the feature variables of the products.

[4]The key features used for our definition include body type, transmission type, fuel type, weight, power, fuel consumption, length, width, and height.

Sales are approximated by the number of subscribed compulsory vehicle insurance policies. In 2006, China launched the Regulation on Compulsory Traffic Accident Liability Insurance (CTALI) for Motor Vehicles, specifying that the administrative department of motor vehicles will not register motor vehicles lacking compulsory motor vehicle liability insurance. Since all vehicles on the road must have a registered license, this regulation means that new vehicle owners have to buy CTALI when they purchase their vehicle, making the sales of CTALI a perfect proxy for sales.[5] Sales are converted to market shares using the city population as the market size. The population data are obtained from the City Statistical Yearbook of China (2017–2020). The summary statistics are listed in Table 3.

Vehicle features and MSRP are collected from Autohome Inc., an online auto information platform. Weight is measured in kilograms and is positively correlated with safety. Size is calculated as the product of width and length in meters. Larger vehicles can provide more space and are thus more comfortable for the passengers. The other features, such as power and fuel consumption, are widely used in the literature (Berry et al., 1995; Li, 2017) as the essential product characteristics that determine consumers' choices. Information about manufacturers and brands, such as the location of their headquarters, is readily available. Using this information, we constructed binary variables measuring their fixed effects and indicating their local status.[6] Other binary variables indicating whether a vehicle is an SUV (= 1 if yes; 0 otherwise), has automatic transmission (AT = 1, if yes; = 0, otherwise), and is imported (import = 1, if yes; = 0, otherwise), are also constructed using the collected categorical data.

Fuel economy is a key product characteristic, but its measurement differs significantly between ICEVs and EVs. Therefore, we convert the fuel economy into operation costs measured by fuel costs per 100-kilometer drive. For ICEVs, the operation costs are determined by vehicle fuel consumption per 100 kilometers and the retail prices of gasoline in each market. The half-month average gasoline retail prices (over stations) of the dominant gasoline retailers, China Petroleum & Chemical Corporation (or Sinopec) and PetroChina Company Limited, are collected for the selected cities. We take the average of the retail prices of gasoline with an octane rating of 92 (or so-called 92 octane gasoline) over these two companies for each city and month and use it as the city-level monthly gasoline price to calculate the operation costs for ICEVs. For EVs, the operation costs are calculated using the electricity consumption per 100 kilometers and the average of the electricity prices for peak and off-peak use, which are collected from the national grid of each city.

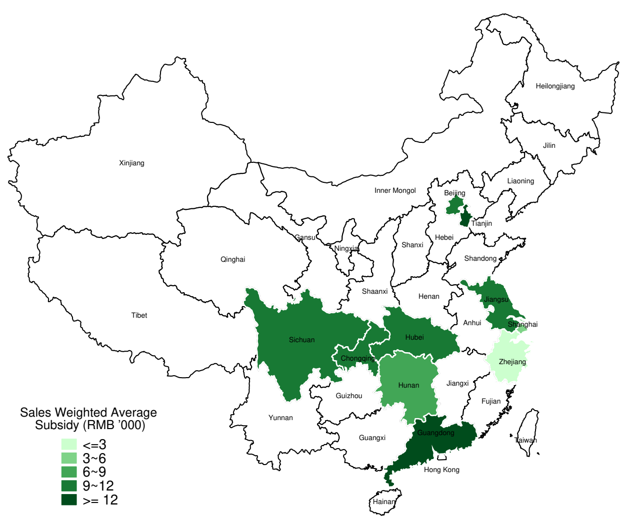
[5] Guo and Xiao (2022) discuss the advantage of CTALI as a proxy for sales over the other measures such as local registration.

[6] Barwick et al. (2021) find that local governments conduct protective policies such as providing extra subsidies for local brands so that local manufacturers can have considerably higher sales in their headquarters provinces than in other provinces. Additionally, local residents may have an innate affinity for local brands because it is simpler to get replacement parts or services.

Some cities, such as Beijing, Tianjin, and Shenzhen in our sample, impose a new vehicle quota, which is rationed by auction or lottery. Hu et al. (2022) provide both theoretical and empirical evidence proving that both rationing mechanisms add opportunity costs to the ownership and therefore influence consumers' choices over vehicles. To take such effects into account, we collect the average monthly winning bids of the auction or winning odds of the lottery from the official websites of cities with the quota being rationed through auction or lottery, respectively. The winning bids directly increase vehicle ownership costs, while the winning odds, or the ratios of the quota to the number of lottery participants, measure the hardship of acquiring a quota for ICEVs, affecting the intrinsic preference for vehicles.

Purchase subsidy and sales tax exemption are two other factors determining the ownership costs of EVs. Purchase tax is levied on the ICEV consumers but EV consumers are exempt from this tax from September 2014 onward. At the same time, purchase subsidies are granted to EV consumers by both central and local governments. The subsidies from the central government are uniform across provinces, but local subsidies are quite different across regions. We collect the subsidy and tax data from the central and local governments' websites. Figure 2 shows the sales-weighted average local subsidy in provinces, where the sample cities are located, in 2019. The cross-sectional variation in subsidies is a unique feature of our data that contributes to the model identification. The sales data are aggregated into product-city-half-year levels

Figure 2: Sales-weighted Average Local Subsidy



Note: The figure shows subsidies from local governments in 2019. Provinces in the areas without color on the map are not included in the sample.

by taking the average of products' monthly sales in a city over each half-year.[7] Table 3 summarizes the statistics of the key variables for our analysis. The EV observations account for 3% of the total.

[7]The observations could be unbalanced due to entry and exits in each half year; therefore, the average rather than the summation is more comparable across observations.

Table 3: Summary Statistics of Variables [a]

Variable	Observation	Mean	Std. Dev.	Min	Max
Sales	87,687	211.85	433.65	10.00	16,157.00
MSRP (RMB ’000)	87,687	175.52	123.79	33.80	798.00
Horsepower (kilowatt)	87,687	116.51	35.98	40.00	487.00
Operation costs (RMB/100 km)	87,687	42.94	9.77	6.20	69.51
Weight (kg)	87,687	1.49	0.26	0.99	3.40
Size (m^2)	87,687	8.37	0.69	4.38	10.54
Subsidy (RMB ’000) [b]	87,687	1.26	8.66	0.00	115.00
Quota odds (%)	87,687	0.54	0.49	0.00	1.00
Local brand [c]	87,687	0.09	0.29	0.00	1.00
Imported vehicles	87,687	0.06	0.24	0.00	1.00
Automatic transmission	87,687	0.59	0.49	0.00	1.00
EV	87,687	0.03	0.16	0.00	1.00
Dummies for quota	87,687	0.46	0.50	0.00	1.00
SUV	87,687	0.46	0.50	0.00	1.00

[a] The sales data cover 13 cities in 10 provinces, including Shanghai, Dongguan, Foshan, Beijing, Nanjing, Tianjin, Guangzhou, Chengdu, Hangzhou, Wuhan, Shenzhen, Chongqing, and Changsha. The sample period is 2016–2019.

[b] Both local and central subsidies are included in subsidies.

[c] The dummy variables *local brand, imported vehicles, automatic transmission, EV, quota*, and *SUV* are equal to one when the variable names indicate the status of the observations.

3.2 Income Data

Two types of income data are used for model identification: the average incomes of residents in subordinate administrative districts of the sample cities and the average incomes of sample vehicle buyers in each sample city.

3.2.1 Average Incomes of Residents by District

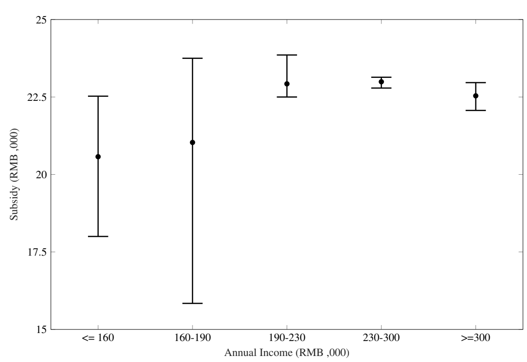
Consumer income is the key factor that determines vehicle choices. As household income is unobservable in our sample, we have to simulate the individuals’ income, employing the estimated income distribution. To estimate the city-level income distribution by applying the methodology specified in Appendix A, we collect the average incomes of residents in the city-governed districts from the China City Statistical Yearbook (2017–2020). We use individual disposal incomes for this variable.

3.2.2 Buyers' Income

The buyers' incomes are collected by CVSC-TNS Research (CTR)[8]. CTR conducts the survey on passenger vehicle buyers both online and offline in 61 cities of 30 provinces or municipalities from 2016 to 2019. The survey data cover 760 vehicle models from 60 manufacturers, including most Chinese manufacturers and the international manufacturers of the primary imported brands. The survey data provide the average monthly individual incomes of each sample vehicle model in each year.

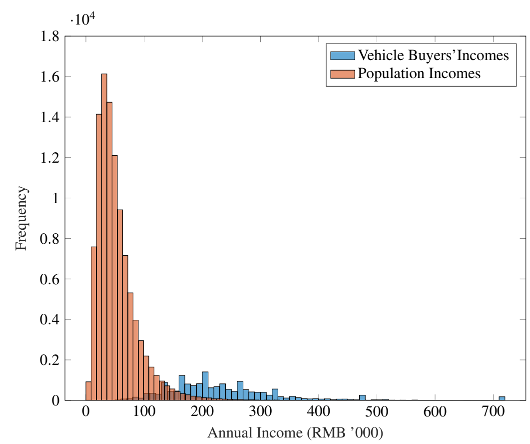
Using the subsidies on various EVs and the surveyed income data, we plot the subsidies on EV buyers by income groups in Figure 3. Although low-income buyers' subsidies disperse, the average subsidies received are in general regressive on incomes.

Figure 3: Subsidy Distribution Based on Income



Note: The figure shows subsidies from the central government and the annual income of car consumers in 2020. The subsidies are aggregated to consumers with similar incomes. The top and bottom borders of the line are the minimum and maximum subsidies. The black dot in each box is the mean.

Figure 4: Population Income Distribution (Simulated) and Buyer Income Distribution (Surveyed) Distribution



Note: The population incomes are drawn from estimated log-normal distributions with market-year-specific parameters. The vehicle buyers' income distribution is based on the surveyed vehicle-level buyers' average incomes, which are also market-year specific.

Figure 4 plots the distributions of the simulated incomes (of all potential consumers) and the surveyed average incomes (of the actual buyers). The income distribution of EV buyers lies to the right of that of the city population, suggesting that vehicle buyers include a disproportionately larger share of households in high-income groups. A well-identified model should take this difference into account.

[8] CTR (http://www.ctrchina.cn) is a joint venture of China International Television Corporation and Kantar Group, a data analytics and brand consulting company based in England, established in 1995. CTR has a million-level sampling pool that covers 500 cities in China, covering residents who are 15–69 years old. CTR adopts a probability-proportional-to-size sampling methodology based on household addresses. Each sample is validated and reviewed by re-interview or call. CTR receives a national certificate from the China Market Information Research Association and the China Information Association Market Research Branch and complies with the ISO20252 market research international standard.

4 Stylized Facts from Reduced-from Analyses

We first examine the subsidy pass-through and income distribution through reduced-form analyses of the correlation between EV subsidies and their final prices (subsidy inclusive) and the association of buyers' income and the central-government subsidies they finally received.

4.1 Evidence on Subsidy Pass-through from Hedonic Regression

For the analysis of subsidy pass-through, we apply a hedonic pricing model to the EV models. The hedonic regression decomposes a product into its constituent characteristics and obtains estimates of the contributory value for each. We can apply this approach to the EV models and estimate the values of car features. As the MSRP is subsidy-inclusive, manufacturers' MSRP decisions will respond to subsidies. Therefore, we also include the subsidies into the hedonic regression. The contribution of subsidies to MSRP could be used to examine the subsidy pass-through to MSRP. A manufacturer can determine the subsidy pass-through, so it is possible that MSRP could over-respond (under-respond) to subsidies if a one-unit increase in subsidy causes more (less) than a one-unit increase in MSRP.

As MSRP is usually constant for a model, we do not observe the response of MSRP to the variation in subsidies over time. We assume that manufacturers have complete information on the expected changes in subsidies from the central government since the government has made that clear in their industry policy. Therefore, MSRP could be set based on expected subsidies. An EV model subject to low subsidies should have a higher MSRP than a model with high subsidies if the manufacturers apply the same pass-through rates. Therefore, the variation in MSRPs of models introduced to the market at periods of different subsidies enables us to identify the correlation between subsidies and MSRPs.

Table 4a presents the results from the hedonic regression of logarithmic MSRPs on the ratio of subsidies to MSRPs. These results yield an interesting insight: there could be an overshifting of subsidies to the consumers. Our results suggest that when the subsidy-MSRP ratio increases by 1%, the MSRP decreases by about 2.26%, implying that manufacturers cut their prices more than the subsidies they received.

Some confounding factors may bias the estimates. For instance, the market structure and so the markup could have been changing over time; or, the pass-through rates are different over time. The simple reduced-form analysis could not discern the effects of these factors on the subsidy pass-through.

Table 4a: Stylized Facts of Subsidy Pass-through from Hedonic Pricing Analysis

	log(MSRP)
Subsidy-MSRP ratio[a]	-2.262***[b]
	(0.191)
log(Power)	0.0666
	(0.060)
log(Energy consumption) [c]	-0.571***
	(0.137)
log(Weight)	1.196***
	(0.187)
log(Size)	-0.0270
	(0.208)
SUV	0.0149
	(0.028)
Constant	4.006***
	(0.596)
Observations[d]	271

[a] Only central subsidies are used for the ratio calculation. As central subsidies do not vary across cities but vary over time, we take the average of the model-level subsidies over the sample period and then calculate the ratio of the expected subsidies to MSRP for each model.

[b] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[c] Energy consumption measures the electricity consumed for a given travel distance. The unit is Kilowatt-hours per 100 kilometers.

[d] The sample only includes EVs. The observations are at the model level. Brand and time fixed effects are controlled.

4.2 Evidence on Income Distribution of EV Subsidies

We investigate income distribution of EV subsidies by looking into the survey data of EV buyers.

For each car model, the buyers' average income is collected through survey. Hence, a one-to-one mapping between buyer average income and the central subsidy could be constructed. We regress the subsidies on incomes, controlling for the time and city fixed effects, to analyze the income distribution of subsidies.

Table 4b presents the results from this reduced-form analysis. The coefficient of income is positive and statistically positive, suggesting that when consumers' income increases by RMB 1,000, they buy cars with subsidies of RMB 198 more than before.

Similar to the stylized fact analysis of the subsidy pass-through, we also acknowledge that the results in Table 4b could also be biased by confounding factors. The next section builds on these insights by proposing a structural model of the partial equilibrium of the auto market. Applying this model, we can conduct counterfactual analysis to estimate both pass-through and income distribution of the EV subsidies, controlling for the confounding factors.

Table 4b: Stylized Facts about the Correlation between Subsidies and Individual Incomes

	Central Subsidy[a]
Buyer income (Thousand)	0.198***[b]
	(0.006)
Constant	31.142***
	(0.030)
Observations[c]	2416

[a] The central subsidy received by an EV model is measured in RMB 1,000.
[b] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[c] Only EV models are included. The observations are at EV model level. City×Time fixed effects are controlled to capture the regional and time variation in consumers' preference over vehicles.

5 Methodology

We apply the structural model proposed by Berry et al. (1995) to investigate the pass-through and distributional effects of the EV subsidies in China. This analytical framework features a random coefficient discrete choice model on the demand side and a Bertrand competition model on the supply side, which can capture the strategic interaction among automakers in this market.

5.1 Demand Side

In each market, consumers select products from a choice set to maximize their utility. In alignment with our data, each city is defined as an isolated market; therefore, consumers can only choose products available in the city where they reside. Assume the indirect utility of consumer i getting from product j in market m at time t is given by

$$u_{ijmt} = \alpha_i ln(p^o_{jmt}) + \mathbf{X}_{jmt}\beta_i + \xi_{jmt} + \varepsilon_{ijmt} \tag{1}$$

where p^o_{jmt} is the ownership cost of product j, factoring in subsidies, quota costs, and taxes, or specifically, $p^o_{jmt} = p^s_{jmt} - sb_{jmt} + \tau^c_{mt} + \tau^T_{jmt}$, where p^s_{jmt} is the manufacturer's price, sb_{jmt} is the subsidy for j, τ^c_{mt} is the quota cost, and τ^T_{jmt} is the sales tax. This cost varies across markets and over time since some of these price-driving factors, including subsidies, are market-time specific. The price coefficient α_i measures the marginal utility of ownership costs, and it varies across individuals owing to heterogeneous preferences. Specifically, we parameterize α_i as follows:

$$\alpha_i = \alpha_0 + \alpha_y y_i + v_i \sigma_\alpha$$

where α_0 is consumers' mean preference for ownership cost. y_i is the annual income of consumer i. The coefficient α_y measures the impact of income on the consumer's price sensitivity, and v_i captures the unobserved individual characteristics that affect the consumer's price preference. Accordingly, σ_α measures the variation in consumers' unobserved price preferences.

The vector $\mathbf{X}_{jmt}$ consists of entries of product characteristics and fixed effects that capture the impact of brands, markets, and time. The observed vehicle characteristics include the weight, horsepower,size, and operation cost. All these variables are expressed in logarithmic terms. For the kth characteristic, the corresponding parameter $\beta_{i,k}$ measures consumer i's preferences over this characteristic, and it can be decomposed into two parts: the mean preference to the kth feature and individuals' deviation from the mean level. Specifically, we have $\beta_{i,k} = \beta_k + v^k_{imt}\sigma_k$, where β_k is the mean preference to characteristic k, which is invariant across consumers, and v^k_{imt} is consumer i 's idiosyncratic preference for product characteristic k and is assumed to follow a standard normal distribution. σ_k is the variance in idiosyncratic preferences for product characteristic k. Vehicle characteristics unobserved in the data may also affect the consumers' utility. We denote such characteristics using ξ_{jmt} and assume that the unobserved characteristics are mean independent of the observed characteristics; that is, $\mathbf{E}(\xi_{jmt}|\mathbf{X}_{jmt}) = 0$. Taking these specifications into account, we can rearrange equation 1 into the following:

$$u_{ijmt} = \delta_{jmt} + (\alpha_y y_i + v_i\sigma_\alpha)ln(p^o_{jmt}) + \sum_k \sigma^k x^k_{jmt} v^k_{imt} + \varepsilon_{ijmt}$$

where $\delta_{jmt} = \alpha_0 ln(p^o_{jmt}) + \mathbf{X}_{jmt}\beta + \xi_{jmt}$ is the mean utility from product j.

If a consumer chooses to buy a vehicle that is not included in our data (e.g., a used car) or chooses not to buy at all, we assume that the consumer chooses the outside option. For identification purposes, we normalize the feature values of this outside option to zero. Consumers may be heterogeneous in their preference for this outside option, so we specify the utility of the outside option as follows:

$$u_{i0mt} = \sigma_0 v^k_{i0} + \varepsilon_{i0mt}$$

where v^k_{i0} is consumers' heterogeneous intrinsic preference for the outside goods, and σ_0 measures the variation in this preference.

The last term ε_{ijmt} is the consumer's idiosyncratic taste, which is assumed to be an independent and identically distributed variable following type I extreme value distribution. Following this assumption, the market share of product j is given by

$$s_{jmt}(p^o, \mathbf{X}, \xi; \theta) = \int\int_{A_{jmt}} \frac{e^{\delta_{jmt} + (\alpha_y y_i + v_i \sigma_\alpha) ln(p^o_{jmt}) + \sum_k \sigma^k x^k_{jmt} v^k_{imt}}}{1 + \sum_{g=1}^{J} e^{\delta_{gmt} + (\alpha_y y_i + v_i \sigma_\alpha) ln(p^o_{gmt}) + \sum_k \sigma^k x^k_{gmt} v^k_{imt}}} dv dy \tag{2}$$

where $\theta = (\alpha, \beta, \sigma)$ is a vector of parameters in the utility function. A_{jmt} is the set of heterogeneous characteristics of consumers whose optimal choice is product j. Formally, it is defined as $A_{jmt} = \{(v_i, y_i) : u_{ijmt}(p_j, x_j, \xi_j, v_i, y_i; \theta) \geq u_{igmt}(p_g, x_g, \xi_g, v_i, y_i; \theta), \text{ for } g = 0, 1, ..., J_{mt}\}$. The integrand in equation 2 is the purchase incidence of product j for consumer i. By integrating the individual purchase incidence over consumers whose optimal choice is product j, $s_{jmt}(p^o, \mathbf{X}, \xi, \theta)$ is the aggregate market share of product j.

5.2 Supply Side

The auto manufacturers of multiple products compete via pricing to maximize their profits. In each market at a time, manufacturer f decides on the prices p^s for all their products in the set V_f, which solves the following profit maximization problem:

$$\max_{p^s_{j\in V_f}} \pi_f = \sum_{j \in V_f} (p^s_{jmt} - mc_{jmt})(M s_{jmt}(p, x, \xi; \theta))$$

where $p^s_{j\in V_f}$ is the tax-exclusive price received by manufacturer f on any product j in their product set V_f. Manufacturers make their optimal price choices simultaneously. M is the market size, measuring the aggregate demand of a market. mc_{jmt} is the marginal cost of product j in market m at time t.

The equilibrium prices $\mathbf{P}^s$ should satisfy the following first-order conditions in each market and period:

$$s_{jmt}(p^o, \mathbf{X}, \xi; \theta) + \sum_{r \in V_f} (p^s_{rmt} - mc_{rmt}) \frac{\partial s_{rmt}(p^o, \mathbf{X}, \xi, \theta)}{\partial p^s_{jmt}} = 0 \tag{3}$$

Intuitively, when a manufacturer increases the price of product j by 1, their revenue increases by s_{jmt}. However, the increased price leads to a decline in demand for product j by $\frac{\partial s_{jmt}(p^o, \mathbf{X}, \xi, \theta)}{\partial p^s_{jmt}}$, which results in a profit loss of $(p^s_{jmt} - mc_{jmt})\frac{\partial s_{jmt}(p^o, \mathbf{X}, \xi, \theta)}{\partial p^s_{jmt}}$. Moreover, the change in price will also affect the demand and thus the profits of the other products of the same manufacturer by $\sum_{r \in V_f, r \neq j}(p^s_{rmt} - mc_{rmt})\frac{\partial s_{rmt}(p^o, \mathbf{X}, \xi, \theta)}{\partial p^s_{jmt}}$. Therefore, the first-order condition (equation 3) shows that the benefits and costs from this price change should be equal in equilibrium.

To derive the explicit form of the costs, we write the first-order condition in the matrix as follows:

$$MC = \mathbf{P}^s + (D_{p^s} .* I)^{-1} \mathbf{S} \tag{4}$$

where **S** is the vector of market shares of products in the market. D_ps. is the partial derivative matrix of market shares with respect to prices given by

$$D_{p^s} = \begin{bmatrix} \frac{\partial s_1}{\partial p_1^s} & \cdots & \frac{\partial s_J}{\partial p_1^s} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial p_J^s} & \cdots & \frac{\partial s_J}{\partial p_J^s} \end{bmatrix}$$

and I is the ownership matrix expressed as

$$I_{jr} = \begin{cases} 1 & \text{if } j \in V_f \text{ and } r \in V_f \\ 0 & \text{otherwise} \end{cases}$$

5.3 Model Estimation

We estimate the parameters in the demand-side model by applying the generalized methods of moments (GMM) with micro-moments proposed by Petrin (2002), which is developed from GMM estimation strategy of Berry et al. (1995).

The GMM micro-moments estimator minimizes the following objective function:

$$\min_{\theta} G'(\theta) W^{-1} G(\theta)$$

where $G(\theta)$ consists of moment conditions, and W is the matrix assigning weights to the multiple moments. $G(\theta)$ consists of two sets of moments. The first set of traditional moment conditions is based on the assumption of exogeneity of the unobserved car features conditional on the observed features, while the second set of micro-moments is based on the Bayesian average of buyers' incomes for each vehicle.

The exogeneity of the unobserved car features is formalized as follows:

$$E(\xi_{jt}(\theta)|Z_{jt}) = 0$$

where Z_{jt} includes the independent variables measuring the car features and the fixed effects driving consumers' utility. The parameters of the car features could be identified using this set of moments; however, the price coefficients could not be identified because of the endogeneity problem with price since the unobserved characteristics determine the prices. Instrumental variables (IVs) are needed for identification. We discuss this in section 5.4.

The second-moment condition is built based on the summary statistics of household incomes conditional on vehicle purchases. Applying the Bayesian rule to individuals' purchase incidence in equation 2, we can predict the buyers' average incomes. The micro-moments match these predicted conditional average incomes to the surveyed average incomes for car buyers. In particular, we have the following micro-moment condition for car j at time t.

$$E(\hat{y}_{jt} - \bar{y}_{jt}|Z_{jt}) = 0$$

where $\bar{y}_{jt}$ is the observed average income of buyers of vehicle model j, and $\hat{y}_{jt}$ is the predicted average income using the Bayesian rule as follows:

$$\hat{y}_{jt} = \sum_i y_i Pr(y_i|A_j) = \sum_i y_i \frac{Pr(A_j|y_i) \times Pr(y_i)}{Pr(A_j)} = \sum_i^{ns} \frac{s_{ijt} y_{it}}{\sum_i s_{ijt}} \tag{5}$$

where A_j is the set of heterogeneous characteristics of consumers whose optimal choice is product j as defined in equation 2. The first equality is the application of the Bayesian rule, while the second equality holds for two reasons. First, the probability of purchasing j conditional on the consumer income y_i is the same as s_{ijt}, while the unconditional probability of choosing product j is the market share of j, or $Pr(A_j) = s_{jt}$. Second, the integration in equation 2 is practically calculated in the following numeric way:

$$s_{jt} = \frac{1}{ns} \sum_{n=1}^{ns} s_{ijt} = \frac{1}{ns} \sum_{n=1}^{ns} \frac{e^{\delta_{jt} + (\alpha_y y_i + v_i \sigma_\alpha) ln(p_{jt}^o) + \sum_k \sigma^k x_{jt}^k v_{it}^k}}{1 + \sum_{g=1}^{J} e^{\delta_{gt} + (\alpha_y y_i + v_i \sigma_\alpha) ln(p_{gt}^o) + \sum_k \sigma^k x_{gt}^k v_{it}^k}} \tag{6}$$

where ns is the number of random draws of incomes y_i and idiosyncratic taste v_i from their respective distributions. Therefore, the density of each type of consumer, $Pr(y_i)$, is the inverse of ns, or $Pr(y_i) = \frac{1}{ns}$. Intuitively, $\frac{s_{ijt}}{\sum_i s_{ijt}}$ is the density of income type i among all the buyers of product j, and thus, equation 5 means that $\hat{y}_{jt}$ is the sales-weighted average of vehicle j buyers' incomes, which is supposed to match the surveyed average incomes, justifying the micro-moment conditions. According to Petrin (2002), these micro-moments can significantly improve model estimation.

These two sets of moment conditions are stacked as follows:

$$G(\theta) = \begin{bmatrix} \frac{1}{N} \sum z'_{jt} \xi_{jt}(\theta) \\ \frac{1}{N_1} \sum z'_{jt} (\hat{y}_{jt}(\theta) - \bar{y}_{jt}) \end{bmatrix}$$

where N is the number of all observations, and $N_1 \subset N$ is the number of observations with income data.

We follow the standard two-step GMM estimation approach (Hansen, 1982). In the first step, we compute a preliminary, consistent estimator based on the prespecified weighting matrix $W = Z'Z$. Using the estimates, we compute a consistent estimator for the covariance matrix of the stacked moment conditions and use its inverse as the optimal weighting matrix. Specifically, denoting the first-step estimator to be $\hat{\theta}_1$, the optimal weighting matrix is given by

$$\hat{W} = \begin{bmatrix} \frac{1}{N}\sum(z'_{jt}\xi_{jt}(\hat{\theta}_1))'(z'_{jt}\xi_{jt}(\hat{\theta}_1)) & 0 \\ 0 & \frac{1}{N_1}\sum[z'_{jt}(\hat{y}_{jt}(\hat{\theta}_1)-\bar{y}_{jt})]'[z'_{jt}(\hat{y}_{jt}(\hat{\theta}_1)-\bar{y}_{jt})] \end{bmatrix}$$

The two-step GMM estimator is computed as

$$\theta_{GMM} = arg\min_{\theta} G'(\theta)\hat{W}^{-1}G(\theta) \tag{7}$$

We adopt the identification strategy proposed by Berry et al. (1995) to estimate the parameters. Specifically, we first make $ns = 2,000$ random draws of (v_i, y_i). Starting with an initial set of random coefficients, $\hat{\sigma}_0$, we estimate the mean utility δ using the contraction mapping method. Given (v_i, y_i) and $\hat{\sigma}_0$, the only unknowns in equation 6 are δ. The contraction mapping approach starts with initial values of δ_0,[9] and then δ values are updated using the path $\delta^{t+1} = \delta^t + log(s^o_{jmt} - log(s_{jmt}(p^o, \mathbf{X}, \xi; \hat{\theta})$, where s^o_{jmt} is the observed market share. The iteration process stops when the difference between δ^{t+1} and δ^t is below the preset tolerance level 10^{-13}. The estimated mean utility δ, conditional on σ, is used to calculate the stacked moment conditions. For each set of σ, the GMM estimator of the parameters in the mean utility should solve the optimization problem as specified in equation 7. Finally, we search σ values that minimize the objective function in (7).

5.4 Instrumental Variables

The endogeneity issue with price arises because of its correlation with the unobserved product characteristics ξ_{jmt}. We need IVs to identify the price coefficients. Following Berry et al. (1995), we use three sets of IVs.

The first set of IVs consists of the exogenous product features and fixed effects in the utility function 1. The second set of IVs stems from the first set, including the sum of the exogenous characteristics (including fuel economy, size, weight, and horsepower) of the other products by the same manufacturer, and the sum of these exogenous characteristics over products of the rival manufacturers. The sum of these key features measures the aggregate qualities of cars made by the manufacturers themselves and their rivals, which determines the product prices and so satisfies the relevance condition. At the same time, as the unobserved

[9] These initial values are estimated from a simplified regression $log(s_{jmt}) - log(s_{omt}) = \alpha ln(p^o_{jmt}) + \mathbf{X}_{jmt}\beta_i + \xi_{jmt}$, where s_{omt} is the market share of outside option. This regression equation could be derived from equation 2 with an assumption of homogeneous preference (Berry, 1994).

feature is mean independent of the observed features and thus is also mean independent of the sum of these features, these sums of features satisfy the exogeneity condition.

The second set of IVs is the number of markets with the product's presence. This number primarily depends on the entry costs and retailing costs in each market. Xiao et al. (2017) suggest that car models with a larger market presence can benefit from the economy of scale. The vehicle models can share costs such as logistics between markets, and lower prices can thus be charged. This justifies the validity of this number as an IV.

6 Estimation Results

This section first reports the results from the demand estimation and then presents the results from the welfare analysis.

6.1 Results from Demand Estimation

Table 5 reports the results from demand estimation. The first column lists variables used in different model specifications. Other than the key vehicle features such as power, operation costs, size, and weight, two interaction terms are included in the regression. As several cities adopted VQS to control the number of ICEVs, the utility of EVs is enhanced there. To capture this structural break effect of the VQS, we add the interaction terms of VQS $\times$ EV and VQS $\times$ EV $\times$ Odds to our regression.[10] The coefficient of VQS $\times$ EV captures the impact of VQS on the intrinsic preference for EVs, and the coefficient of VQS $\times$ EV $\times$ WP measures how this preference changes with the chance (or the winning probability, denoted by WP) of getting the quota for ICEVs.

Another important factor driving vehicle demand is the local protection. Barwick et al. (2021) suggest that local governments usually protect the local vehicle brands, enhancing the utility of local brands. Accordingly, we include a dummy variable, *local brand*, to the model. Its coefficient measures the enhanced preference to the local brands. Brand, city, and time fixed effects are also included in all the model specifications.

The second column presents the results from a logit model regression, which could be derived from an indirect utility function with the assumption of homogeneous preference, as specified in footnote 9. The price coefficient is negative and significant, but it is small in magnitude. Most car models have inelastic

[10] As all the cities with VQS started their vehicle control before the starting time of our sample, the independent term of VQS is collinear with the city fixed effects and is therefore omitted from the model specification.

Table 5: Estimation Result for the Demand Side [a]

Variable	OLS	TSLS	GMM Mean	GMM Random	GMM Income [b]
log(Price)	-0.161*** [c]	-6.151***	-22.383***	-0.016	3.000***
	(0.028)	(0.474)	(0.385)	(0.199)	(0.007)
Constant	-10.276***	-6.850***	-0.018	-0.076	
	(0.327)	(0.486)	(0.152)	(0.364)	
log(Horsepower)	-0.507***	2.922***	3.560***	0.027	
	(0.037)	(0.275)	(0.227)	(0.155)	
log(Operation costs)	-1.228***	-1.649***	-2.198***	0.018	
	(0.050)	(0.070)	(0.079)	(0.167)	
log(Weight)	0.607***	8.138***	10.132***	-1.132*	
	(0.094)	(0.606)	(0.476)	(0.513)	
log(Size)	2.819***	2.697***	2.726***	0.027	
	(0.117)	(0.145)	(0.179)	(0.199)	
EV	-2.601***	-1.014***	-1.841***		
	(0.106)	(0.181)	(0.234)		
Import	-0.979***	-0.305	-0.053		
	(0.221)	(0.278)	(0.279)		
AT	0.282***	0.638***	0.755***		
	(0.011)	(0.031)	(0.026)		
EV$\times$VQS	0.205	-2.578***	-1.855***		
	(0.142)	(0.281)	(0.413)		
EV$\times$VQS$\times$WP	-0.098***	-0.454***	-0.387***		
	(0.024)	(0.041)	(0.067)		
Local	0.460***	0.452***	0.416***		
	(0.016)	(0.02)	(0.025)		
SUV	0.360***	0.367***	0.402***		
	(0.012)	(0.015)	(0.02)		

[a] There are 87,687 observations at the brand-city-half-year level in all regressions. Time, brand, and city fixed effects are included for all regressions.
[b] The demographic characteristic is household disposal income, which is assumed to follow a log-normal distribution.
[c] Standard errors are reported in parentheses; *, **, and *** indicate that the estimators are statistically significant at the levels of 5%, 1%, and 0.1%, respectively.

demand according to this small price coefficient, which is not reasonable because this means that the derived costs of the car models are negative according to the Lerner index.

The coefficients of some key vehicle features are also counterintuitive. For example, as horsepower translates to speed, vehicles featuring high horsepower usually go faster and get up to speed more quickly; therefore, horsepower is a desirable vehicle feature. The negative and significant coefficient of horsepower is contrary to expectation. Similarly, imported cars are usually characterized by outstanding technologies that may not be fully captured by the key feature variables, implying that the coefficient of Import is expected to be positive. However, it is negative and significant in our results.

These counterintuitive results are attributed to the endogeneity of the price and the subsequent contamination on the other variables. The price coefficient is overestimated due to the positive correlation between unobserved features and prices. The coefficients of the other variables are also influenced and are biased as well. To address this issue, we apply the two-stage least squares (TSLS) estimation to the logit model, employing IVs as specified in section 5.4. Estimation results are reported in the third column of Table 5.

A salient difference between the TSLS and OLS results lies in the price coefficient, which is accentuated with TSLS. This difference confirms the positive correlation between prices and unobserved features: A increase in sales could be driven by either an improvement in the unobserved features or a decrease in prices. When IVs are not used to control for the positive correlation between price and unobserved features in OLS estimation, the price effect is partially offset by the omitted unobserved features, resulting in the price coefficient having a smaller magnitude, compared with that from TSLS estimation.

The coefficients of the other key features are also accentuated by different scales. More importantly, the counterintuitive estimates from the OLS regression become reasonable: The coefficient of horsepower is positive and significant, while the coefficient of Import becomes insignificant even though it is still negative.

The results from the GMM estimation of the full model are presented in the last three columns of Table 5. The coefficients in the mean utility are close to those estimated by TSLS and have the expected signs. Our results suggest that larger horsepower, weight, and size are generally deemed to be preferred features of vehicles, while lower operation cost is considered more desirable. Vehicles with local brands or automatic transmission (AT) are preferred. An SUV is preferred to a sedan. The coefficient of $EV \times VQS$ is negative and statistically significant, which is counterintuitive since we expect that preference for EV is stronger in the cities with VQS. Hu et al. (2022) suggest an explanation for this finding: VQS could generate selection effects: Only consumers with a strong preference for having a car will participate in the quota rationing process. These quota winners are the ICEV buyers, while the losers or non-participants of the quota rationing process have to choose to buy ICEVs but register them to the other places, or to buy EVs. Therefore, the EV buyers on average have a weaker preference for car purchase than ICEV buyers.[11] The coefficient of the triple interaction term $EV \times VQS \times WP$ is negative and statistically significant, implying that EVs buyers' preference for vehicles, compared with ICEV buyers' preference, is less weaker in the cities with a lower chance to get quota for ICEVs since a higher portion of ICEV buyers are losers or non-participants of quota auction/lottery and so their average preference are less stronger.

Except for weight, all the key features have statistically insignificant random coefficients, suggesting that consumers have homogeneous preferences over most vehicle characteristics. Weight is special in that it could be related to both safety (steel structure) and acceleration of vehicles.

The price coefficients are of primary interest. As there are three components of price effects, we explain their aggregate effects by analyzing the price elasticity of demand in the next section.

6.2 Elasticities Analysis

The price elasticities of product j with respect to price k (omitting the market and time subscript for the moment), η_{jk}, are given by

$$\eta_{jk} = \begin{cases} \frac{1}{ns}\frac{1}{s_j}\sum_i(\hat{\alpha}_0 + v_i\hat{\sigma}_\alpha + y_i\hat{\alpha}_y)s_{ij}(1-s_{ij}) & \text{if } j = k \\ \frac{1}{ns}\frac{1}{s_j}\sum_i(\hat{\alpha}_0 + v_i\hat{\sigma}_\alpha + y_i\hat{\alpha}_y)s_{ij}s_{ik} & \text{otherwise} \end{cases}$$

The above equations show that the elasticities depend on the vehicles' market shares and consumers' price preferences, but not on vehicle prices. Table 5 shows that the random coefficient of income is 3, which is much larger in magnitude than those in the previous literature using the same data (Guo and Xiao, 2022). This coefficient estimate is refined by the micro-moments. This refinement of identification is crucial since the price coefficient eventually has critical effects on welfare analysis.

The positive coefficient of income suggests that all other things being equal, high-income consumers are less sensitive to price changes than low-income consumers, and so their price elasticities are lower. Moreover, as high-income consumers are more likely to choose high-price vehicles, considering the budget constraint, we can also infer that the price elasticities of the high-price vehicles could be lower than those of the low-price vehicles.

[11] The ICEV buyers could be the winners, losers or non-participants of quota auction/lottery, while EV buyers usually do not need to participate in auction/lottery.

Table 6 presents the brand-level own- and cross-price elasticities of selected manufacturers. The diagonal numbers are their own elasticities, and the off-diagonal numbers are the cross-price elasticities, which are defined as the percentage changes in the quantity of the column brands with respect to 1% changes in prices of the row brands. BYD has the lowest brand-level price and highest elasticity, while the FAW-Audi has the highest brand-level price and lowest elasticity among all domestic manufacturers. Basically, for domestic brands, the price elasticities are lower when prices are higher, except for the joint ventures of Toyota. The price elasticities of imported brands range from -5.8 to -6.1, and the elasticities also descend as prices ascend. The cross-price elasticities are small in magnitude relative to the own-price elasticities.

The price elasticities can provide hints on the subsidy incidence. Even though the supply-side elasticities are unavailable, the estimated price elasticities suggest that manufacturers of high-price vehicles face less-elastic demand and so, compared with manufacturers of low-price vehicles, they have to pass more subsidies through to their customers to get the market shares. In other words, the subsidies are less cost-effective for high-price vehicles than they are for low-price vehicles. We will conduct counterfactual analyses to reveal the subsidy pass-through in the next section.

To examine the substitution between EV and ICEVs, we calculate the category-level cross-elasticities and report them in Table 7. The individual elasticity is the average of the individual cross-price elasticities between each pair of categories, while the aggregate elasticity is the average of the cross-price elasticities of aggregate demand for all the products in the column category in response to the 1% price changes of all products in the row category. For the self-category, the average is taken using within-category cross-elasticities. The self-category and cross-category aggregate elasticities are very close in their magnitudes, suggesting that the within-category and cross-category vehicle substitutabilities are similar and so ICEVs and EVs are substitutes. At the aggregate level, the cross elasticity of EV demand with respect to ICEV prices is higher than the cross elasticity of ICEV demand with respect to EV prices. Our findings echo Xing et al. (2021), suggesting that EVs are substitutes for a particular type of ICEVs (fuel-efficient vehicles) rather than all types in general.

6.3 Welfare Analysis of the Subsidy

We employ counterfactual analysis to assess the incidence and distributional effects of EV purchase subsidies and compare the effectiveness of alternative subsidy schemes. The observations of Shanghai in the second half of 2019 are chosen as the observed scenario for counterfactual analysis. During that time, Shanghai did not grant local subsidies on EVs; therefore, all EV subsidies were granted by the central government. On average, each EV was subsidized RMB 23,274. As the average MSRP of EVs was RMB 195,718 in this market, the subsidies accounted for about 11.9% of the EV prices on average.

Table 6: Average Price and Own- and Cross-Price Elasticities for Selected Brands

	Price (RMB 10,000)	FAW-VW	BYD	Dongfeng-Honda	SAIC-VW	Guangzhou-Toyota	FAW-Toyota	FAW-Audi	Lexus (imported)	VW (imported)	Tesla (imported)	BMW (imported)	Audi (imported)
FAW-VW	14.232	-6.469	0.061	0.073	0.077	0.025	0.036	0.348	0.140	0.019	0.061	0.043	0.022
BYD	15.259	0.238	-6.653	0.078	0.082	0.027	0.038	0.371	0.149	0.021	0.066	0.046	0.023
Dongfeng-Honda	16.848	0.177	0.049	-6.523	0.061	0.020	0.029	0.283	0.116	0.016	0.051	0.036	0.019
SAIC-VW	17.072	0.413	0.114	0.137	-6.456	0.048	0.068	0.663	0.273	0.037	0.120	0.086	0.044
Guangzhou-Toyota	18.111	0.109	0.031	0.036	0.038	-6.555	0.018	0.177	0.073	0.010	0.033	0.023	0.012
FAW-Toyota	21.353	0.095	0.027	0.032	0.033	0.011	-6.460	0.158	0.067	0.009	0.030	0.022	0.011
FAW-Audi	33.033	0.146	0.044	0.052	0.052	0.019	0.027	-5.908	0.122	0.017	0.056	0.042	0.022
Lexus (imported)	32.900	0.046	0.014	0.016	0.017	0.006	0.008	0.085	-6.122	0.005	0.018	0.013	0.007
VW (imported)	37.558	0.072	0.022	0.026	0.026	0.010	0.013	0.135	0.063	-6.127	0.029	0.022	0.012
Tesla (imported)	43.990	0.009	0.003	0.003	0.003	0.001	0.002	0.018	0.008	0.001	-6.036	0.003	0.002
BMW (imported)	50.667	0.099	0.031	0.037	0.036	0.014	0.019	0.197	0.097	0.013	0.046	-5.898	0.019
Audi (imported)	51.909	0.063	0.020	0.024	0.023	0.009	0.012	0.127	0.063	0.009	0.030	0.023	-5.891

Notes: The own- and cross-elasticities for selected brands are reported in the table. The cross-price elasticities are the percentage changes in quantity for products of the column brands in response to changes in price for products of the row brands.

Table 7: Cross-Price Elasticity between Product Categories

		Domestic		Imported	
		EV	ICEV	EV	ICEV
EV	Individual	0.0290	0.0015	0.0025	0.0018
	Aggregate	2.0915	1.0787	0.0025	0.1203
ICEV	Individual	0.0274	0.0014	0.0023	0.0017
	Aggregate	1.9986	1.0331	0.0023	0.1138

Notes: This table shows the cross-price elasticity of demand for the products in the column categories in response to a 1% change in the price of the products in the row categories. The individual elasticity is the average of the individual cross-price elasticities between each pair of categories, while the aggregate elasticity is the average of the cross-price elasticities of aggregate demand for all the products in the column category in response to the price changes of each product in the row category. For the self-category, the average is taken using within-category cross-elasticities.

We simulate four scenarios. In scenario (1), assuming that the subsidies have been retained at their 2015 levels, we simulate a scenario in which the low subsidies are replaced by high subsidies. For scenario (2), we simulate the case in which subsidies are completely removed. In scenario (3), we design a progressive subsidy scheme that discounts the observed subsidies in the observed scenario based on buyers' income categories. Referring to the income tax scheme of China in 2022, we set a multiplier τ on subsidies as follows:

$$\tau = \begin{cases} 1 & \text{if income} \leq \text{RMB } 60{,}000 \\ 0.97 & \text{if RMB } 60{,}000 < \text{income} \leq \text{RMB } 144{,}000 \\ 0.95 & \text{if income} > \text{RMB } 144{,}000 \end{cases} \tag{8}$$

The effective subsidies that consumers finally get are the product of the multipliers and the subsidies at each income level over the period of counterfactual analysis. With this scheme, low-income consumers can still get the same subsidies as they could in the second half of 2019; however, high-income consumers cannot get full subsidies as they previously did. Therefore, this scheme is progressive on consumers' incomes. However, as the subsidies depend on both vehicle ranges and consumers' income, high-income consumers can still choose to buy the vehicles with higher ranges and end up receiving the most subsidies.

Finally, in scenario (4), we fix the government budget on subsidy at the same level as the one in the observed scenario and solve for an optimal progressive subsidy scheme that depends on both range and income. We set the policy objective to be maximum sales in order to maximize consumer surplus from vehicle consumption. The optimal subsidy scheme solved from this optimization problem is given by $sb_{ij} = 8.1227 - 1.445 \times y_i + R_j \times 0.004$, where R_j is the range of vehicle j. The subsidy is in RMB 10,000. Intuitively, this subsidy scheme sets an intrinsic level of RMB 81,227 for the qualified EVs.[12] Consumers are subsidized RMB 4,000

[12] Only vehicles with ranges larger than 250km are eligible for subsidies for the second half of 2019. See Table 1 for details.

more for vehicles with an increase in range by 100 kilometers, and they are subsidized by RMB 14,450 less for an increase in their income by RMB 10,000. By design, this scheme is also progressive on income. Also, as the total subsidies are fixed at the observed-scenario level, we can employ cost-effectiveness analysis to compare the subsidies in effect with this alternative policy.

Manufacturers may strategically determine the pass-through of the subsidies in each scenario. Therefore, we solve for the equilibrium consumer prices p^o, producer prices p^s, and market shares s, using equations 6 and 3 simultaneously. Using the equilibrium prices, we study the subsidy pass-through and examine the subsidy distribution over income categories. Finally, we conduct cost-benefit analyses across scenarios. The cost-benefit analysis is based on four components: consumer surplus, profits, externality, and government expense. Appendix B specifies the methodology of estimating the changes in consumer surplus, measured by compensating variation (cv), and the externalities.

6.3.1 Subsidy Pass-through

Following Weyl and Fabinger (2013), we measure the subsidy pass-through (ρ) for vehicle j in scenario t, using the decrease in price to consumers for each unit of specific subsidy granted. Specifically,

$$\rho_{jt} = \frac{\Delta p^o_{jt}}{sb_{jt}} = \frac{p^o_{jt} - p^o_{j0}}{sb_{jt}}$$

where p^o_{jt} and p^o_{j0} are the demand-side prices in scenario t and the scenario without subsidies, respectively. As scenario (2) simulates the no-subsidy policy, p^o_{j0} is in fact the set of equilibrium prices in scenario (2).

Table 8 presents the subsidy pass-through by different types of vehicle manufacturers. In all scenarios, the overshifting of subsidies is observed. These findings could be explained by the theory proposed by Weyl and Fabinger (2013), who suggest that the pass-through rate in imperfect competition depends on the elasticities of demand and supply and the curvature of demand function as follows:[13]

$$\rho = \frac{1}{1 + \frac{\theta}{\varepsilon_\theta} + \frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}}$$

where ε_D, ε_S, and $\frac{1}{\varepsilon_{ms}}$) denote the elasticities of demand and supply and demand function curvature, respectively. Pless and van Benthem (2019) discuss that $\frac{\theta}{\varepsilon_\theta}$ is usually zero, so ρ is largely determined by the last two terms in the denominator of this formula. We can prove (in Appendix C) that our demand function is

[13] See Appendix C for details.

convex, and so $\varepsilon_{ms} < 0$. Although there is no way for us to estimate the elasticity of supply, our estimates suggest that ε_D is fairly small. Therefore, overshifting is observed.

The findings of the more than complete pass-through are not new in the empirical literature. Pless and van Benthem (2019) document a pass-through rate of over 150% in the solar system industry. Our findings of subsidy overshifting to consumers are attributed to the imperfect competition between EVs and ICEVs. When the EVs are subsidized, EV manufacturers may fully pass the subsidies through to the consumers to compete for the market shares. Since pricing decisions are strategic complements, ICEV manufacturers also have to lower their prices in response. This imposes pricing pressure on the EV manufacturers, forcing them to further lower their prices. Consequently, the subsidy pass-through to consumers exceeds 100%.

As shown in the first two columns of Table 8, the manufacturers solely producing EVs, pass through a larger share of the subsidies to their consumers than the manufacturers producing both EVs and ICEVs since the hybrid manufacturers have to take into account the spillover effects of reduced EV prices on their ICEVs.

Table 8: Subsidy Pass-through to Consumers

Scenarios [a]	observed	(1)	(3)	(4)
EV manufacturers[b]	121.32%	121.08%	120.35%	114.01%
Hybrid manufacturers [c]	120.92%	120.74%	120.00%	114.88%
All manufacturers[d]	120.99%	120.80%	120.06%	114.73%

[a] The equilibrium prices in scenario (2) are used as the benchmark for the pass-through calculation since scenario (2) simulates the zero-subsidy policy. In the other scenarios, the pass-through is defined as the ratio of the price decrease, relative to the no-subsidy price, to the subsidies.

[b] This row presents the average pass-through of EVs made by firms only producing EVs, including Beijing Electric Vehicle, Nio, WM Motor, and Xpeng.

[c] This row presents the average pass-through of EVs made by firms producing both EVs and ICEVs, including Beijing Benz, Beijing Borgward, Beijing Hyundai, BAIC Motor, BYD, Chery, Chongqing Changan, Dongfeng Honda, Dongfeng Motor, FAW-Volkswagen, GAC Honda, GAC Mitsubishi, GAC Motor, Geely, JAC Motor, SAIC-GM, SAIC Motor, and SAIC-Volkswagen.

[d] This row presents the average pass-through of EVs produced by all firms.

6.3.2 Subsidy Progressivity

Using the Bayesian rule applied to the prediction of buyers' income (equation 5), we calculate the sales-weighted average subsidies for each income level as follows:

$$\hat{sb}_i = \sum_j \frac{s_{ij} sb_j}{\sum_j s_{ij}}$$

Figure 5 plots the estimated buyers' subsidies by incomes. As the subsidies are zero in scenario (2), we use the prices in this scenario as the benchmark to calculate the subsidy pass-through to the consumers in the other scenarios.

Visually, the subsidy schemes independent of buyers' income (scenarios observed and 1) generate actual regressive subsidies. This finding suggests that the current subsidy policy subsidizes high-income buyers

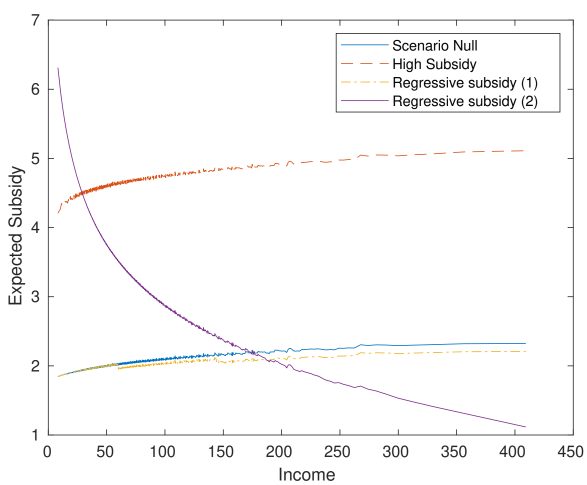
Table 9: Subsidy Pass-through to Consumers by EV Price Quantiles

EV price quantiles	**1st quartile**	**2nd quartile**	**3rd quartile**	**4th quartile**
Pass-through to consumers	119.89%	120.82%	121.17%	122.20%

more. The reason is that the vehicle choices of high-income consumers are disproportionately distributed to high-price vehicles, compared with those of low-income consumers. As the subsidies on the high-price EVs are higher and the pass-through of high-price EVs is usually higher, as summarized in Table 9 using data in the observed scenario, most of the subsidies go to the high-income consumers.

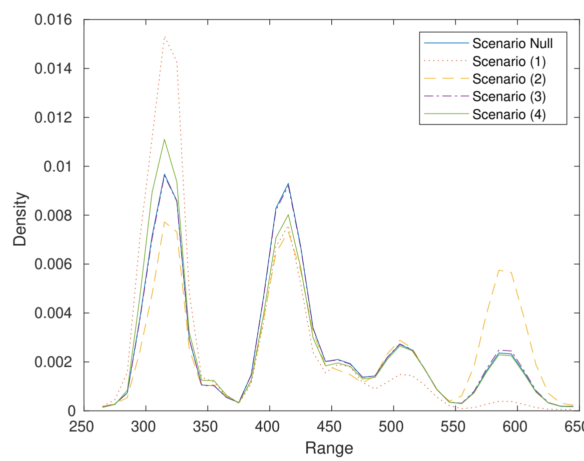
The schemes that are conditional on buyers' income generate progressive subsidies. In particular, the scheme in scenario (4) is a continuous function of income whereby the subsidies diminish as buyers' income increases.

Figure 5: Subsidy Distribution over Income



Note: The figure shows the subsidy received by EV buyers with different incomes. The horizontal axis measures the annual income of consumers. The vertical axis measures the subsidies received by EV buyers. Both subsidy and income are in RMB thousands.

Figure 6: Subsidy Distribution over Vehicle Ranges



Note: The figure shows the density of EVs with different ranges. The horizontal axis measures the range of EVs. The vertical axis measures the density.

6.3.3 Pass-through and Progressivity

Results in Table 8 provide rare empirical evidence shedding light on the interaction between subsidy pass-through and progressivity. The pass-through in the scenarios with progressive-subsidy designs is lower than that in the scenarios with regressive-subsidy schemes. Weyl and Fabinger (2013) theoretically imply that subsidy pass-through decreases in demand elasticity in the imperfect competition: When consumers are less price sensitive, manufacturers have to pass more subsidies through to the consumers to gain market shares. By design, the progressive subsidy scheme is supposed to be more effective in promoting EV sales than the regressive subsidy scheme since it disproportionately targets the high price-sensitive consumers. In imperfect competition, however, the manufacturers can take advantage of the scheme design, and pass a smaller fraction of subsidies through to the EV buyers to achieve the same sale target. Therefore, the subsidy pass-through is lower in the scenarios of progressive subsidy schemes than in the scenarios of regressive subsidy schemes. This explains our findings in Table 8.

6.3.4 Cost-Benefit Analysis

Welfare Excluding Externalities

Table 10 presents the estimates of cv, profits, subsidy, and externalities for welfare analysis. Compared with scenario observed, cv increases when EV buyers are compensated more (scenario 1), but decreases when the EV subsidies are completely removed (scenario 2).

Similarly, the EV manufacturers' profits increase when EV subsidies are higher (scenario 1 versus observed), while their profits decrease when EV subsidies are lower (scenario 2 versus observed). The ICEV manufacturers, however, observe the opposite trend; they lose when EV consumers are subsidized. We analyze the reasons in the last section: Pricing decisions are strategic complements, and thus, ICEV manufacturers have to lower their price passively, which lowers their markup and sales and leads to lower profits.

Government expense on subsidy increases dramatically when the subsidy per vehicle increases (scenario 1 versus observed). This outcome is due to the changes in both the intensive margin and extensive margin of subsidy expense. The intensive margin refers to the subsidy per vehicle. Table 1 shows that following the 2015 scheme, each EV buyer is subsidized around RMB 30,000 more than they could have gotten following the 2019 scheme. The extensive margin consists of two parts: (1) the increase in EV sales, and (2) the expansion of the set of the eligible EVs. As shown in Table 1, only EVs with ranges of more than 250 kilometers are eligible for subsidies in scenario observed, while EVs with ranges of more than 80 kilometers are eligible for subsidies in scenario (1). The increases of both intensive margin and extensive margin contribute to the dramatic increase in government subsidy expenses.

Another interesting finding is that the subsidy can generate distortion. Comparing scenarios (1) and (2) to observed, we find that the subtotal surplus, including consumer surplus and producer surplus, net of subsidy, is negatively correlated with subsidies. This distortion arises owing to imperfect competition; therefore, it increases when the manufacturers have more market power. When EV subsidies are higher, the manufacturers have more market power as demand is shifted up. Consequently, the pass-through is lower (as

Table 10: Cost-Benefit Analysis of EV Subsidies

Scenarios [a]		Observed	(1)	(2)	(3)	(4)
Compensating variation[b]			2.0532	-0.2873	-0.0233	-0.0040
Profits						
Domestic	EV manufacturers	6.3308	6.8948	6.2084	6.3223	6.3453
	ICEV manufacturers	2.8460	2.5154	2.9076	2.8510	2.8595
Imported	EV manufacturers	0.1548	0.1361	0.1585	0.1551	0.1557
	ICEV manufacturers	1.2584	1.1080	1.2881	1.2608	1.2661
Subsidy		0.4085	5.2583	0.0000	0.3804	0.4085
Subtotal for sales		10.1815	7.4492	10.2753	10.1855	10.2141
Externalities[c]						
EVs	(Coal-fired electricity)	89.1917	484.5169	37.4508	84.978	92.8927
EVs	(Natural-gas-powered electricity)	19.0276	103.3636	7.9895	18.1286	19.8171
ICEVs		364.7407	327.1915	371.2565	365.2693	365.8749
Subtotal	(Coal-fired electricity)	453.9324	811.7084	408.7073	450.2473	458.7676
Subtotal	(Natural-gas-powered electricity)	383.7683	430.5551	379.2460	383.3979	385.6920
Total	(Coal-fired electricity)	-443.7509	-804.2592	-398.4320	-440.0618	-448.5535
Total	(Natural-gas-powered electricity)	-373.5868	-423.1059	-368.9707	-373.2124	-375.4779

[a] Scenario observed: the subsidy scheme is the same as that for 2019. Scenario (1): the subsidy scheme is the same as that for 2015. Scenario (2): subsidy is zero for all EVs. Scenario (3): the base of this subsidy scheme is designed for the lowest income group (with annual income less than RMB 60,000) and it is the same as the scheme for 2019. The effective subsidies of high-income groups are the product of subsidies in the observed scenario and the multipliers shown in equation 8. Scenario (4): the subsidies depend on both income and vehicle ranges. The subsidy is given by $sb_{ij} = 8.1227 - 1.445 \times y_i + R_j \times 0.004$, where R_j is the range of vehicle j. The subsidy is in RMB 10,000.

[b] All values are in RMB billions. The estimates are for Shanghai in the second half of 2019.

[c] The estimates depend on the energy source of electricity generation. Electricity can be generated by coal-fired power plants or by natural gas-fired power plants, which are cleaner. See Appendix B.2 for details of the marginal externalities of power generation by energy sources.

shown in Table 8), resulting in lower consumer surplus, but manufacturer profits increase as shown above; overall, the distortion is increased.

In addition, the size of the distortion is related to the subsidy distribution. As the subsidy schemes are regressive in scenarios observed, (1), and (2), most subsidies go to high-income buyers. As these consumers are less price sensitive, their surplus does not change much. This explains a small change in cv relative to a large change in subsidy (scenario 1 versus observed), even though the pass-through is more than complete.

Overall, higher subsidies lead to a welfare loss. Comparing scenario (2) to scenarios observed and (1), we find that complete removal of the subsidies could lead to a welfare gain, which can justify the government's policy of lowering the subsidies gradually and eventually terminating them in the near future.

Columns (3) and (4) report the costs and benefits of two progressive subsidy schemes. The scheme corresponding to scenario (3) is the same as that in scenarios (observed) and (1) except that high-income consumers are taxed on their subsidies. Consequently, the total subsidy size is smaller. Subsidy in scenario (4) is fixed at the same level as that in scenario observed. By examining the results in scenarios (3) and (4), we find that the progressive subsidies may generate welfare gain, without the need to increase the subsidy size. In particular, comparing scenario (3) with observed, we conclude that holding the subsidy program based on EV ranges but reducing the subsidies to the high-income consumers will reduce consumer surplus and domestic manufacturers' profits, but the savings of subsidies will dominate these losses, resulting in an overall increase in the subtotal welfare from vehicle transactions, without considering the externalities.

In scenario (4), compared with scenario observed, with equal-size subsidies, the proposed optimal progressive subsidy scheme may lead to a welfare gain (subtotal for sales), excluding externalities. Seemingly, the decrease in cv is counterintuitive since the same-size subsidies are more skewed to the low-income consumers in scenario (4) than in scenario observed. In fact, the distributional effects of subsidies are the key to explaining this welfare effect. The progressive subsidy design reallocates the EV subsidies from high-income consumers with lower price sensitivities to low-income consumers with higher price sensitivities. The manufacturers can take advantage of this effective scheme design and pass a smaller fraction of subsidies through to the consumers to achieve the same sale target. As shown in Table 8, the subsidy pass-through is lower in the scenarios of progressive subsidy schemes than that in the scenarios of regressive schemes, which is owing to the EV manufacturers' strategic response to higher aggregate price elasticities. Consequently, the sales increase but part of the consumer surplus is transferred to manufacturers, resulting in a lower consumer surplus but a higher producer surplus. The subtotal welfare of sales increases due to larger sales.

Finally, in light of the policy designs that prioritize encouraging product innovation, our focus now shifts to examining the impact of various subsidy policies on technological innovation. This will be achieved through an analysis of the distribution of the maximum driving range of electric vehicle sales, as depicted in Figure 6. Notably, both progressive and regressive designs (scenarios 4 and observed, respectively) exhibit no significant difference in their promotion of high-range vehicles when the subsidy sizes are equal under these two approaches. However, the progressive design proves to be less effective in encouraging the adoption of middle-range vehicles compared to the regressive design, while demonstrating a greater inclination towards vehicles with ranges below 350km.

Externalities

As fossil fuel is still the primary energy for electricity generation, EV consumption will generate externalities. In fact, the unit externalities from EVs could be even higher than those from ICEVs (Guo and Xiao, 2022). Therefore, externalities should be also considered in a comprehensive welfare analysis.[14]

Columns observed - (2) in Table 10 suggest that the increases in subsidies lead to higher externalities in EVs, which dominate the decrease in externalities from ICEVs, regardless of whether high or low marginal externalities are used for the calculation. This is because most electricity generation is coal-fired, generating more pollution than the ICEVs do.[15]

Compared with scenario observed, the externalities in scenario (3) are lower because the EV sales are lower as the total subsidies are lower. When the subsidy size is fixed, however, the progressive subsidy scheme (scenario 4) generates more negative externalities than the regressive subsidy scheme (senario observed). The dominant driving force of these results is the increase in externalities from EVs due to larger sales of EVs. Considering the externalities, our conclusion on the welfare effects of different subsidy schemes could be reversed.

7 Conclusion

As the world's largest carbon emitter, China has endeavored to reduce vehicle emissions by stimulating the sales of EVs to replace ICEVs. EV subsidies are employed for this purpose, but the effectiveness of such policies has been understudied. Many factors, such as the substitution pattern between EVs and ICEVs, the methods of electricity generation, and consumers' price sensitivity, can affect the policy effectiveness, making its assessment an empirical question.

The incidence and distributional effects of the subsidies also play an important role in determining the policy effectiveness and welfare effects. This paper analyzes the incidence (or pass-through)—the subsidy distribution between manufacturers and consumers, and progressivity—the subsidy distribution over consumers of different incomes. Our findings suggest that the subsidy pass-through to the consumers is more than complete: The manufacturers not only pass through the subsidies to the EV buyers but also further lower their prices in response to ICEV manufacturers' strategic response to the EV decline caused by subsidies.

The current subsidy program is regressive, with the majority of subsidies going to high-income consumers who are less price-sensitive, implying that the policy design may be not optimal in the sense that it has not maximized its effectiveness in promoting EV sales. We proposed alternative subsidy schemes, by which

[14] Holland et al. (2016) document the empirical evidence of EV externalities in the U.S. and suggest that 90% of local environmental externalities from driving electric vehicles in one state are exported to others. Due to the separation of electricity production and consumption, parts of the externalities generated in the experiment city will also be exported to other regions in China. When we calculate the externalities, we do not take into account the exports of externalities.

[15] See Appendix B.2 for details.

the subsidies are progressive on incomes. Counterintuitively, we find that the progressive subsidy scheme reduces consumer surplus, compared with the regressive subsidy schemes. The reason is that manufacturers could take advantage of the more effective scheme design and pass a smaller fraction of subsidies through to the consumers for the same market shares. In terms of total welfare, the progressive subsidy designs could generate a welfare gain over the regressive subsidy schemes.

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Appendix A Income Simulation

Following previous research (Guo and Xiao, 2022; Wu and Perloff, 2005), we assume that the income follows a log-normal distribution, with $log(y) \sim N(\mu_y, \sigma_y)$, where y is household income, and μ_y and σ_y are the mean and standard deviation of a normal distribution. We estimate these two parameters for each city using the income statistics from China Statistics Yearbook (2017–2020).

We employ the method of simulated moments to estimate the parameters using per capita disposal income and population data at the district level. These districts are subdivisions of a municipality or a prefecture-level city. It should be noted that the income distributions of various districts within the same city may overlap, rendering the application of the maximum entropy density approach proposed by Wu and Perloff (2005) unfeasible. This particular method relies on summary statistics obtained from exclusive income intervals. Therefore, we propose an alternative approach to tackle the issue of overlapping income distributions across districts.

First, we make NS random draws[16] from a standard log normal distribution. We permutate the random draws with repetition to generate J sets of income samples.[17] The random draw is denoted as $(y_{j,k})$, where the first dimension of the subscript indicates the set and the second dimension of the subscript indicates the position of the random draw in set j.

Next, using the population as weights, we assign the m_n^{th} fraction of the random draws in each set to the n^{th} district in a city, where the order of districts is random. Then, we have a matrix of income random draws for each city given as follows:[18]

$$\begin{bmatrix} y_{1,1}^{m_1} & y_{1,2}^{m_1} & y_{1,3}^{m_1} & \cdots & y_{1,k}^{m_2} & \cdots\cdots & y_{1,NS}^{m_n} \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ y_{J,1}^{m_1} & y_{J,2}^{m_1} & y_{J,3}^{m_1} & \cdots & y_{J,k}^{m_2} & \cdots\cdots & y_{J,NS}^{m_n} \end{bmatrix}$$

in which each row corresponds to a permutation of the random draws. As the permutations are with repetition, each row simulates a scenario of overlap in income distributions over districts.

We estimate the log-normal distribution parameters (μ_y, σ_y) for each city by applying Wu and Perloff (2005) approach to each set of random draws. Specifically, given a set of estimates, $(\hat{\mu_y}, \hat{\sigma_y})$ we calculate the district-level average incomes using each set of random draws and derive the difference between the predicted and

[16]In this paper, we assume $NS = 20,000$.
[17]In this paper, we assume $J = 1,000$.
[18]For example, Beijing has 16 districts in total, so the subscript will range from m_1 to m_{16}.

observed average incomes. Using the j^{th} row of the matrix, we search for $(\hat{\mu}_y^j, \hat{\sigma}_y^j)$ to minimize the sum of squared difference over districts:

$$(\hat{\mu}_y^j, \hat{\sigma}_y^j) \in \underset{(\mu_y, \sigma_y)}{\arg\min} M_I^j = \sum_n (\frac{1}{N_{m_n}} \sum_k y_{j,k}^{m_n} - \bar{y}^{m_n})^2$$

where N_{m_n} is the number of observations for district n and $\bar{y}$ is the observed district average income. The estimated moment value is $\hat{M}_I$.

Finally, we use the row that generates the minimum value of moments, $\hat{M}_I$, and the corresponding estimates of the distribution parameters for our model estimation because this permutation of income random draws can generate the district average incomes that fit the observed values the best. This process will be carried out for each of the sample cities.

Appendix B Welfare Analysis

B.1 Compensating Variation

The welfare effects on consumer surplus caused by subsidy changes are measured by compensating variation (cv). Following Herriges and Kling (1999); Xiao et al. (2017), we calculate cv by simulations. Specifically, as cv refers to the amount of additional money buyers would need to reach their initial utility after a change in subsidies, it can be solved from the following equation:

$$Max_{j \in J}\, u(p_0^o, \mathbf{X}, \hat{\xi}, \hat{\varepsilon}; y_i) = Max_{j \in J}\, u(p_1^o - cv, \mathbf{X}, \hat{\xi}, \hat{\varepsilon}; y_i) \tag{9}$$

where subscript 0 and 1 indicate original and simulated scenarios, respectively. The optimal choice in these two scenarios could be different, depending on the changes in ownership cost p^o. The values of the unobserved product features $\hat{\xi}$ are derived from the residuals of the GMM estimation. $\hat{\varepsilon}_j^t$ is drawn from type I extreme value distribution. One million sets of $\hat{\varepsilon}$ are generated using the pseudo-random number generator. For each consumer i, we find the optimal choice for each scenario and then derive the cv_i that solves equation 9. The expected cv is the average of cv_i. The total cv is calculated using the market size and the average of cv.

B.2 Externalities

Parry et al. (2014) estimates the external cost of vehicle consumption in China and reports the total marginal cost to be US$0.55/liter for gasoline cars, reflecting combined damages from carbon and local pollution emissions, congestion, and accidents. Parry et al. (2007) decomposes the external cost of vehicle consumption into these major components and finds that greenhouse warming and local pollution account for roughly 20% of the total external cost of vehicle driving. Applying the shares of greenhouse warming and local pollution in marginal externality in the United States to the reported cost in China, we estimate the external cost of ICEV emission to be US$0.11/liter.

Parry et al. (2014) also reports the corrective taxes for coal-fired power plants to be US$15/gigajoule (GJ) in China, reflecting combined damages from carbon and local pollution emissions. The Chinese government set the target of efficiency of coal consumption of coal-fired power units at 318 grams of standard coal equivalent per kilowatt-hour and the target of transmission losses at 6.64%.[19] Accordingly, using these numbers, we can estimate the corrective taxes for coal-fired power plants to be $.154/kWh.[20] After taking into account the transmission losses, the external cost is US$.165/kWh (or RMB 1.155/kWh at an exchange rate of RMB 7/US$).

The corrective tax for natural-gas power plants is estimated to be US$3.2/GJ in China (Parry et al. (2014)). Therefore, if power generation transitions from coal fired to natural gas in China, we expect the marginal external costs to be roughly one-fifth of the above estimates, or US$0.0352/kWh (RMB 0.246/kWh), which will significantly change the estimates of the total externalities. We apply both marginal externalities to our welfare analysis.

Appendix C Pass-through under imperfect competition

C.1 Pass-through rates

Under perfect competition, taxes or subsidies are predicted to be passed on to consumers, ranging from 0 to 100 percent. However, the actual pass-through can vary depending on the shapes of demand and supply curves and the competition structure. This appendix will discuss the pass-through rate under imperfect

[19] Notice on the issuance of the 13th Five Year development plan for energy, by the National Development and Reform Commission and National Energy Administration, December 26, 2016.

[20] The conversion rate between coal equivalent and GJ is 1 ton of coal equivalent = 29.3076 GJ, and the conversion rate between gram and ton is 1 ton = 907,185 grams.

competition. We first illustrate the pass-through rate in a monopoly market and then generalize it to the other imperfect competition structure.

Following Weyl and Fabinger (2013), the monopolist's revenue is $R = p(q)q$ with $MR = p'(q)q + q$, and his marginal cost is $MC = c'(q)$. When the producer is taxed t per unit, the producer still maximizes his profits at $MR(q) = MC(q) + t$. Thus,

$$mr' \frac{dq}{dt} = mc' \frac{dq}{dt} + 1 \Rightarrow \frac{dq}{dt} = \frac{1}{mr' - mc'} \Rightarrow \rho = \frac{dp}{dt} = p' \frac{dq}{dt} = \frac{p'}{mr' - mc'}$$

where, $mr' = \frac{\delta MR}{\delta q}$ and $mc' = \frac{\delta MC}{\delta q}$.

The pass-through rate to consumers, ρ, is defined as the ratio of the change in price p to the change in tax t. As the marginal revenue MR is the sum of price p and the negative of the marginal consumer surplus $ms = -p'(q)q$, the pass-through rate can be simplified as follows:

$$\rho = \frac{1}{\frac{p' - ms'}{p'} - \frac{mc'}{p'}} = \frac{1}{1 + \frac{\varepsilon_D}{\varepsilon_{ms}} \frac{ms}{p} + \frac{\varepsilon_D}{\varepsilon_S} \frac{mc}{p}}$$

where the elasticities of demand (ε_D), supply (ε_S) and marginal consumer suplus (ε_{ms}) are defined as $\varepsilon_D = -D'p/q$, $\varepsilon_S = S'p/q$ and $\varepsilon_{ms} = ms/(ms'q)$, respectively. Applying Lerner (1934)'s rule, we can simplify the pass-through rate even further.

$$\frac{p - mc}{p} = \frac{1}{\varepsilon_D} \Rightarrow \frac{mc}{p} = \frac{\varepsilon_D - 1}{\varepsilon_D}$$

$$\rho = \frac{1}{1 + \frac{\varepsilon_D - 1}{\varepsilon_S} + \frac{1}{\varepsilon_{ms}}}$$

Pass-through for symmetric imperfect competition can be derived by following similar steps, as demonstrated by Weyl and Fabinger (2013).

$$\rho = \frac{1}{1 + \frac{\theta}{\varepsilon_\theta} + \frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}} \tag{10}$$

where $\theta = \frac{p - MC}{p} \varepsilon_D$ is a conduct parameter ranging between zero for perfect competition and one for a pure monopoly. Pless and van Benthem (2019) discuss that the term $\frac{1}{\varepsilon_\theta} = 0$ for many standard models of imperfect competition, such as Cournot. Therefore, the pass-through rate largely depends on the last two terms in the denominator, $\frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}$.

C.2 Overshifting

If the curve is sufficiently convex, the pass-through rate is likely over 100 percent. Namely, the overshifting may happen if ε_{ms} is negative.

$$\frac{\varepsilon_D - \theta}{\varepsilon_S} = \frac{\varepsilon_D(1 - \frac{p-MC}{p})}{\varepsilon_S} = \frac{\varepsilon_D}{\varepsilon_S}\frac{MC}{p} > 0$$

$$\frac{1}{\varepsilon_{ms}} = \frac{ms'q}{ms} = \frac{(p''q + p')q}{p'q} = 1 + \frac{p''q}{p'}$$

Given that $q > 0 > p'$, the term $\frac{p''q}{p'}$ is positive if $p'' < 0$ and $\frac{1}{\varepsilon_{ms}} > 1$ for concave demand, and vice versa. As Weyl and Fabinger (2013) explains the inverse elasticity of marginal surplus ms is demand's logarithmic curvature. Thus,

$$(logD)' = \frac{D'}{D} = \frac{\frac{dq}{dp}}{q} = \frac{1}{\frac{dp}{dq}q} = \frac{1}{p'q} = -\frac{1}{ms}$$

$$(logD)'' = \frac{ms'}{ms^2}\frac{1}{p'} = -\frac{1}{\varepsilon_{ms}}\frac{1}{ms}\left(-\frac{1}{p'q}\right) = -\frac{1}{\varepsilon_{ms}}\frac{1}{ms^2}.$$

Hence, log-concave demand always has $\frac{1}{\varepsilon_{ms}} > 0$ and log-convex demand always has $\frac{1}{\varepsilon_{ms}} < 0$.
The demand function and its first and second derivatives in this paper are

$$s = \frac{e^\delta}{1+\sum e^\delta} \Rightarrow ln(s) = \delta - ln(1+\sum e^\delta)$$

$$\frac{\partial ln(s)}{\partial p} = \alpha\frac{1}{p} - \frac{e^\delta \alpha \frac{1}{p}}{1+\sum e^\delta} = \alpha\frac{1}{p}(1 - \frac{e^\delta}{1+\sum e^\delta}) = \alpha\frac{1}{p}(1-s)$$

$$\frac{\partial}{\partial p}(\frac{\partial ln(s)}{\partial p}) = -\alpha[\frac{1}{p^2}(1-s) + \frac{1}{p}\frac{\partial s}{\partial p}] = -\frac{\alpha}{p}(1-s)(\frac{1}{p}+s) > 0$$

Thus, our demand curve is log-convex with $\frac{1}{\varepsilon_{ms}} < 0$. According to Equation 10, when the elasticity of demand is not much larger than the elasticity of supply, the magnitude of their ratio could be lower than the curvature of the demand function and so the pass-through rate is expected to be greater than 100%, resulting in overshifting.