ABSTRACT

Title of Dissertation: ESSAYS ON ENVIRONMENTAL POLICIES AND VEHICLE MARKET

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This dissertation analyzes the impacts of energy efficiency standards, vehicle ownership restrictions, and passenger vehicle emission standards on the vehicle market and evaluates the welfare consequences of these environmental policies.

The first chapter focuses on China's vehicle license allocations. Many megacities in China use lotteries and auctions to allocate vehicle licenses and restrict vehicle ownership, making people wait several years for a license. Recently, to promote electric vehicles, some cities introduced a separate system for electric vehicle licenses with shorter expected wait times. This chapter estimates a structural model to quantify the welfare effects of vehicle license allocation and its impact on electric vehicle adoption. I find that vehicle license allocation significantly increases electric vehicle sales. However, it also imposes a high implicit cost of waiting on consumers, engendering a consumer welfare loss of 26-52 billion Yuan in Beijing and Shanghai. Vehicle

ownership restrictions also reduced automobile externalities, offsetting more than 80 percent of the consumer welfare loss.

The second chapter evaluates the corporate average fuel consumption (CAFC) standard in China. I set up a structural model of vehicle supply under the CAFC standard and simulated the impacts of China's CAFC standards on the firm's profit, vehicle prices, fuel consumption, and sales. I find that the Phase III CAFC standard reduced the producers profit by 1.07 billion Yuan per year. Moreover, the more stringent Phase IV standard reduced the producers profit by 4.66 billion Yuan per year. Allowing the trading of CAFC credits will reduce the compliance costs to producers.

The third chapter focuses on the welfare consequences of the passenger vehicle greenhouse gas emission standards in Europe. I show that in a differentiated product market, standards can affect virtually any product attribute, and those effects have ambiguous implications for consumer welfare. This chapter implements a novel strategy to estimate the causal welfare effects of standards on product attributes. Considering European carbon dioxide emissions standards for passenger vehicles, I find that these standards have reduced fuel consumption and emissions. However, the standards have unintentionally reduced vehicle quality, which undermines 26 percent of the welfare gains of the standards.

ESSAYS ON ENVIRONMENTAL POLICIES AND VEHICLE MARKET

by

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Foreword

The third chapter of the following dissertation is a jointly authored work with Joshua Linn. The Dissertation Committee aknowledges that Yujie Lin made substantial contributions to the relevant aspects of the chapter.

Dedication

I dedicate this dissertation to my parents for their constant care and love to me. Thanks to their unconditional support, I am able to chase my dream.

Acknowledgments

I owe my gratitude to all the people who help me with my dissertation and because of whom my graduate experience has been one that I will cherish forever.

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Chapter 1: China's Vehicle License Allocations and Electric Vehicle Adoption

1.1 Introduction

Scarce resource allocation has been a longstanding topic in economics. Both market-based tools (e.g., auctions) and non-market-based tools (e.g., lotteries) have been used widely to ration scarce resources. These allocation mechanisms have significant implications for allocative efficiency, inequality, and environmental impact that are not easily measured. At the same time, these allocation mechanisms sometimes are time-consuming and generate an implicit cost of waiting to consumers. They delay people's access to the resource and may not allocate the scarce resource to people who want the resource the most urgently, causing a dynamic inefficiency.

In this paper, I focus on a scarce resource: vehicle licenses in China. As China experiences rapid economic growth, vehicle ownership is growing fast as well. From 2010 to 2017, privately-owned vehicles soared from 65 million to 187 million in China (China Association of Automobile Manufacturers, 2018). The rapid growth in vehicle ownership benefits households, but it also leads to severe traffic congestion and air pollution in large cities in China. Emissions from the transportation sector account for 9 percent of China's GHG emissions (IEA 2017). Furthermore, the traffic is so extreme in China's megacities that the average traffic speed during rush hours is usually less than 15 miles per hour.

Many of these cities, keen to reduce congestion and air pollution, discourage private car ownership by restricting the supply of license plates. So far, eight cities in China have implemented vehicle license allocations, accounting for about 8 percent of the total population. Both lotteries and auctions have been used to allocate vehicle licenses. The vehicle license allocations have reduced the new vehicle sales successfully. For instance, Shanghai has implemented vehicle license auctions since 1994. In 2011, Beijing started vehicle license lotteries with a monthly quota of 20,000 new licenses, reducing vehicle ownership growth by more than two-thirds.

However, the vehicle license allocations also impose an implicit cost on consumers. The win rates of lottery/auction are very low, and people on average have to wait for more than five years to win a vehicle license. For example, the win rates of vehicle license lotteries in Beijing dropped from 10% in 2011 to 0.1% in 2017. In addition to long wait times, people in Shanghai also have to pay a bidding price for vehicle licenses as high as one-third of the vehicle price. Thus, the allocation systems delay people's access to vehicle licenses and generate a high cost of waiting, reducing consumer welfare.

To reduce transportation emissions, the Chinese government actively promotes electric vehicles and announced an ambitious plan for the Development of the Energy-saving and New Energy Automobile Industry in 2012. In China, electric vehicles are also referred to as new energy vehicles (NEV), including battery electric vehicles, plug-in hybrid electric vehicles, range-extended electric vehicles, and fuel cell electric vehicles. The Chinese government aimed at increasing the accumulated NEV production and sales from less than 20,000 units in 2011 to 5 million units by 2020. Initially, the Chinese government relied on purchase subsidies to boost electric vehicle sales. However, China has gradually reduced purchase subsidies since 2016 and intends to replace them with other tools. The vehicle license allocation is one example of these tools that the government uses to encourage electric vehicle adoption.

To promote electric vehicle sales, cities with vehicle license allocations introduced new allocation systems for electric vehicle licenses. The Chinese government prefers vehicle license regulations because they are more politically feasible and have no fiscal cost. Beijing added a new lottery pool for electric vehicle licenses in 2014. Shanghai lifted the restrictions on electric vehicle licenses in 2013. As a result, the win rates of electric vehicle licenses are much higher, and people do not need to pay for electric vehicle licenses in the case of auctions. For example, in Beijing, the win rates of NEV licenses were almost 100 times larger than non-NEV licenses, and people only wait several months to obtain a NEV license. The much shorter wait times and the zero-bidding price for electric vehicle licenses incentivize people to purchase NEVs. The new allocation system for electric vehicle licenses appears to have been successful. From 2015 to 2017, electric vehicle sales in cities with vehicle license allocations were much higher than in other cities. However, compared to other instruments such as direct fuel taxes, the vehicle license allocation is less efficient and not the first-best tool to internalize the externalities associated with vehicle usage. Furthermore, vehicle license allocations make people wait several years for a license and generate a waiting cost to consumers. Therefore, the net welfare effects of vehicle license allocations remain ambiguous.

This paper investigates the impact of vehicle license allocation on adopting electric vehicles in China and quantifies its welfare effects. I focus on two cities with vehicle license allocations—Beijing and Shanghai. This paper adds to the existing literature by revealing that the implicit cost of waiting generated by vehicle license allocations causes a non-trivial welfare loss to consumers and plays an essential role in the welfare analysis of vehicle license allocations. This paper also distinguishes itself from the existing literature in that it focuses on a more recent allocation system with separate allocations for electric and non-electric vehicle licenses, whereas the rest of the literature has just looked at allocation systems for non-electric vehicle licenses. Notably, this paper finds that this separate system encourages electric vehicle adoption because of the shorter wait times for electric vehicle licenses and has an advantage over a combined allocation system for electric and non-electric vehicle licenses in terms of dynamic efficiency.

The first part of this paper presents results from reduced-form estimations and serves two purposes. First, I use the synthetic control approach (SCM) to select cities with no allocation systems. The two selected cities are Chongqing and Suzhou. I add these two cities to the estimation because, in the structural model, the implicit waiting costs are identified by comparing electric vehicle market shares in Beijing and Shanghai with other cities without vehicle license allocations. The SCM justifies my selection of other cities. The selection is not subjective and is driven entirely by data. Most importantly, SCM ensures the selected cities have the same trend in vehicle sales as Beijing in the pre-policy period, which is essential for identifying the implicit costs in the structural model. Second, it illustrates the effects of vehicle license allocations on vehicle sales. From the reduced-form estimation, Beijing's license lotteries have reduced vehicle sales by 61 percent in 2011. Moreover, the current vehicle license allocation system has significantly encouraged electric vehicle adoption in Beijing and Shanghai.

The second part of this paper sets up a theoretical model for the vehicle demand and supply under the allocation system. In the demand model, consumers are divided into two types: first-time buyers and second-time buyers. First-time buyers need to win the lottery/auction and obtain a license before buying a car. In contrast, second-time buyers do not need to participate in the lottery/auction. The first-time buyers need to determine whether to apply for a NEV license or a non-NEV license, which is affected by the implicit cost imposed by the allocation system. On the supply side, the vehicle producers choose the vehicle price to maximize their profit. The supply model explains how we can recover the marginal production costs and how the demand changes affect the vehicle prices.

The third part of this paper quantifies the implicit cost of the license allocations on vehicle purchases. I use highly disaggregated data for the above four cities from 2010 through 2017. I estimate a discrete choice model using the GMM method and methods by Berry et al. (1995) and Nevo (2001). The demand estimation is complicated because the bidding price for vehicle licenses and the implicit cost vary across both people and vehicle types. Hence, even for a simple Logit model where people have homogeneous preferences, a part of the utility is still individual-specific, and we cannot find an analytical solution mapping the observed market share to the vehicle's mean utility. Thus, I follow the method by Berry et al. (1995) to recover the mean utilities from a contraction mapping algorithm.

My identification strategy departs from most literature because the total vehicle price (price plus bidding price) and the implicit cost vary across both consumers and vehicles, and thus are uncorrelated with the city-specific time-varying unobserved demand shocks. The implicit cost of vehicle license allocations is identified by comparing the NEV share in Beijing and Shanghai with the NEV share in cities without vehicle license allocations. Intuitively, without the policy, NEVs should have the same market shares in all cities. It is the lower waiting cost for NEV licenses that shifts consumers from non-NEVs to NEVs in Beijing and Shanghai. The demand estimation reveals that the implicit cost imposed by the vehicle license allocation is about 10 percent of the vehicle price, around 31,000 Yuan in Beijing and 26,000 Yuan in Shanghai.

Finally, I do two counterfactual analyses. The first counterfactual illustrates the effect of Beijing's separate-lottery system on electric vehicle adoption and quantifies its welfare effects. It assumes a combined lottery for NEV and non-NEV licenses in Beijing. However, the actual allocation system in Beijing has separate lotteries for NEV and non-NEV licenses. The wait times for NEV and non-NEV licenses would be the same under the one-lottery system, and people would not be motivated to buy NEVs. The results show that compared with the one-lottery system, the actual separate-lottery system increased NEV sales by three times in Beijing. The NEV sales would have been much lower under the one-lottery system, leading to an increase in externalities of 0.03-0.36 billion Yuan. In addition, the one-lottery system would have reduced consumer welfare by 0.1 billion Yuan in 2017. This is because, under the separate-lottery system, consumers can shift from non-NEVs to NEVs to avoid waiting, while under the one-lottery system, consumers have no other choice but to wait a long time. Therefore, the one-lottery system is less dynamic-efficient than the separate-lottery system.

The second counterfactual assumes no vehicle license allocations, but instead, the government taxes non-NEVs to subsidize NEVs. The tax-subsidy program is such that electric vehicle market shares are the same under the counterfactual and the actual policy, and the government is revenue-neutral. The second counterfactual estimates the effect of vehicle ownership restrictions on NEV sales and their welfare effects in Beijing and Shanghai. The results suggest that the NEV share would have decreased by almost two-thirds without vehicle license allocations from 2013 to 2017. Without the policy, the government would have had to subsidize 21-44% of the NEV price to achieve the same NEV share as observed. Moreover, removing the vehicle license allocation would have increased consumer welfare by 26-52 billion Yuan in Beijing and 25-36 billion Yuan in Shanghai. The consumer welfare increase is due to shorter wait times and more vehicle sales, and the former accounts for around 10%. However, removing vehicle license allocations would have increased the externalities due to more vehicle sales, offsetting more than 80 percent of the consumer welfare gain.

This paper contributes to several aspects of literature. First, it contributes to the empirical studies on the welfare analysis of resource allocations. Abundant theoretical studies compare the welfare outcomes of lottery and auction in allocating scarce resources (e.g., Harris and Raviv 1981, Taylor et al. 2003). However, only a few empirical studies quantify the welfare effects of resource allocations. Most empirical research finds a significant welfare loss for lottery due to misallocation (e.g., Davis and Kilian 2011, Glaeser and Luttmer 2003). My paper quantifies the welfare effects of vehicle license allocations, and considers a more recent allocation system where non-NEV and NEV licenses are distributed via different mechanisms.

Second, this paper contributes to the welfare analysis of vehicle ownership restrictions. Most empirical studies investigate vehicle license allocation's impact on vehicle sales, pollution, congestion, employment, and travel behaviors (e.g., Yang et al. 2020;Liu et al. 2017;Yang et al. 2014; He and Jiang 2021;Li and Jones 2015;Zhang et al. 2018;Chi et al. 2021; Lin et al. 2016). Several studies explore the welfare effects of vehicle ownership restrictions. For example, Li (2018) compares welfare effects of vehicle license lotteries with auctions and estimates the social welfare loss from Beijing's lotteries is around 30 billion Yuan in 2012. He also points out that since there is a positive correlation between the WTP for vehicle license and the negative externalities, lotteries have an advantage over auctions in reducing automobile externalities. Liu et al. (2020) consider Beijing's license lottery in a dynamic framework and find that households move their participation decisions at least four years earlier. Changes in participation decisions cause welfare loss, accounting for over half of the total welfare loss from the lottery. Qin et al. (2021) conducted a contingent valuation survey of the lottery participants' WTP for the vehicle license plates. They find that the lottery has reduced private welfare by 26 billion Yuan, and the net welfare gain from replacing the lottery with an auction is about 20 billion yuan. Xiao et al.

(2017) quantify the welfare outcomes of the vehicle quota system (VQS) in Shanghai. They find the VQS reduced consumer welfare by about 12.57 billion Yuan due to fewer vehicle transactions and increased social welfare by 11.25 billion Yua because of fewer negative externalities.

This paper differs from the previous literature by emphasizing another reason that causes consumer welfare loss—the long wait time for a vehicle license. The existing literature considers the consumer welfare loss due to fewer transactions and misallocation. However, this paper shows that the policy makes people wait several years for a license and imposes an implicit cost on purchasing vehicles, reducing consumer welfare substantially. Additionally, this paper compares the separate-lottery system with the one-lottery system in Beijing and shows that the current separate system for NEV and non-NEV licenses increases allocative efficiency by allowing people to shift from non-NEVs to NEVs to avoid waiting. Moreover, to my knowledge, this paper is the first to use a structural model to evaluate the overall welfare effects of vehicle ownership restrictions compared to no restrictions in Beijing and Shanghai. The existing literature focuses more on comparing lotteries with auctions to allocate scarce resources, while this paper focuses more on quantifying the welfare loss due to the implicit cost of waiting and the policy's impact on electric vehicle adoption.

Third, this paper contributes to the growing literature on electric vehicle adoption. Most studies discuss the design and impact of subsidies on the adoption of NEVs (e.g., Clinton and Steinberg 2019,DeShazo et al. 2017, Borenstein and Davis 2016). Recently, growing literature points out the indirect network effect of the charging station on the NEV's adoption (e.g., Li et al. 2017, Li 2016). For example, Li et al. (2017) argues that subsidizing charging station deployment could have been more than twice as effective in promoting electric vehicle adoption than the federal income tax credit in the US. In addition, some literature finds the access to HOV or carpool lanes will increase the adoption of electric vehicles (e.g., Diamond 2008, Gallagher and Muehlegger 2011, Sheldon and DeShazo 2017).

Unlike the above studies on electric vehicle adoption, this paper considers a new instrument to promote electric vehicles—vehicle license allocation. This paper also compares the vehicle license allocation with other policies to promote NEV adoption, such as purchase subsidies. I show that shorter wait times and lower implicit cost of purchasing NEVs encourage electric vehicle adoption substantially. Moreover, the government would have had to subsidize 21-44% of the NEV price to achieve the same NEV share as observed if there were no vehicle license allocations from 2013 to 2017. This paper's findings have important policy implications. The Chinese government has been reducing NEV subsidies since 2016, and this paper suggests that vehicle license allocation is an efficient instrument to promote NEV adoption.

This paper's results should be of interest to many developing countries, whose vehicle ownership is increasing rapidly as they become wealthier. Many cities have implemented vehicle ownership restrictions to control transportation emissions and fuel consumption. The existing studies show that vehicle ownership restrictions substantially reduce consumer welfare by reducing new vehicle transactions. This paper shows that, besides fewer new vehicle transactions, vehicle ownership restrictions also generate a high waiting cost for consumers, which should not be ignored when evaluating the welfare effects of vehicle ownership restriction policies.

Moreover, electric vehicles have become the trend nowadays, and many countries have ambitious plans to increase electric vehicle sales. However, most countries rely on subsidies to promote electric vehicles. EV subsidies have significantly boosted EV sales. However, they also generate high fiscal costs. As a result, recently, more and more countries have sought regulations instead of direct subsidies to promote electric vehicles. This paper shows that separating the allocations of EV licenses and non-EV licenses is another instrument to boost electric vehicle adoption. It is as efficient as EV subsidies but induces a much lower fiscal cost. Therefore, cities with vehicle ownership restrictions could consider this regulation approach to promoting electric vehicles.

1.2 Policy and Data Description

In this section, I first introduce the policy background of vehicle license allocations and electric vehicle adoption in China and then present my data.

1.2.1 Policy description

To ease traffic congestion and air pollution, many megacities in China use vehicle license allocations to restrict private car ownership. This paper focuses on two cities with vehicle license allocations—Beijing and Shanghai. In Shanghai, vehicle licenses are allocated only by auctions, and Beijing allocates vehicle licenses only through lotteries. [1]

Vehicle licenses are needed for first-time buyers and those who purchase an old vehicle, accept a gifted vehicle, or transfer out-of-state registration to the regulated city. Vehicle owners who replace the used vehicle do not need a new license. City residents and non-residents who have been paying income tax for at least five years are eligible to apply for vehicle licenses and participate in the license allocation systems.

To apply for vehicle licenses, the eligible person needs to register online. Online regis-

[1]Other cities that newly started vehicle license allocations, such as Tianjin, Guangzhou, Shenzhen, and Hangzhou, use a hybrid mechanism whereby licenses are allocated both via auctions and lotteries. Figure A.1 in the Appendix shows the vehicle license regulations in six major cities in China.

tration is very easy, and people only need information from their ID card and Hukou booklet[2]. There is no registration fee. Shanghai's auction requires a deposit of 1,000 Yuan and charges a 60 Yuan service fee per auction.

Lotteries/auctions for private licenses are held monthly, and the winners have six months to register a new vehicle before the winning certificates expire. Most importantly, the license is non-transferable. Registering a non-NEV with a NEV license is illegal. In the lottery, the licenses are assigned to winners through random drawings. The online auction can be viewed as a multi-unit pay-as-you-bid auction without a reservation price. Applicants who pay no lower than the winning bidding price win the vehicle licenses.

Figure 1.1 summarizes the timing of regulations on vehicle license allocations in Beijing and Shanghai. Bejing started the vehicle license lotteries in January 2011. Initially, the non-NEV licenses and NEV licenses were allocated via the same lottery pool. The annual total quota for private and institutional vehicle licenses was 240,000 from 2011 through 2013. Lotteries for private and institutional vehicle licenses are separated. The private vehicle license accounts for 88% of the total quota. The private vehicle license lotteries were held every month. Since January 2014, Beijing has separated the lotteries for non-NEV licenses and NEV licenses to encourage electric vehicle adoption, and license lotteries are now held every two months. The annual total non-NEV license quota decreased from 240,000 in 2013 to 150,000 in 2017, and the annual total NEV license quota increased from 20,000 in 2014 to 60,000 in 2017. Since 2014, Beijing has varied the winning odds depending on the waiting time of the lottery applicants. It gives lottery applicants who have been applying for license plates for longer periods higher odds of winning. However, the win rates of non-NEV licenses still dropped from 10% in 2011 to 0.1% in 2017 due

[2] Hukou is a certificate of household registration.

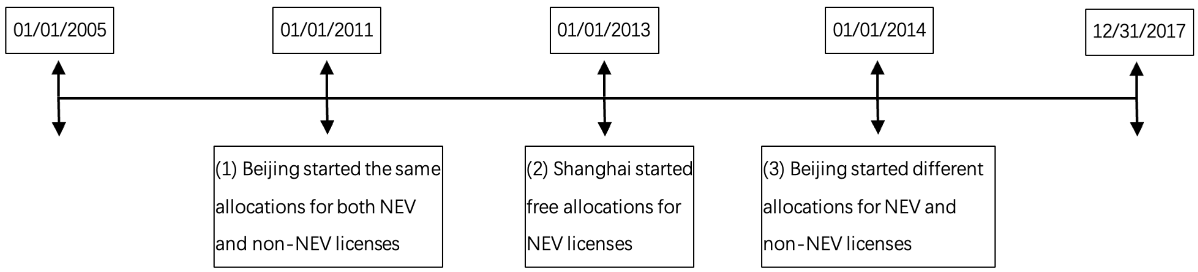
to more applicants. The win rates for NEV licenses are much higher than non-NEV licenses but decreased from 100% in 2014 to 34% in 2017. The certificate of winning a license is valid for six months, and lottery applicants need to register a car before the certificate expires.

Shanghai has implemented vehicle license allocations since 1994. It uses only auctions to allocate vehicle licenses, and the auction system has evolved over time. From 2010 to 2017, the auction can be viewed as a multi-unit pay-as-you-bid auction without a reservation price. The auctions are held monthly. The annual quota for private vehicle licenses increased from 103,200 in 2010 to 133,385 in 2017, while win rates dropped from 40% in 2010 to 5% in 2017. The average winning bidding price for a vehicle license increased from 38,311 Yuan in 2010 to 92,800 Yuan in 2017. Since January 2013, Shanghai has lifted restrictions on NEV licenses, and people do not need to pay for the NEV license.

The online auction runs for 90 minutes. In the first round, bidders will submit a single initial bid. In the second round, bidders can revise their bids after observing the current lowest accepted bid. The revised bid must be within a window of 300 Yuan below and above the current lowest accepted bid. This second round significantly reduces the volatility of the bidding price, as shown by the tiny difference between the average winning bid and the lowest winning bid (on average, the difference won't exceed 500 Yuan, or 1% of the average winning bid). Before 2014, winners were allowed three months to register a car after winning the auction. From 2014, the validation of the winning certificate has been extended to six months.

Since 2010, the Chinese government has introduced several other policies to encourage electric vehicle adoption, including tax exemptions and purchase subsidies. The vehicle purchase tax is 10% of the vehicle price. Electric vehicles have been exempted from the purchase tax since September 2014. Vehicles whose displacement is less than or equal to 1.6 liters enjoy lower

Figure 1.1: Timing of Regulations in Beijing and Shanghai



purchase tax rates ranging from 7.5% in 2010 to 5% in 2016. Since January 2012, NEVs have been exempted from the vehicle ownership tax as well. The vehicle ownership tax varies across provinces, and the baseline tax rate depends on vehicle displacement. The larger the vehicle displacement, the higher the tax rate. The vehicle ownership tax rate ranges from 180 to 5280 Yuan per car. In my data, taxes on NEVs decreased from 11% to 3% of the vehicle purchase price on average from 2014 to 2017.

There have been three waves of the purchase subsidy program. In the first wave, from June 2010 to 2012, the federal government selected six cities to start the pilot program, subsidizing individual purchases of NEVs. The subsidies depend on the electric vehicles' battery capacity, with a maximum of 50,000 Yuan for plug-in hybrid electric vehicles (PHEV) and 60,000 Yuan for battery electric vehicles (BEV). In the second wave, from 2013 to 2015, there were 28 cities in total selected to implement the purchase subsidies. The subsidies depended on the range of the electric vehicles and were reduced year by year. During the third wave, from 2016 onwards, the subsidy program was introduced to most major cities. Besides the national subsidy, some provinces and cities also have extra subsidies for NEV purchases and usage. In my data, on average, the total subsidy accounts for around 40% of the NEV purchase price in 2014, and about 22% in 2017.

1.2.2 Data description

This paper focuses on two cities with vehicle license allocations, Beijing and Shanghai, and two cities without vehicle license allocations, Chongqing and Suzhou. The two control cities are selected based on the synthetic control matching approach, which will be explained in detail in the following sections.

I use highly disaggregated data for the China market covering the years 2010 through 2017. Observations are by city, year-quarter, and vehicle. A unique vehicle is a unique model (nameplate), model year, origin (domestic or foreign), fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), engine displacement, and transmission configuration (manual or not). There are 81,056 observations in total and 1,396 unique vehicles. The average quarterly sales for a vehicle in a city is about 136.

Another auxiliary data includes information on vehicle attributes. These attributes include price, fuel economy, engine displacement, length, width, height, wheelbase, curb weight, engine horsepower, number of doors, number of seats, number of cylinders, number of valves, drive type, number of gears, segment, and body type. The price includes the manufacturer suggested retail price, tax, and subsidies, and does not include the production subsidies. In my dataset, vehicle's attributes won't change across city and time. Variations in price come from vehicle tax and subsidies as well as the bidding price. Variations in fuel cost are due to the energy price changes across cities and time.

Table 1.1 shows the summary statistics of these attributes for non-NEVs and NEVs. The average quarterly sale is about 136 for a unique non-NEV and 130 for a unique NEV. The average price of NEV is slightly lower than non-NEVs, probably due to the NEV subsidies. The average winning bid in Shanghai is 75,600 Yuan or 32% of the total vehicle price. As expected, the average fuel consumption rate for NEVs is much lower than non-NEVs. Other attributes have no significant differences between non-NEVs and NEVs.

Table 1.1: Summary Statistics by Vehicle Type

	Total			Non-NEV			NEV		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Quarterly sales by city	81,056	135.61	252.54	79,408	135.73	247.05	1,648	129.67	442.86
Price (10000 Yuan)	81,056	23.63	19.50	79,408	23.72	19.51	1,648	19.20	18.53
Average winning bid (10000 Yuan)	20,264	7.56	2.05	19,852	7.84	1.46	412	0.04	0.54
Dummy for domestic cars	81,056	0.91	0.29	79,408	0.91	0.29	1,648	0.92	0.27
Displacement (L)	81,056	1.80	0.49	79,408	1.82	0.45	1,648	0.60	0.78
Fuel cost (Yuan/100 km)	81,056	52.52	14.95	79,408	53.38	13.77	1,648	8.95	1.59
Fuel consumption (liter/100 km)	81,056	7.42	1.57	79,408	7.54	1.36	1,648	1.70	0.24
Horsepower (100 hp)	81,056	1.13	0.39	79,408	1.13	0.37	1,648	1.18	0.90
Curb weight (ton)	81,056	1.47	0.28	79,408	1.47	0.27	1,648	1.69	0.38
Horsepower/weight (hp/kg)	81,056	0.76	0.14	79,408	0.76	0.13	1,648	0.66	0.35
Size (cubic meters)	81,056	12.85	1.71	79,408	12.86	1.70	1,648	12.32	2.04
Wheelbase (meter)	81,056	2.70	0.15	79,408	2.70	0.15	1,648	2.63	0.17
Number of doors	81,056	4.45	0.53	79,408	4.45	0.53	1,648	4.47	0.55
Number of seats	81,056	5.12	0.58	79,408	5.13	0.57	1,648	4.84	0.54
Number of cylinders	81,056	4.07	0.70	79,408	4.12	0.54	1,648	1.50	1.92
Number of valves	81,056	3.91	0.54	79,408	3.95	0.32	1,648	1.53	1.94
Number of gears	81,056	5.23	1.97	79,408	5.28	1.92	1,648	2.31	2.10

Notes: means are sales-weighted. Price, bid, and fuel cost are all normalized to 2017 Yuan. Only observations in Shanghai have values in average winning bid.

Table 1.2 compares the vehicle sales, price, and fuel economy by city. Each vehicle's quarterly sales are higher in the treated cities than in the control cities. The average annual vehicle sales are 482,232 in Beijing, 288,912 in Chongqing, 328,261 in Shanghai, and 274,664 in Suzhou. Treated cities sold more electric vehicles than control cities. A unique NEV's quarterly sale in the treated cities is about 20 times larger than in Chongqing and 40 times larger than in Suzhou. On average, NEV sales account for 2.8% of the total sales in Beijing and 3.3% of the total sales in Shanghai. However, in Chongqing and Suzhou, only 0.2% of the total sales are electric vehicles. The huge difference in NEV shares between treated and control cities may partly result from the license allocations, which this paper will explore more in the following context. People in treated cities tend to buy more expensive cars than the control cities, as Beijing and Shanghai are the two richest cities in China. The average fuel consumption rates in these four cities are close, although people in Beijing buy more vehicles with higher horsepower and lower fuel economy.

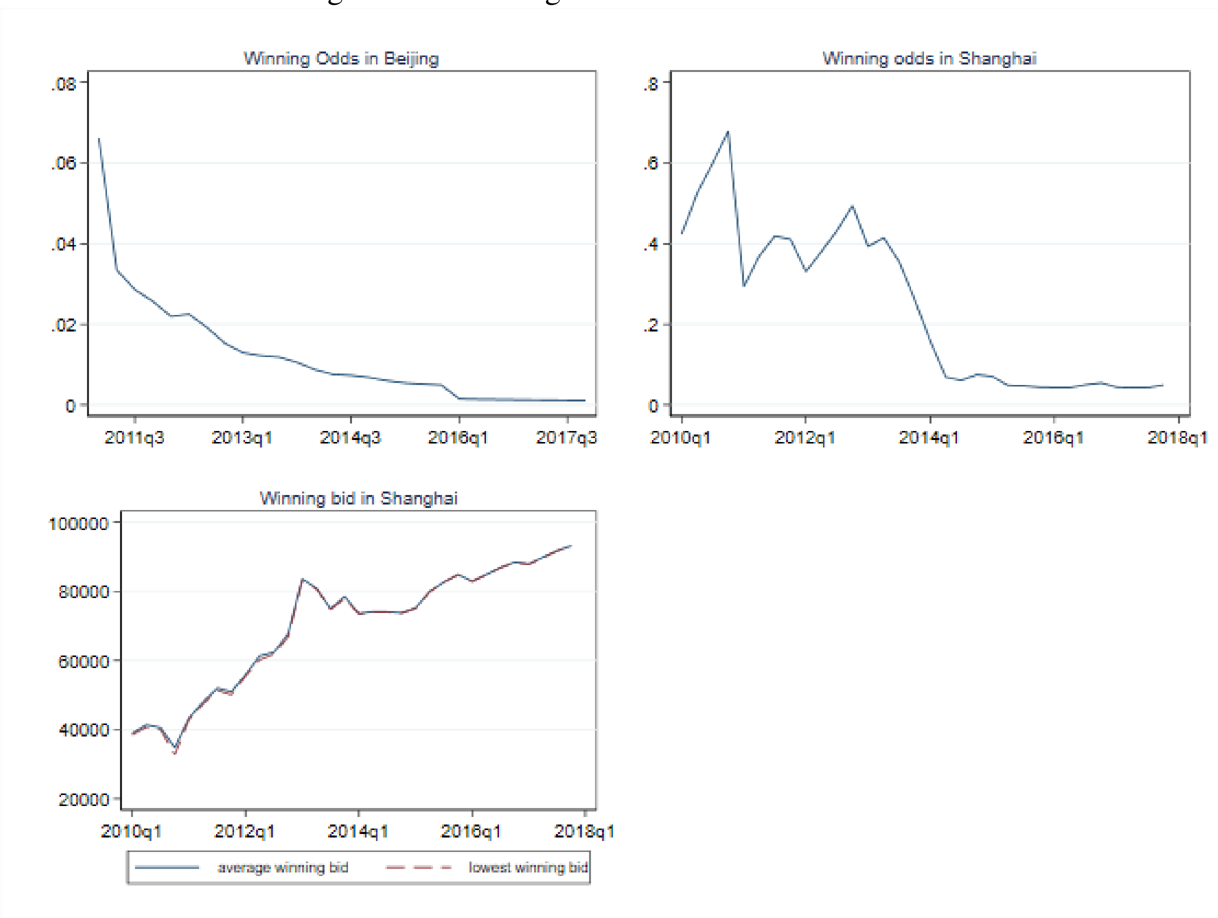
Table 1.2: Summary Statistics by City

			Quarterly sales by vehicle			
City	Number of observation	Mean	Median	Standard deviation	Min	Max
Beijing	20,264	190.38	69	330.86	0	4591
Chongqing	20,264	114.05	37	206.97	0	3526
Shanghai	20,264	129.59	42	251.61	0	4920
Suzhou	20,264	108.42	35	187.81	0	2565
			Quarterly sales by vehicle (NEV)			
City	Number of observation	Mean	Median	Standard deviation	Min	Max
Beijing	412	267.47	40	550.22	0	3840
Chongqing	412	11.36	1	56.64	0	745
Shanghai	412	234.72	16	647.40	0	4837
Suzhou	412	5.12	1	34.35	0	679
			NEV shares of annual sales			
City	Annual total sales	Mean	Median	Standard deviation	Min	Max
Beijing	482,232	0.028	0.006	0.037	1.060E-05	0.092
Chongqing	288,912	0.002	0.001	0.003	1.280E-05	0.009
Shanghai	328,261	0.033	0.032	0.036	8.800E-06	0.094
Suzhou	274,664	0.001	0.001	0.001	1.030E-05	0.004
			Sales-weighted price			
City	Number of observation	Mean	Median	Standard deviation	Min	Max
Beijing	20,264	26.66	21.30	21.95	3.29	517.64
Chongqing	20,264	19.72	14.50	16.86	3.15	516.22
Shanghai	20,264	25.51	19.61	20.06	3.20	516.98
Suzhou	20,264	20.18	15.41	15.09	3.15	516.22
			Sales-weighted fuel consumption rate			
City	Number of observation	Mean	Median	Standard deviation	Min	Max
Beijing	20,264	7.6	7.5	1.8	0.7	17.5
Chongqing	20,264	7.4	7.1	1.3	0.7	17.5
Shanghai	20,264	7.4	7.3	1.7	0.7	17.5
Suzhou	20,264	7.3	7.0	1.2	0.7	17.5

Besides the sales data and information on vehicle attributes, this paper also collects information on the vehicle license allocations in each city. This data includes the number of applicants, quota amount, winning odds, average winning bid price, and lowest bid price in each treated city. As shown in Figure 1.2, the winning odds of non-NEV licenses in Beijing dropped rapidly, from 10% in 2011 to 0.1% in 2017. Shanghai's auctions have higher winning odds than lotteries in Beijing. However, the winning odds of non-NEV licenses in Shanghai also decreased a lot, from

40% in 2010 to 5% in 2017. The average winning bid increased from around 40,000 Yuan to 90,000 Yuan in 2017, accounting for about one-third of the total vehicle price.

Figure 1.2: Winning Odds of Non-NEV Licenses



The fourth dataset includes city-level demographics, including the number of households, GDP per capita, and income distributions. I obtain the average income by income quantiles from the statistical yearbooks of each city.

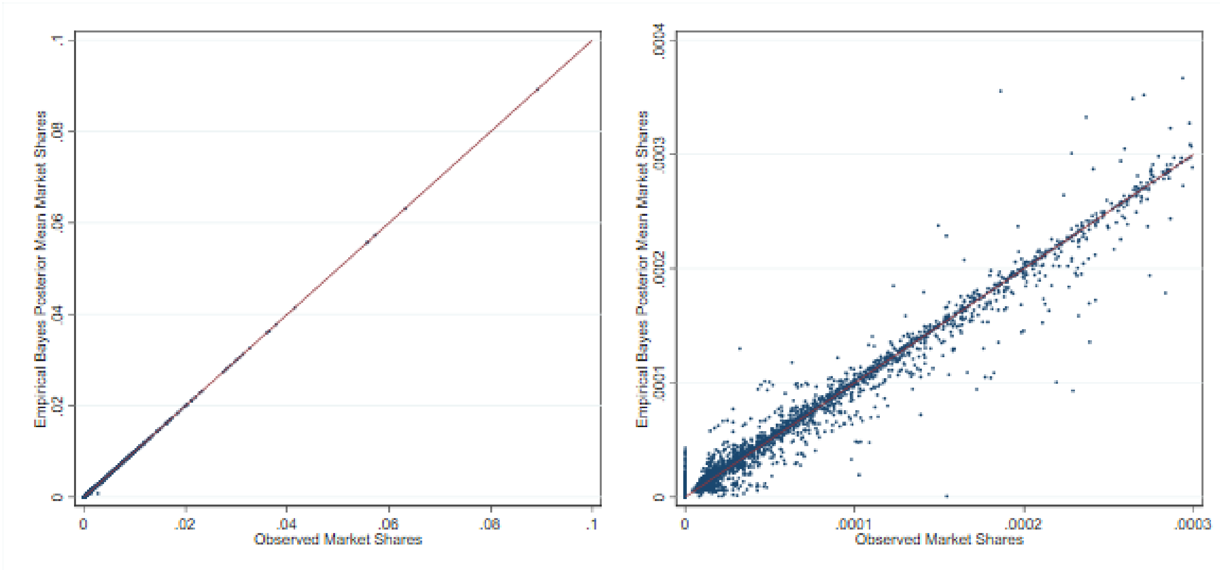
1.2.2.1 Zero market share problem

This paper studies China's vehicle license allocations from 2010 through 2017 when the market of NEVs was still in an embryonic stage. Since NEVs first appeared in 2010 in China, they initially sold zero quantities in many local markets. Appendix Table A.1 shows that in Beijing, Chongqing, Shanghai, and Suzhou, 40% of NEV observations have zeroes market shares, ranging from 34% (2017) to 50% (2014). The large share of zero market shares in 2014 is due to the introduction of new NEV models in 2014 when the second wave of the NEV subsidy program started. Since those NEVs just appeared on the market, their underlying purchasing probability is very low. Hence, sales of these electric vehicles usually appeared in one quarter and disappeared in another quarter, which led to a large number of zero sales in my dataset.

The method by Berry et al. (1995) assumes that the observed market shares can be used as estimates for the underlying purchase probabilities. However, the zero market shares mask the true underlying purchase probabilities and make the inversion step impossible in the method by Berry et al. (1995). In this paper, I follow the method used by Li (2016) to impute the true purchase probabilities of these zero market shares. The basic idea is to use the sales information in other markets to generate strictly positive Bayes posterior estimates of the true purchase probabilities underlying the zero market shares. The details of the imputation method by Li (2016) are described in Appendix Section A.2.

Figure 1.3 shows the correlation between the observed and imputed market shares in my data. The right graph zooms in on observations with very low market shares ranging from 0 to 0.0003. The horizontal axis represents the observed market shares and the vertical axis represents the imputed market shares using the above method. As shown in the figure, the imputed market shares are very close to the observed market shares and all zero market shares now become positive. As shown in the third part of Appendix Table A.1, the means of the observed and imputed market shares are very similar, 0.001064 and 0.001068, respectively.

Figure 1.3: Correlation between Imputed Market Shares and Observed Market Shares



Notes: line in the figure is the 45 degree line. An observation is the sale of a unique vehicle by city and year-quarter. The horizontal axis represents the observed market shares and the vertical axis represents the imputed market shares.

1.3 Evidence from Reduced-form Estimation

This section provides evidence from reduced-form estimation that supports the following structural model. The reduced-form estimation serves two purposes:1) selects control cities; 2) shows preliminary results of the vehicle license allocation's impact on vehicle sales. I use aggregated data from 20 major cities in China from 2005 through 2017. There are two treated cities—Beijing and Shanghai. Beijing implemented the policy in January 2011, and Shanghai began the policy by the end of the twenty century. The treatment is a vehicle license allocation event. First, I use the synthetic control approach to select control cities for the two treated cities. Then, I estimate a triple-difference model (DDD) to show the impact of vehicle license allocations on vehicle sales. The DDD estimation finds that vehicle license allocations reduced the non-NEV sales and encouraged more people to purchase electric vehicles.

1.3.1 Synthetic control approach for matching

This paper focuses on two treated cities with vehicle ownership restrictions: Beijing and Shanghai. I use the Synthetic Control Methodology (SCM) (Abadie and Gardeazabal 2003; Abadie et al. 2010) to select control cities with no vehicle ownership restrictions. I add these control cities to the estimation because, in the structural model, the implicit waiting costs are identified by comparing electric vehicle market shares in Beijing and Shanghai with control cities. The SCM justifies my selection of other cities. It is usually ambiguous about how to choose control units, and researchers often select control units subjectively. However, the selection of control cities by SCM is driven entirely by data and not subjective. Most importantly, SCM ensures the selected control cities have the same trend in vehicle sales as treated cities in the pre-policy period, which is essential for identifying the implicit costs in the structural model.

Following the model by Abadie et al. (2010), let D_{it} be an indicator for treatment on unit i at time t. $i = 0, 1, ..., J$, and $i = 0$ represents the treated unit, $1 \leq i \leq J$ are control units. $t = 1, ..., T_0, T_0 + 1, ...$,T, where $1 \leq t \leq T_0$ are the pre-treatment period, and $T_0 + 1 \leq t \leq T$ are post-treatment period. α_{it} is the treatment effect, Y_{it} is the observed outcome under treatment, and Y_{it}^N is the counterfactual outcome assuming there were no treatments. Then Y_{it} equals the sum of Y_{it}^N and $\alpha_{it} D_{it}$.

$$\begin{aligned} Y_{it} &= Y_{it}^N + \alpha_{it} D_{it} \\ &= (\delta_t + \theta_t Z_i + \lambda_t \mu_j + \varepsilon_{it}) + \alpha_{it} D_{it} \end{aligned} \tag{1.1}$$

where, δ_t is a time fixed effect Z_i are the observed covariates exogenous to the treatment, λ_t represents an unknown common factor with varying factor loadings μ_i across units. ε_{it} are idiosyncratic error terms.

The synthetic control approach constructs a synthetic cohort which is a weighted average of control units. The optimal weights equal the outcome of the treated unit and synthetic control over the pre-treatment period and equal the observed characteristics of the treated unit and the synthetic control. That is, we choose weights $w^* = (w_2^*, w_3^*, ..., w_J^*)$' such that:

$$\sum_{j=1}^{J} w_j^* \bar{Y}_j^k = \bar{Y}_0^k, \quad \sum_{j=1}^{J} w_j^* Z_j = Z_0 \tag{1.2}$$

$k = (k_1, k_2, ..., k_{T_0})'$ are weights on the outcome variable of each time during the pre-treatment period. Then, $\bar{Y}_j^k = \sum_{t=1}^{T_0} k_t Y_{it}$ is the average of the outcome variables for the pre-treatment period. Therefore, the first part in equation 1.2 means that the optimal weights will equal the outcome of the weighted average of control units with the outcome of the treated unit over the pre-treatment period. And the second part in equation 1.2 means that the optimal weights will equal the observed characteristics of the weighted average of control units with the observed characteristics of the treated unit.

In the matching, I restrict the candidates for control cities to cities that enjoy similar NEV subsidies and tax exemptions as Beijing and Shanghai. There are 20 candidates in total, and these cities participated in the NEV subsidy program around the same time as Beijing and Shanghai. This method aims to reduce the difference in NEV sales between control and treated cities due to the NEV subsidy programs. Then I use the synthetic control approach to select control cities for Beijing and Shanghai. The outcome variable is the log of the vehicle sales per household in a city by year-quarter. The treatment is the vehicle license allocation, which started in 2011 in Beijing. There is no pre-policy period for Shanghai since Shanghai started the vehicle license auction in 1994. I select the control cities by equaling the weighted average of the control units' outcome variables in the pre-policy period (before 2011) to the outcome variable of Beijing and Shanghai in the pre-policy period. Also, observed variables are used for the matching, including the number of permanent households, average household income, GDP per capita, population, and each city's share of the total national NEV sales over the pre-policy period.

The SCM selected two control cities to construct the synthetic control group—Chongqing and Suzhou. It gives a weight of 0.494 to Chongqing and a weight of 0.506 to Suzhou. Chongqing is one of the most populous cities in China and is one of four municipalities under the central government's jurisdiction (the other three cities are Beijing, Shanghai, and Tianjin). Suzhou is about 100 km away from Shanghai and is located in the Yangtze River Delta, one of China's most economically active, open, and innovative regions.

Figure 1.4 shows the trends in the log of vehicle sales per household in Beijing and the synthetic control group. The log of vehicle sales per household is higher in Beijing than in control cities because Beijing is the most populous and the biggest vehicle market in China before 2011. Other cities' vehicle sales are much lower than Beijing before 2011. However, the trends of vehicle sales in Beijing and other control cities were very similar before the vehicle license allocation started in Beijing (January 2011). The policy strictly reduced the vehicle sales in Beijing in 2011, and shrank the difference in vehicle sales between Beijing and the control cities. Appendix Figure A.2 also shows the trends in the market shares of EVs in Beijing, Shanghai, and the synthetic control group. Before the separating the allocations of EV and non-EV licenses in Beijing and Shanghai (2013 and 2014), the EV market shares are very small and the trends in the

EV market shares are similar in Beijing, Shanghai and other control cities. However, after 2013, the EV market shares in Beijing and Shanghai are much higher than in control cities.

Table 1.3 compares the means of the observed predictors of treated and control cities. After matching, the total number of households and the population are similar between treated and control cities. Treated cities are slightly richer than control cities. Beijing accounted for 7% of the NEV market, and Shanghai accounted for 5% of the NEV market in the pre-policy period. The synthetic control group accounted for about 4% of the NEV market, slightly lower than the treated cities.

Figure 1.4: Trends in the Log of Vehicle Sales per Household: Beijing vs. Synthetic Control

Notes: The dependent variable is the log of vehicle sales per household in each city and year-quarter. The dashed vertical line represents the start of vehicle license allocation in Beijing in January 2011.

Table 1.3: Predictor Means: Treated Cities vs. Synthetic Control

	Beijing	Shanghai	Synthetic Control
Number of households (10,000)	697	855	784
Urban household income (Yuan)	117,700	128,128	103,132
GDP per capita (Yuan)	100,718	98,725	86,767
Population (10,000)	1,766	2,137	1,802
City share of national NEV sales	0.07	0.05	0.04

Figure A.3 in Appendix shows the results for other outcome variables. I compare the trends of treated cities and the synthetic control group in sales-weighted MSRP (manufacturer suggested retail price), fuel consumption, horsepower, vehicle curb weight, vehicle size, and engine displacement. As shown in the figure, the treated cities have similar trends as the control cities before the policy started (January 2011). However, after the introduction of vehicle license allocations, divergences appeared in the trends of MSRP, horsepower, weight, and engine displacement for treated and control cities.

1.3.2 Impact of vehicle license allocations on vehicle sales

Because the SCM matching only selects two control cities—Chongqing and Suzhou and it gives almost the same weights to these two control cities, the SCM estimation of the treatment effect will be very similar to the difference-in-difference estimation. Therefore, in this part, I estimate a triple-difference model to examine the impact of vehicle license allocations on non-NEV and NEV sales. A unique observation is a unique combination of vehicle type (non-NEV or NEV), city, and year-quarter. The outcome variable is the log of the sales per household for non-NEV/NEV in a city and year-quarter. I estimate the following regressions:

$$
\begin{aligned}
logS_{vmt} =& \sum_{s=1}^{3} \gamma_s TreatedCity_m^s \times Post_t^s \times NEV_v + \sum_{s=1}^{3} \beta_s TreatedCity_m^s \times Post_t^s \\
&+ \sum_m \theta_m City_m \times NEV_v + \sum_t \alpha_t Time_t \times NEV_v \\
&+ \xi_m + \xi_t + \varepsilon_{vmt}
\end{aligned}
\tag{1.3}
$$

where m represents for city, t represents year-quarter, and s corresponds to the regulation event as shown in Figure 1.1. S_{vmt} is the sales of NEVs or non-NEVs per household in a city by year-quarter. v represents for the vehicle type (non-NEV or NEV). NEV_v equals one for NEV sales. $TreatedCity_m^s$ is a dummy variable that quals one if city m is treated under a new regulation s. $Post_t^s$ equals to one if the year-quarter t belongs to the post-treatment period of the regulation event s. ξ_m, ξ_t represent the city fixed effect and year-quarter fixed effect repectively. $\sum_m \theta_m City_m \times NEV_j$ allows the city-specific trend for NEV sales. $\sum_t Time_t \times NEV_j$ allows the time trend for NEV sales.

The treated effect of regulation event s on the NEV and non-NEV sales are captured by the parameters γ_s and β_s. And I assume that $\beta_1 < 0$ for non-NEV sales under event 1, which implies the vehicle license allocation in 2011 will reduce the non-NEV sales in Beijing. And $\gamma_2 > 0, \gamma_3 > 0$ for NEV sales under event 2 and 3, indicating that the separate allocations for NEV and non-NEV licenses will increase the NEV sales.

Table 1.4 shows the estimation results of regressions 1.3. Column 1 is the preferred estimation, and each column corresponds to different fixed effects. As expected, the vehicle allocation system reduced vehicle sales significantly and substantially increased NEV sales. The treatment effects on NEV sales are all positive and the treatment effects on non-NEV sales are all negative. Also, the treatment effects are statistically significant at 1 percent level. The second panel in Table 1.4 shows the impact of the policy. From estimation, the vehicle license allocation in Beijing has reduced vehicle sales by almost 61% (The coefficient on TreatedCity 1 x Post 1). This implies that without the policy, vehicle sales would have been 760,821 units in 2011 and 1.2 million units in 2012. The average annual vehicle sales would have been 1.22 million units after 2011 (the actual average annual sale after 2011 was around 472,300 units). These results are close to the estimation of Li (2018). Li (2018) estimated that the lottery policy in Beijing reduced vehicle sales by 60.6% in 2011 and 50.7% in 2012, which means that the sales without the policy in 2011 and 2012 would have been 847,000 and 1.05 million units, respectively.

Allowing for free allocation of NEV licenses in Shanghai (Event 2) increased NEV sales in Shanghai. Moreover, separating the lottery pools for non-NEV and NEV licenses (Event 3) increased NEV sales in Beijing. The bottom of 1.4 shows the impact of policy on NEV sales. Lifting the limits of NEV licenses in Shanghai increased the NEV sales by 19.36 times (The coefficient on TreatedCity 2 x Post 2 x NEV). And the separation of NEV and non-NEV lottery pools increased NEV sales by about 5.46 times in Beijing (The coefficient on TreatedCity 3 x Post 3 x NEV). This implies that without the policy, the annual NEV sales would have been 6,505 units in Beijing and 1,815 units in Shanghai in 2017. In comparison, the actual annual NEV sales were around 46,322 units in Beijing and 36,957 units in Shanghai in 2017.

Table 1.4: Impact of Vehicle License Allocations on Vehicle Sales

	(1)	(2)	(3)	(4)
TreatedCity 1 x Post 1 x NEV	1.9563***	1.9440***	1.0515***	1.9440***
	(0.3218)	(0.3029)	(0.3038)	(0.3029)
TreatedCity 2 x Post 2 x NEV	3.0472***	3.4426***	3.4212***	3.4426***
	(0.2925)	(0.2952)	(0.2939)	(0.2952)
TreatedCity 3 x Post 3 x NEV	1.9993***	2.0266***	1.9898***	2.0266***
	(0.4843)	(0.4545)	(0.4599)	(0.4545)
TreatedCity 1 x Post 1	-0.9490***	-0.8194***	-0.7965***	-0.8194***
	(0.0875)	(0.0801)	(0.0845)	(0.0801)
TreatedCity 2 x Post 2	-1.2036	-0.5548***	-0.5681***	-0.5548***
	(0.7315)	(0.0842)	(0.0830)	(0.0842)
TreatedCity 3 x Post 3	-0.3047***	-0.4000***	-0.4030***	-0.4000***
	(0.1098)	(0.0855)	(0.0786)	(0.0855)
City fixed effects	X	X	X	X
Year-quarter fixed effects	X	X	X	X
Specific time trend for Shanghai	X			
City by NEV	X	X		X
Year-quarter by NEV	X	X	X	X
Treated city by NEV			X	
NEV				X
Number of observations	305	305	305	305
Adjusted R-squared	0.9783	0.9805	0.9791	0.9805
Impact of license allocations on NEV sales				
Event 1	5.46	5.43	1.31	5.43
Event 2	19.36	29.84	29.17	29.84
Event 3	6.12	6.26	5.98	6.26
Impact of license allocations on non-NEV sales				
Event 1	-0.61	-0.56	-0.55	-0.56
Event 2	-0.70	-0.43	-0.43	-0.43
Event 3	-0.26	-0.33	-0.33	-0.33

Notes: Dependent variable is the log of vehicle registrations per household by vehicle type (non-NEV/NEV), city and year-quarter. The impact of license allocations on vehisales is the percentage change of the vehicle sales under treatment compared to the scenario where there was no treatment. Event 1 is the start of vehicle license allocation in Beijing in 2011. Event 2 is lifting restrictions on NEV licenses in Shanghai in 2013. Event 3 is adding a new lottery for NEV licenses in Beijing in 2014. Standard errors are clustered by city and year.

Appendix Table A.2 reports the results from the common trend test for vehicle sales. I use data from the pre-policy period (2005-2010) to do a placebo test. The dependent variable is the log of vehicle registrations per household by city and year-quarter. Here, I include Beijing by year fixed effects that capture the time-varying demand shocks that are specific to the treated city Beijing. The common trend assumptions for DID assume that these unobserved demand shocks are the same across treated cities and control cities in a given year. Therefore, if the common trend assumption holds, the fake treatments should have no significant effects and the coefficients on the interactions of Beijing and years should be insignificant. As shown in A.2, coefficients on the Beijing by year fixed effects are all insignificant, which does not reject the common trend assumptions.

The above results from reduced-form estimations suggest that the vehicle license allocations have significant impacts on non-NEV and NEV sales. However, since there were very few electric vehicles on the market before 2013, there are not enough NEV observations before the pre-policy period in my data. As a result, I cannot test the common trend assumption for NEV sales. Therefore, we should treat the above results with caution. Moreover, the reduced-form estimation does not explain why the policy encourages NEV adoption. In the following sections, I derive a structural model to quantify the implicit cost of vehicle license allocations, which explicitly explains the mechanism that incentivizes people to purchase electric vehicles.

1.4 Model of Vehicle License Allocations

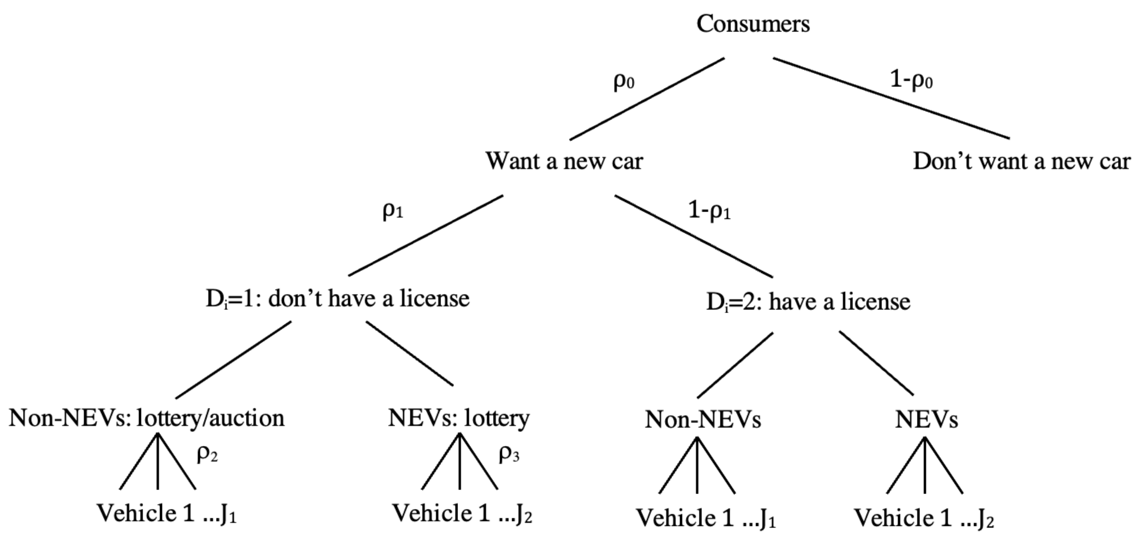
This section sets up a structural model to illustrate the impact of vehicle license allocations on vehicle demand and supply and to explain how the implicit cost of this policy encourages electric vehicle adoption.

1.4.1 Vehicle demand

1.4.1.1 Utility function specification

Figure 1.5 illustrates the choice structure under the vehicle license allocations. The market size is defined as the total number of households in each city and year-quarter. Among the households, some households want a new car while others do not. New car buyers account for ρ_0 of the total number of households. The new car buyers are divided into two types: 1) type 1 ($D_i = 1$)—people who do not have a vehicle license, such as first-time buyers and those who purchase an old vehicle, accept a gifted vehicle, or transfer our-of-state registration to the regulated city; 2) type 2 ($D_i = 2$)—people who already have a license, such as those who replace old vehicles. The probability that a consumer belonging to type 1 consumers is ρ_1. The type 1 consumers need to participate in license lotteries/auctions and win a vehicle license before purchasing a new car, while the type 2 consumers do not need to apply for a vehicle license and they can buy whatever car they like. For type 1 consumers, they need to decide on whether to join the lotteries/auctions for non-NEVs or participate in the lotteries for NEVs. The winning odds of non-NEV lotteries/auctions are ρ_2, and ρ_3 for NEV lotteries. Once they win the license lottery/auction, they can purchase a car allowed by the corresponding type of license.

Figure 1.5: Choice Structure Under Vehicle License Allocations



For simplicity, assume consumers have homogenous tastes for the vehicle attributes. Thus we can write a consumer i's utility from purchasing vehicle j in market m at year-quarter t as:

$$\begin{aligned} U_{ijmt} &= \alpha log(P_{jmt} + B_{iv(j)mt}) + \lambda_{iv(j)mt} + X_{jmt}\beta + \xi_{jmt} + \varepsilon_{ijmt} \\ &= \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt} \end{aligned} \tag{1.4}$$

And,

$$\delta_{jmt} = X_{jmt}\beta + \xi_{jmt} \tag{1.5}$$

$$\mu_{ijmt} = \alpha log(P_{jmt} + B_{iv(j)mt}) + \lambda_{iv(j)mt} \tag{1.6}$$

where i is for consumer, j is for consumer, m is for city, t is year-quarter, and v is for the vehicle type (non-NEV or NEV). P_{jmt} is the vehicle's price including the MSRP, tax, federal subsidies and local subsidies, which varies across vehicle, city and time. $B_{v(j)mt}$ is the average winning bidding price. X_{jmt} includes observed vehicle attributes. ξ_{jmt} includes other unobserved vehicle attributes.

$\lambda_{v(j)mt}$ is the term capturing the implicit cost generated by the vehicle license allocations, which could include the cost of waiting to obtain a vehicle license and the cost associated with uncertainties. I assume this implicit cost of waiting equals to zero for NEVs in the treated cities and for all vehicles in the control cities. For non-NEVs in the treated cities, $\lambda_{v(j)mt}$ is strictly negative. Since the implicit cost of waiting varies across vehicle type, we can also view it as a vehicle attributes.

Utility in 1.4 can then be divided into two parts—(1) the mean utilities δ_{jmt} which are common to all consumers and consist of utility from the observed vehicle attributes X_{jmt} as well as the unobserved attributes ξ_{jmt}; (2) the individual-specific utility μ_{ijmt} that varies across consumers.

Notably, in this model, even if we assume the homogenous tastes across consumers, we still have an individual-specific utility μ_{ijmt}. This model is more complicated than the standard Logit model. The individual-specific utility arises from the bidding price $B_{iv(j)mt}$ and the implicit cost $\lambda_{iv(j)mt}$. The average bidding price $B_{iv(j)mt}$ varies across consumer type, vehicle type, city, and time. It equals zero for all cities except Shanghai, because only Shanghai uses auctions to allocate the licenses. For consumers who already have licenses (i.e., type 2 consumers), they don't need to participate in the auctions, and thus their $B_{iv(j)mt}$ equals zero. Type 1 consumers who don't have a license need to join the auctions, and their $B_{iv(j)mt}$ are positive. Also, $B_{iv(j)mt}$ varies across vehicle type. Shanghai's vehicle license allocation experienced two periods: (1) before 2013, when the allocation mechanism for non-NEV and NEV licenses are the same; (2) 2013-2017, NEV licenses are free allocated. Before 2013, type 1 consumers paid bidding prices for both NEV and non-NEV licenses and $B_{iv(j)mt}$ is positive. From 2013, the bidding price $B_{iv(j)mt}$ for NEV license becomes zero, while $B_{iv(j)mt}$ for non-NEV license is still positive.

The implicit cost $\lambda_{v(j)mt}$ is more complicated to understand. It varies across consumer type, vehicle type, city, and time as well. $\lambda_{v(j)mt}$ equals zero for the control cities and is positive for the treated cities during the treated time. Type 2 consumers do not need to apply for licenses and their $\lambda_{v(j)mt}$ are zero. Type 1 consumers are subject to the implicit cost. Beijing's policy experienced three periods: (1)pre-policy period (before 2011); (2) 2011-2013, one lottery for non-NEV and NEV licenses; (3) 2014-2017, separate lotteries for non-NEV and NEV licenses. In Beijing, in the pre-policy period, there was no license allocations, and $\lambda_{v(j)mt}$ remains zero. In the second period, from 2011 through 2013, there was only one lottery pool for non-NEV and NEV licenses, and thus all vehicles are subject to the same implicit cost $\lambda_{v(j)mt}$. From 2014, NEV and non-NEV licenses have separated lottery pools, and the winning odds of NEV licenses are much greater than non-NEV licenses. Therefore, NEV and non-NEV are subject to different implicit costs by the allocation policy. I assume the implicit cost for NEV after 2014 is very small and can be regared as zero.

In Shanghai, there is no pre-policy period in my data, and thus initially, all vehicles are subject to $\lambda_{v(j)mt}$. From 2013, Shanghai has no limits on NEV licenses. Type 1 consumers do not need to wait to win the auction for NEV license, and thus $\lambda_{v(j)mt}$ becomes zero to NEVs. However, non-NEVs are still subject to the policy, and their $\lambda_{v(j)mt}$ are still negative.

1.4.1.2 Choice probabilities and aggregated demand

I devide all vehicles into non-NEVs ($v = 1$; $\Theta_1 = \{j|j = 1, ..., J_1\}$) and NEVs ($v = 2$; $\Theta_2 = \{j|j = 1, ..., J_2\}$). And a variable D_i is used to indicate the consumer's type. $D_i = 1$ represents type 1 consumers such as first-time buyers who need a license, and $D_i = 2$ represents the type 2 consumers who do not need licenses.

The conditional probability that a type 1 consumer i chooses a vehicle j in the post-treated period is:

$$S^{(1)}_{jmt} = \frac{exp[\alpha log(P_{jmt} + B_{mt}) + \lambda_{mt} + \delta_{jmt}]}{\sum_j^{J_1} exp[\alpha log(P_{jmt} + B_{mt}) + \lambda_{mt} + \delta_{jmt}] + \sum_r^{J_2} exp[\alpha log(P_{rmt} + B_{mt}) + \lambda_{mt} + \delta_{rmt}]} \tag{1.7}$$

For Beijing, B_{mt} is always zero. There are three time period in Beijing: (1) pre-policy period (year 2010, $t < 5$); (2) period 2 with same lottery pool for non-NEV and NEV license (2011-2013, $5 \leq t < 17$); (3) period 3 when there are different lotteries for non-NEV and NEV licenses (2014-2017, $t \geq 17$). λ_{mt} is negative except for NEVs ($r = 1, ..., J_2$) in period 3.

For Shanghai, B_{mt} is positive. There's no pre-policy period in my data, and the time periods can be divided to two parts: (1) same allocation for non-NEV and NEV license (2010-2013, $t < 13$); (2) free allocations of NEV licenses (2013-2017, $t \geq 13$). B_{mt} and λ_{mt} are zero for NEV licenses in period 2.

For the treated cities, the conditional probability that a type 2 consumer i chooses a vehicle

j is:

$$S_{jmt}^{(2)} = \frac{exp(\alpha logP_{jmt} + \delta_{jmt})}{\sum_{r}^{J_1+J_2} exp(\alpha logP_{rmt} + \delta_{rmt})} \tag{1.8}$$

For the control cities in all periods and treated cities in the pre-policy periods, the probability that a consumer i chooses a vehicle j is:

$$S_{jmt} = \frac{exp(\alpha logP_{jmt} + \delta_{jmt})}{\sum_{r}^{J_1+J_2} exp(\alpha logP_{rmt} + \delta_{rmt})} \tag{1.9}$$

Based on the conditional probabilities as above, the aggregated demand for a non-NEV j in the treated cities during the post-treatment period can be written as:

$$\begin{aligned} S_{jmt} &= \rho_{0mt} \cdot \int [I\{D_{imt} = 1\} \cdot S_{jmt}^{(1)} \cdot \rho_{2mt} + I\{D_{imt} = 2\} \cdot S_{jmt}^{(2)}] dF(D_{imt}) \\ &= \rho_{0mt}[\rho_{1mt} \cdot S_{jmt}^{(1)} \cdot \rho_{2mt} + (1 - \rho_{1mt}) \cdot S_{jmt}^{(2)}] \end{aligned} \tag{1.10}$$

As shown in equation 1.10, the aggregated demand of a vehicle j consists of two parts. The first part is the demand of type 1 consumers, which equals the probability that a consumer wants a new car ρ_{0mt} times the conditional probability that this consumer needs a vehicle license ρ_{1mt}, times the conditional probability that this type 1 consumer buys the vehicle $S_{jmt}^{(1)}$, and then times the winning odds of the non-NEV lottery/auction ρ_{2mt}. The second part is the demand of type 2 consumers, which equals the probability that a consumer wants a new car ρ_{0mt} times the conditional probability that this consumer does not need a vehicle license $1-\rho_{1mt}$, and then times the conditional probability that this type 2 consumer wants to buy the vehicle $S_{jmt}^{(2)}$.

Similarly, the aggregated demand for a NEV j in the treated cities during the post-treatment period can be written as:

$$\begin{aligned} S_{jmt} &= \rho_{0mt} \cdot \int [I\{D_{imt}=1\} \cdot S^{(1)}_{jmt} \cdot \rho_{3mt} + I\{D_{imt}=2\} \cdot S^{(2)}_{jmt}] dF(D_{imt}) \\ &= \rho_{0mt}[\rho_{1mt} \cdot S^{(1)}_{jmt} \cdot \rho_{3mt} + (1-\rho_{1mt}) \cdot S^{(2)}_{jmt}] \end{aligned} \tag{1.11}$$

where ρ_{3mt} is the winning odds of NEV lottery.

The aggregated demand for a vehicle j in the control cities or in the treated cities during the pre-policy period simply equals the probability that a consumer wants a new car times the probability that the consumer wants the vehicle j:

$$S_{jmt} = \rho_{0mt} \cdot S_{jmt} \tag{1.12}$$

The demand for non-NEV and NEV licenses can be expressed as:

$$Q_{1mt} = \rho_{0mt} \cdot \rho_{1mt} \cdot \sum_{j=1}^{J_1} S^{(1)}_{jmt} \tag{1.13}$$

$$Q_{2mt} = \rho_{0mt} \cdot \rho_{1mt} \cdot \sum_{r=1}^{J_2} S^{(1)}_{rmt} \tag{1.14}$$

From this demand model, we can explain explicitly how the implicit cost generated by the allocation policy $\lambda_{v(j)mt}$ affects the vehicle's demand. For the treated cities during the treated period, NEVs are not subject to $\lambda_{v(j)mt}$ while the non-NEVs are subject to $\lambda_{v(j)mt}$. The implicit cost generates disutility to the consumers who buy non-NEVs. For example, they need to wait for more than five years to obtain a license and there will be many uncertainties during the waiting period. Type 1 consumers take the implicit cost into consideration when they are applying for vehicle licenses. Higher implicit cost shifts consumers from applying for non-NEV licenses to applying for NEV licenses. Hence, the aggregated demand of NEVs increases.

1.4.2 Vehicle supply

Assume a firm f sets the national vehicle price to maximize its profit from all cities by quarter. The vehicle set of firm f in city m and quarter t is Θ_{fmt}. Let c_{rt} denote the marginal cost of producing vehicle r. In this paper, I assume the marginal cost of production is the same across cities. N_{mt} denotes the quantity of all vehicles sold in the market. Then, its profit is:

$$\pi_{ft} = \sum_{m} \sum_{r \in \Theta_{fmt}} (P_{rt} - c_{rt}) \cdot S_{rmt}(P_{rt}, B_{vmt}, \lambda_{mt}, X_r; \theta) \cdot N_{mt} \tag{1.15}$$

The first order condition of the profit maximization w.r.t vehicle r's price is:

$$\sum_{m} [S_{jmt} + \sum_{r \in \Theta_{fmt}} (P_{rt} - c_{rt}) \frac{\partial S_{rmt}}{\partial P_{jt}}] = 0 \tag{1.16}$$

In the treated cities, the demand changes with respect to the price changes are:

$$\frac{\partial S_{rmt}}{\partial P_{jt}} = \begin{cases} \rho_{0mt}[\rho_{1mt} \cdot \rho_{2mt} \cdot S^{(1)}_{jmt}(1 - S^{(1)}_{jmt}) \cdot \frac{\alpha}{P_{jt}+B_{v(j)mt}} + (1-\rho_{1mt})S^{(2)}_{jmt}(1 - S^{(2)}_{jmt}) \cdot \frac{\alpha}{P_{jt}}], r = j \\ \rho_{0mt}[\rho_{1mt} \cdot \rho_{2mt} \cdot S^{(1)}_{jmt}S^{(1)}_{rmt}\frac{-\alpha}{P_{jt}+B_{v(j)mt}} + (1-\rho_{1mt})S^{(2)}_{jmt}S^{(2)}_{rmt} \cdot \frac{-\alpha}{P_{jt}}], r \neq j \end{cases} \tag{1.17}$$

where the conditional market shares $S^{(1)}_{jmt}$ and $S^{(2)}_{jmt}$ can be computed by equations 2.82.9 after we estimate the demand and obtain the preference parameters.

For the control cities, the demand changes with respect to price changes are:

$$\frac{\partial S_{rmt}}{\partial P_{jt}} = \begin{cases} \alpha \cdot \rho_{0mt} \cdot S_{jmt}(1 - S_{jmt}) \cdot \frac{1}{P_{jt}}, r = j \\ -\alpha \cdot \rho_{0mt} \cdot S_{jmt}S_{rmt} \cdot \frac{1}{P_{jt}}, r \neq j \end{cases} \tag{1.18}$$

where the unconditional market shares S_{jmt} is shown by equation 2.11.

$\frac{\partial S_{rmt}}{\partial P_{jt}}$ for the treated cities also includes implicit costs of allocation policies $\lambda_{v(j)mt}$, which implies that the implicit cost will also affect manufacturers' pricing strategy. Plugging equation 2.7 into the first order conditions 1.15, we can now compute the marginal production costs.

1.5 Estimation and Identification

Section 3.2 explains how the implicit cost of vehicle license allocations affects vehicle demand and supply. This section specifies estimation methods to recover the preference parameters as well as the implicit cost. It also discusses the identification strategy.

1.5.1 Estimating preference parameters and implicit cost

As shown in Section 1.4.1, the utility of a vehicle j consists of the mean utility and the consumer-specific utility even if we assume a common taste among consumers. I replicate the equations 1.4 1.6 below:

$$U_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt} \tag{1.19}$$

$$\mu_{ijmt} = \alpha log(P_{jmt} + B_{iv(j)mt}) + \lambda_{iv(j)mt} \tag{1.20}$$

In the estimation, the mean utility can be specified as following:

$$\delta_{jmt} = \beta log(fc_{jmt}) + \delta_j + \xi_{my} + \xi_m + \xi_t + I\{m = 3\} \cdot \eta_t + \xi_{sy} + \xi_{fy} + e_{jmt} \tag{1.21}$$

where fc_{jmt} is the fuel cost that varies across vehicle, city and time. δ_j is the unobserved vehicle attributes such as vehicle quality and safety that do not change over city and time. ξ_{my}, ξ_m, ξ_t are city by year fixed effects, city fixed effects and year-quarter fixed effects. ξ_{my} captures the city-specific time trend. I also allow a specific time trend for Shanghai $I\{m = 3\} \cdot \eta_t$, because Shanghai has the vehicle license auctions from the beginning of my data. ξ_{sy} is the segment by year fixed effects and controls for common shocks to vehicles belonging to the same segment varying across years. ξ_{fy} is the fuel type by year fixed effects and controls for common shocks to vehicles of the same fuel type varying across years. Other vehicle attributes X_j do not change across cities and time in my data, and therefore are absorbed into the vehicle fixed effect δ_j.

Parameters to be estimated can be divided to the linear parameters $\theta_1 = (\beta, \delta_j, \xi_{my}, \xi_m, \xi_t, \eta_t, \xi_{sy}, \xi_{fy})$ and nonlinear parameters $\theta_2 = (\alpha, \lambda_{mt})$ as in Berry et al. (1995). Other parameters are the probability parameters $\theta_3 = (\rho_{0mt}, \rho_{1mt}, \rho_{2mt}, \rho_{3mt})$. The probability parameters are estimated directly from the data. I define the market size as the total number of households in a city. ρ_{0mt} is the probability that a consumer wants a new car, which equals the ratio of total new vehicle demand to the total number of households. The total new vehicle demand consists of two parts: (1)the demand of type 1 consumers, which can be estimated by the number of applicants for vehicle licenses, and (2) the demand of type 2 consumers, which equals the total new vehicle sales minus the license quota. ρ_{1mt} is the probability that a new car buyer needs a vehicle license, which can be estimated by the ratio of the total number of license applicants to the total new vehicle demand. ρ_{2mt} and ρ_{3mt} are the winning odds of non-NEV lotteries/auctions, and the winning odds of NEV lotteries. The winning odds are simply the ratio of the quota to the number of applicants.

After computing the probability parameters θ_3 from data, only θ_1 and θ_2 are left to be estimated. I use the same method by Nevo (2001) to estimate those parameters. This method requires three steps. In this first step, the mean utilities are recovered from a contraction mapping based on given values for the nonlinear parameters. In the second step, linear parameters are computed analytically from the mean utility regression, and the regression residuals are calculated. In the third step, we construct the moments and use GMM to estimate the nonlinear parameters.

Berry's inversion (Berry 1994) proves that under mild regularity conditions, for given values of nonlinear parameters, a unique vector of $\{\delta_{.mt}\}$ exits that equalizes the predicted market shares with the observed market shares. In the standard Logit model, the mean utilities can be backed out analytically from the observed market shares. In the structural model described above, however, it's impossible to find an analytical solution to the mean utilities. Hence, I use the contraction mapping algorithm to back out the mean utilities.

After obtaining the mean utilities from the above contraction mapping algorithm, the linear parameters θ_1 can be calculated analytically from the regression of mean utility in equation 1.21. We can then compute the residuals e_{jmt} from the mean utility regression.

Finally, I construct two sets of moments and use GMM to estimate the nonlinear parameters. The first set of moments is formed based on the exogeneity of instruments as follows:

$$E[e_{jmt}(\theta_2, \theta_3)|Z_{jmt}] = 0 \tag{1.22}$$

e_{jmt} are time-variant and city-specific demand shocks to each vehicle. Instruments include all variables on the right-hand side of the equation 1.21. The vehicle price and fuel cost are included as instruments because I assume that after controlling for the vehicle fixed effects as well as all other fixed effects in equation 1.21, vehicle price and fuel cost are exogenous. This holds because the vehicle price in my data is the sum of manufacturer suggested retail price, tax, and subsidy. And the manufacturer suggested retail price does not change across city and time in my data. Similarly, variations in the fuel cost all come from variations in energy prices, and the fuel consumption rate remains constant in my data.

Also, the city by year fixed effects ξ_{my} are included in Z_{jmt}, which are very important for the DID design to estimate the policy's impact as shown in Li (2018). I assume city-specific and time-varying demand shocks are mean independent of city by year fixed effects, i.e., $E(e_{jmt}|\xi_{my}) = 0$. This assumption amounts to the common trend assumption in DID design.

This assumption implies that after controlling the time trend common to all cities, what is let from the time trend of e_{jmt} is not systematically different across cities.

The second set of moments is constructed based on the market clearing conditions for vehicle licenses. When the market for vehicle licenses is clearing, we should have the predicted demand for vehicle licenses $\hat{Q}_{1mt}(\theta_2, \theta_3)$ equals to the license quota Q_{mt}. This new set of moments helps to pin down the implicit costs. The moments are as follows:

$$E[\rho_{2mt} \cdot \hat{Q}_{1mt}(\theta_2, \theta_3) - Q_{mt}] = 0 \tag{1.23}$$

The predicted demand for vehicle licenses equals the predicted number of applicants for vehicle licenses times the winning odds of the lottery/auction. And the predicted number of applicants is computed according to equations 1.13.

1.5.2 Identification strategy

This paper quantifies the implicit cost by comparing the NEV shares in the treated and control cities. Intuitively, without the policy, electric vehicles should have the same market shares in the control and treated cities. The policy divides the consumers into two types in the treated cities. It is the implicit cost λ that brings disutility to purchasing non-NEVs for the type 1 consumers, and shifts consumers from non-NEVs to NEVs. Therefore, by comparing the market shares of new energy vehicles in the treated cities and control cities, we will be able to quantify the implicit cost.

The identification challenges arise mainly from two aspects. The first challenge is that whether the control cities are good matches to the treated cities. If there are different trends in

NEV sales or unobserved time-varying demand shocks to NEVs between the control and treated cities, then the difference between the NEV sales may not be due to the vehicle license allocations. I use two methods to mitigate this problem. First, in the reduced-form estimations, I use the synthetic control approach for the matching, which equals the vehicle shares of the treated unit and the synthetic control group over the pre-treatment period and equals the observed characteristics of the treated unit and the synthetic control group. I also test for the Common Trend assumption using the aggregated data. The SCM matching shows a parallel trend between treated and control cities, and the Common Trend Test is not violated.

Second, in the GMM estimation, I include the city by year fixed effects ξ_{my} to control for the unobserved city-specific and time-varying demand shocks. I also include the segment by year ξ_{sy} and fuel type by year fixed effects ξ_{fy} to control for the unobserved demand shocks that are common to vehicles of the same segment and fuel type.

Moreover, part of the identification of λ comes from comparing the trend in the differences of the NEV shares between the control and treated cities. The winning odds of lottery/auction changes a lot over the post-treatment period, which implies significant changes in the implicit cost. For example, the winning odds of non-NEV licenses in Beijing dropped rapidly, from 10% in 2011 to 0.1% in 2017. Also, the winning odds of non-NEV licenses in Shanghai decreased a lot, from 40% in 2010 to 5% in 2017. As a result, the implicit cost in treated cities should increase from 2011 to 2017, and the difference in the NEV shares between treated and control cities should become larger as the winning odds decrease in the treated city. Therefore, by comparing the trend in the differences between the control and treated cities, we can also identify the impact of the implicit cost.

The second identification challenge arises from the unobserved attributes and demand shocks. The vehicle price is likely to be correlated with those unobserved attributes and demand shocks. Usually, literature uses BLP type instruments, cost shifters, and Hausman type instruments for the vehicle price. This paper's identification strategy is similar to Li (2018) and different from most literature. It does not require the exogeneity of vehicle attributes. This is because, as shown in equations 1.4 1.6, the vehicle price is included in the consumer-specific utility bundled with the bidding price. As explained in Section 1.4.1, the bidding price varies across vehicle, consumer, city, and time. Therefore, the total vehicle price (vehicle price plus the bidding price) varies across vehicle, city, time and consumers. This consumer-specific total vehicle price is uncorrelated with the unobserved vehicle attributes and demand shocks which vary across vehicle, city and time.

Moreover, I control for the vehicle fixed effects, city by year fixed effects, city fixed effects, time fixed effects, segment by year fixed effects, and fuel type by year fixed effects in the GMM estimation. The vehicle fixed effects absorb the time-invariant unobserved attributes, and city-by-year fixed effects eliminate unobserved shocks that are time-variant and common to all cities. The segment by year and fuel type by year fixed effects also control for unobserved time-varying shocks common to vehicles within the same segment and fuel type. As discussed in the data description section, the manufacturer suggested retail price and observable vehicle attributes (such as fuel cost) remain constant in my data. Thus, after controlling these fixed effects, the variation in what is left from price mainly comes from the variation in the average winning bid for the vehicle licenses.

The average winning bid for vehicle licenses should be uncorrelated to the unobserved vehicle attributes. This is because Shanghai's license auctions include two rounds. In the second round, people can revise their bids after observing the first round's lowest accepted bid. The revised bid must be within a window of 300 Yuan below and above the current lowest accepted bid. The two-round auction significantly reduces the variation of the bidding prices. Therefore, the individual-specific bids are very close to the average winning bid. As shown in the Figure 1.2, the average winning bids for vehicle licenses are very close to the lowest winning bids for vehicle licenses. Moreover, the Appendix Figure A.6 shows the trends in the average winning bids and the average vehicle price in Shanghai from 2010 to 2017. There's no strong correlation between the winning bids and the vehicle price. The correlation between the winning bids and the vehicle price is -0.0315. Therefore, the average winning bids for the vehicle licenses can be treated as exogenous to the unobserved vehicle attributes.

After controlling for the vehicle fixed effects, price variations come from three sources. First, the vehicle price includes the purchase tax and the ownership tax. The purchase tax is 10%, and low-emission vehicles are levied lower purchase tax. For vehicles with displacement no greater than 1.6 L, the purchase tax was reduced to 7.5% in 2010, 5% from 2015 through 2016, and 7.5% in 2017. Different provinces have different ownership taxes varying across time. The ownership tax depends on the engine displacement. Also, from September 2014, electric vehicles were exempted from the purchase tax, and they were exempted from the ownership tax from 2012. Second, subsidies to electric vehicles and low-emission vehicles are included in the vehicle price. There are national-level, province-level, and city-level purchase subsidies to electric vehicles. From 2010 to 2012, the maximum purchase subsidy is 50,000 Yuan to PHEVs (plug-in hybrid electric vehicles) and 60,000 to BEVs (battery electric vehicles), depending on the battery capacity. In 2013, the maximum subsidies were 60,000 Yuan to BEVs and 35,000 Yuan to PHEVs, depending on the battery range. The subsidies decreased by 5% and 10% in 2014 and 2015. In 2016, the maximum subsidies were 55,000 Yuan to BEVs and 30,000 Yuan to PHEVs. The subsidies decreased by 20% in 2017. Third, most variations in the total vehicle price are due to the variations in the average winning bids, which increased from around 40,000 Yuan in 2010 to 90,000 Yuan in 2017, accounting for one-third of the total vehicle price. These sources of variations help us to identify the price coefficient α.

1.6 Results from the Demand Estimation

Table 1.5 shows the results from GMM estimation for two specifications. I report the estimates for the nonlinear parameters $\theta_2 = (\alpha, \lambda)$ and the linear parameter on fuel cost β. I do not report other linear parameters because I do not need them for the policy simulations. The top panel shows the results from specification 1, where I assume the implicit cost parameter λ to be constant across years. The price coefficient is -6.115 and statistically significant at the 1 percent level. The implicit cost parameters λ are negative and statistically significant at the 1 percent level for both Beijing and Shanghai. Column 3 in Table 1.5 reports the implicit costs in monetary values estimated based on λ. The average implicit cost of license lotteries in Beijing is around 30,659 Yuan and the average implicit cost of license auctions in Shanghai is about 25,654 Yuan.

The winning odds of lotteries and auctions change remarkably over the post-treatment period, which implies the implicit cost might vary a lot over time. Therefore, in the bottom panel of Table 1.5, I allow the implicit cost to vary across years. The price coefficient is -6.725 and statistically significant at 1 percent level. The implicit cost parameters λ are statistically significant at 1 percent for 2016 and 2017. This is probably because there are not enough observations of NEVs before 2015. Allowing λ to vary across years, I find that the estimated λ are consistent with my assumption that the implicit cost increases over time. Appendix Figure A.5 shows that the estimated implicit costs increase as the average winning odds decrease from 2013 to 2017 in Beijing and Shanghai. In Beijing, the absolute value of λ increases from 0.157 in 2014 to 0.876 in 2017, implying that the implicit cost increases from 6,535 Yuan to 36,542 Yuan per vehicle. Similarly, in Shanghai, the absolute value of λ increases from 0.265 to 0.658, which means that the implicit cost increases from 11,040 to 27,437 Yuan. The average vehicle price is about 255,000 Yuan, and thus the implicit cost accounts for more than 10 percent of the total vehicle price. In my data, the average winning bids for vehicle license is 78,400 Yuan in Shanghai, and thus the estimated implicit cost accounts for one-third of the average winning bids in Shanghai. Li (2018) estimates the WTP for vehicle licenses in 2012, and finds the average WTP is around 46,020 Yuan in Beijing and 23,278 Yuan in Shanghai. Therefore, the implicit purchasing cost of non-NEVs offsets more than half of the benefit of obtaining a non-NEV license.

Table 1.6 estimates that the sales-weighted own-price elasticities lie between -5 and -7, which is consistent with the fact that the price sensitivity parameter is identified by variation across highly disaggregated vehicles. The estimates are lower than estimates from Li (2018) using a random coefficient logit model, and they find the average own price elasticity to be -9.49 with a range of -7.8 to -14.53.

Table 1.5 also reports the estimate for the linear parameter on the log of the fuel cost. Coefficients on fuel cost are statistically significant at 1 percent level and negative. This is consistent with the fact that fuel cost brings disutility to consumers, and consumers are aware of the fuel cost.

Table 1.5: Parameter Estimates from GMM

	Coefficient	Standard Error	Implicit Cost (Yuan)
(1) Time-invariant Implicit Cost			
Log(Price+Bid) (10,000 2017 Yuan)	-6.115	0.214	
Implicit cost parameter: Beijing	-0.735	0.174	30,659
Implicit cost parameter: Shanghai	-0.615	0.197	25,654
Log(fuel cost) (Yuan/100km)	-12.1289	3.466	
(2) Time-variant Implicit Cost			
Log(Price+Bid) (10,000 2017 Yuan)	-6.725	0.234	
Implicit cost parameter:			
Beijing 2014	-0.157	0.110	6,535
Beijing 2015	-0.285	0.189	11,869
Beijing 2016	-0.625	0.127	26,076
Beijing 2017	-0.876	0.149	36,542
Shanghai 2013	-0.265	0.217	11,040
Shanghai 2014	-0.217	0.212	9,034
Shanghai 2015	-0.353	0.228	14,706
Shanghai 2016	-0.451	0.136	18,812
Shanghai 2017	-0.658	0.171	27,437
Log(fuel cost) (Yuan/100km)	-7.0024	2.5375	

Notes: Each panel includes the vehicle fixed effects, city by year fixed effects, city fixed effects, time fixed effects, a specific time trend for Shanghai, segment by year fixed effects and fuel type by year fixed effects. The top panel assumes time-invariant implicit costs and the bottom panel allows the implicit cost to vary across years. All monetary variables are in 2017 Yuan.

Table 1.6: Sales-weighted Own Price Elasticities

	(1)	(2)
Mean	-5.97	-6.568
Median	-6.08	-6.68
Standard deviation	0.22	0.24
Min	-6.13	-6.73
Max	-5.08	-5.57

Notes: each column corresponds to the panel in Table 1.5.

Table 1.7 shows the results for GMM estimations using different fixed effects. The price coefficient and the implicit cost parameters are all negative and statistically significant at 1 percent. Column 1 replicates the baseline estimation from the top panel in Table 1.5. Column 2 does not allow a specific time trend for Shanghai. The implicit cost for Beijing decreases to 21,382 Yuan and increases to 28,280 Yuan in Shanghai. Allowing a specific time trend for Shanghai is important to control for time-varying demand shocks in Shanghai that are different from the base group and correlated with the average bidding price, because our data starts from 2010, when the allocation policy has already been implemented in Shanghai. Column 3 does not include the fuel type by year fixed effects, and the implicit cost in Shanghai decreases to 11,402 Yuan. Columns 4-6 include the segment by city and fuel type by city fixed effects, controlling for the city-specific demand shocks that are common to vehicles of the same segment or fuel type. The price coefficient is around -8 and the implicit cost in Beijing ranges from 9,000 Yuan to 21,000 Yuan, slightly lower than the baseline estimation. Columns 7 and 8 include model-level fixed effects instead of vehicle-level fixed effects. The price coefficient decreases to around -3.8 as expected, and the implicit costs are estimated to be around 50,000 Yuan in Beijing and 40,000 Yuan in Shanghai.

Table 1.7: Robustness Results for GMM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Price+Bid) (10,000 2017 Yuan)	-6.115	-6.287	-6.950	-8.474	-8.290	-7.211	-3.835	-3.633
	(0.214)	(0.220)	(0.218)	(0.293)	(0.286)	(0.304)	(0.115)	(0.134)
Implicit cost parameter: Beijing	-0.735	-0.527	-0.712	-0.300	-0.526	-0.602	-0.801	-0.802
	(0.174)	(0.125)	(0.175)	(0.060)	(0.167)	(0.154)	(0.142)	(0.165)
Implicit cost parameter: Shanghai	-0.615	-0.697	-0.311	-0.507	-0.656	-0.453	-0.596	-0.595
	(0.197)	(0.224)	(0.111)	(0.134)	(0.199)	(0.107)	(0.164)	(0.189)
Fixed effects:								
Vehicle	X	X	X	X	X	X		
City by year	X	X	X	X	X	X	X	X
City	X	X	X	X	X	X	X	X
Year-quarter	X	X	X	X	X	X	X	X
Specific time trend for Shanghai	X		X	X	X	X	X	X
Segment by year	X	X	X			X	X	X
Fuel type by year	X	X					X	X
Segment by city				X	X			
Fuel type by city				X		X		
Make-model							X	
Make-model by model-year								X
	Implicit Cost (Yuan)							
Beijing	30,659	21,382	26,132	9,034	16,189	21,295	53,250	56,288
Shanghai	25,654	28,280	11,402	15,250	20,196	16,018	39,664	41,812

Notes: Column 1 is the baseline, which replicates the results from the first panel in Table 1.5. Each column uses different fixed effects in the GMM estimation. I use the time-invariant implicit cost parameter for Beijing and Shanghai.

1.7 Counterfactual Simulation

In this section, I compare the current vehicle license allocation system with two counterfactuals. The current system allows separate allocation systems for NEV and non-NEV licenses, and the expected wait times for NEV licenses are much shorter. The first counterfactual assumes one lottery for non-NEV and NEV licenses in Beijing. Comparison of Beijing's current separate-lottery system with counterfactual one-lottery system illustrates the effect of the current separate-lottery system on NEV adoption and its welfare consequences. The second counterfactual assumes no vehicle license allocation system, and the government taxes non-NEVs to subsidize NEVs. Comparison of the current allocation system with no allocation counterfactual reveals the impact of vehicle ownership restriction on NEV adoption and the overall welfare consequences of vehicle ownership restrictions.

First, I quantify the consumer welfare change from the original condition to the counterfactual. To quantify the consumer welfare change, I estimate the compensating variation (cv) following the simulation method by Herriges and Kling (1999). The compensating variation measures the maximum amount of money that can be taken from the consumer while leaving him or her just as well off as before the condition change. For each consumer, the compensating variation is estimated by:

$$max_j U(y - p_j^0 - B^0, \lambda^0, \delta, \varepsilon_j) = max_j U(y - p_j^1 - B^1 - cv, \lambda^1, \delta, \varepsilon_j) \tag{1.24}$$

The subscript for a consumer is ignored. The superscripts "0" and "1" are respectively used to distinguish the original versus the new conditions. The original condition is the current policy. The new condition is the counterfactual condition. Where U is the utility under each situation as shown in equations 1.4, y is the household's income, p represents the vehicle price, B represents the bidding price, λ is the implicit cost imposed by the policy, δ is the mean utility, ε_j is an i.i.d error term following the type I extreme value distribution. The mean compensating variation is the average of the compensating variations across all simulated individuals.

Second, I estimate the externalities from automobile usage under the original and counterfactual conditions. The externalities are computed based on the following equation:

$$Externality = \sum_{t=0}^{T} \frac{FC \times VMT \times \text{marginal external cost} \times Sales}{(1+r)^t} \tag{1.25}$$

where, FC is the fuel consumption rate of the vehicle (liter/km), VMT is the annual vehicle miles traveled (km), and r is the discount rate, assumed to be 5 percent.

To compute the externalities, I need to make some assumptions. First, I assume that the time horizon is either 15 years or 10 years. Second, I take the estimates for the marginal cost of externalities from Parry et al. (2014), where externalities include congestion, CO2 emission, local air pollution, and traffic accident (Parry et al. 2007, 2014). Parry et al. (2014) estimates the corrective tax on vehicle users to internalize the externalities from vehicle usage. They compute the external costs for over 100 countries, including China, and different fuels types. And they estimate the external cost to be \$0.55 per liter (or 4.33 Yuan/liter in 2017 terms) of motor gasoline in China. The external cost of CO2 emissions and local air pollution accounts for about 23 percent of the total external cost, and is about \$0.125 per liter of motor gasoline in China, or 1.01 Yuan (in 2017 terms). I thus use these estimates to estimate the total external cost. Third, I use the estimates from Li (2018) and Xiao et al. (2017) for VMT in Beijing and Shanghai. Li (2018) estimates the vehicle miles traveled in Beijing based on Beijing Household Travel Survey 2010, and reveals that the VMT in Beijing was about 16,350 km in 2012. Xiao et al. (2017) use surveys conducted by SINOTRUST, a leading consulting firm in China on the vehicle market, and they estimate the VMT to be 17,988 km in Shanghai in 2010. Their estimation is consistent with other studies finding that Shanghai's VMT of passenger cars is about 8 percent higher than Beijing's (e.g., Hao et al. 2011; Wang et al. 2008; Ou et al. 2020). In this paper, I use 18,000 km for VMT in Shanghai.

1.7.1 Counterfactual 1: separate lotteries vs. one lottery

Under the current policy, there are separate lotteries for NEV and non-NEV licenses in Beijing with much higher win rates of NEV licenses. As a result, the expected wait times for a NEV license are much shorter than for a non-NEV license. The implicit cost of NEV licenses is zero and is strictly negative for non-NEV licenses. In the first counterfactual, I assume a combined lottery for NEV and non-NEV licenses, and the total quotas of non-NEV and NEV licenses are the same under the current separate-lottery system and the counterfactual one-lottery system. Under the one-lottery system, the win rates of NEV and non-NEV licenses are the same, equaling the sum of the NEV license quota and the non-NEV license quota divided by the total number of applicants for both types of licenses. Also, the implicit costs for both types of licenses are strictly negative. I ignore the impact of the allocation on the vehicle price because Beijing only accounts for a small share of the national vehicle sales, and I assume the license allocation policy in Beijing will not affect the national level vehicle price.

By comparing the share of electric vehicles of the total vehicle sales under the current system with Counterfactual 1, we will understand the impact of the separate-lottery system on electric vehicle adoption. Under the current separate-lottery system, the lower implicit cost of NEV licenses incentivizes people to shift from non-NEVs to NEVs and thus promotes electric vehicle sales. However, under Counterfactual 1, the implicit cost of NEV licenses is as high as that of non-NEV licenses, and people do not have incentives to buy electric vehicles.

As shown in Table 1.8, columns 2-5 show the observed vehicle sales and NEV shares from 2014 to 2017. Columns 6-9 show the vehicle sales and NEV shares under Counterfactual 1. The total sales under the two conditions are the same because the sales from the second-time buyers will not change by the policy, and the sales from the first-time buyers are the sum of the NEV and non-NEV license quotas. However, the NEV share is much higher under the separate system than under the one-lottery system. For example, in 2017, the NEV share under the separate system was 3.8 times as large as the NEV share under the one-lottery system.

Table 1.8: Counterfactual 1: Impact on Vehicle Sales in Beijing

	Separate Lotteries				One Lottery			
	Total	Non-NEV	NEV	NEV Share	Total	Non-NEV	NEV	NEV Share
2014	417,527	414,816	2,711	0.006	417,527	417,305	221	0.001
2015	422,323	408,892	13,431	0.032	422,323	421,310	1,013	0.002
2016	730,686	682,995	47,691	0.065	730,686	717,572	13,114	0.018
2017	497,452	451,862	45,590	0.092	497,452	485,478	11,975	0.024

Notes: The counterfactual simulations are based on demand estimation results from the top panel of Table1.5, where the implicit costs are assumed to be constant across years.

Table 1.9 estimates the welfare changes by combining the separate lotteries for non-NEV and NEV licenses into one lottery. The first row shows the estimates of compensating variation from the current separate system to a one-lottery system based on equation 1.24. For example, the average compensating variation is estimated to be -814 Yuan per household in 2017, implying the consumer would become worse off if we combine the lotteries for non-NEV and NEV licenses. The total consumer surplus change equals the average compensating variation multiplied by the number of first-time buyers. In 2017, the total consumer surplus would have been reduced by 0.1 billion Yuan under the one-lottery system.

The one-lottery system affects consumer welfare in several aspects. First, it will not affect the consumer welfare of second-time buyers. Second, for those who always choose electric vehicles, the one-lottery system reduces their consumer surplus because now they need to wait much longer to obtain a NEV license. Third, those who shift from non-NEVs to NEVs under the current separate system will turn back to non-NEVs under the one-lottery policy because now the waiting periods for non-NEV and NEV licenses are the same, and NEV licenses are no longer attractive. Combining the separate lotteries into one lottery will have two opposite effects on those people's welfare. On the one hand, now their vehicle choice is no longer twisted by the license allocation policy, and they will buy their preferred non-NEV. Therefore, their utility increases. On the other hand, however, they now need to wait much longer for a license which reduces their utility. My estimates reveal that, by putting these opposite effects together, the one-lottery policy reduces consumer welfare. Under the separate system, people can shift from non-NEVs to NEVs to avoid waiting, however, under the one-lottery system, people have no other choice but to wait several years for a vehicle license. Therefore, the one-lottery system is less dynamic-efficient than the separate system.

Table 1.9: Counterfactual 1: Welfare Effects in Beijing

	2014	2015	2016	2017
CV (Yuan)	-17	-85	-407	-814
ΔCS (billion Yuan)	-0.002	-0.01	-0.05	-0.10
15-year horizon:				
External cost of separate lotteries (billion Yuan)	5.91	5.82	9.31	6.44
External cost of one lottery (billion Yuan)	5.94	5.96	9.66	6.80
Δ External cost (billion Yuan)	0.03	0.14	0.35	0.36
Δ Net social welfare (billion Yuan)	-0.03	-0.15	-0.40	-0.46
Δ Net social welfare / Δ NEV sales (Yuan)	10,933	10,986	10,250	10,849
10-year horizon:				
External cost of separate lotteries (billion Yuan)	4.40	4.33	6.92	4.79
External cost of one lottery (billion Yuan)	4.42	4.43	7.19	5.06
Δ External cost (billion Yuan)	0.02	0.10	0.26	0.27
Δ Net social welfare (billion Yuan)	-0.02	-0.11	-0.31	-0.37
Δ Net social welfare / Δ NEV sales (Yuan)	8,133	8,173	7,625	8,071

Notes: The welfare analysis is based on demand estimation results from the top panel of Table1.5, where the implicit costs are assumed to be constant across years. All monetary variables are in 2017 Yuan. CV is the compensating variation from the original condition to the counterfactual condition. I assume the annual vehicle miles traveled is 16,350 km in Beijing and 18,000 km in Shanghai. The discount rate is 5 percent. The externalities include CO2 emissions and local pollution, and the external cost is 1.01 Yuan per liter of gasoline (in 2017 terms). Total change in consumer surplus equals the sum of CS change in current buyers and CS change in new buyers. Net social welfare equals the consumer surplus minus the external cost.

The second part of Table 1.9 shows the results for externalities. I find that the one-lottery policy would increase the external cost by reducing NEV sales and generating more CO2 emissions and local pollution. For example, under the current policy, the external cost is estimated to be 6.44 billion Yuan in 2017, while combining the separate lotteries into one lottery would have increased the external cost by 0.36 billion Yuan. Compared to the current policy, the net social welfare would decrease under the one-lottery policy due to lower consumer welfare and more externalities. For example, in 2017, the net social welfare would have been reduced by 0.46 billion Yuan with a one-lottery system. The one-lottery policy would have reduced NEV sales by 33,615 units, and for a one-unit decrease in NEV sales, the net welfare would have decreased by 10,849 Yuan. If we assume a 10-year vehicle life, the external cost from vehicle usage would be lower. However, the one-lottery policy would still have reduced the net social welfare by 0.37 billion Yuan in 2017 compared to the separate system. In my data, the average NEV subsidy was about 22% of the NEV price in 2017 or about 40,000 Yuan per NEV. The welfare cost of losing one NEV under the one-lottery policy is estimated to be 10,849 in 2017, lower than the NEV subsidy. Moreover, it is about one-third of the implicit cost of waiting, about 30,659 Yuan in Beijing. This is because, as I mentioned above, the one-lottery system reduces welfare due to longer wait times, but it also increases welfare by making people shift back to their preferred non-NEVs. Therefore, the net welfare loss per NEV under the one-lottery system is lower than the implicit cost of waiting.

Appendix Table A.3 and A.4 show the simulation results for one-lottery policy by assuming time-varying implicit costs. Allowing time-varying implicit cost generates similar results for Counterfactual 1 as using time-invariant implicit cost. The NEV share under the one-lottery policy would still be much lower than the current policy. Consumers would be worse off under the one-lottery policy, generating a consumer welfare loss of 0.1 billion Yuan in 2017. Also, the one-lottery policy would bring about extra social welfare loss compared to the current policy by increasing externalities, and the net social welfare would have been reduced by about 0.48 billion Yuan in 2017.

1.7.2 Counterfactual 2: vehicle license allocation vs. no allocation with NEV subsidy and non-NEV tax

In the second counterfactual, I assume no vehicle license allocation. Columns 2-3 in Table 1.10 show the total sales and the NEV share under the current lottery system in Beijing. Columns 4-5 show the total sales and the NEV share in Beijing if there were no vehicle license allocations. The total vehicle sales decreased by around 60% under Beijing's lotteries, which is very close to my results from the reduced-form estimation and the results of Li (2018) and Xiao et al. (2017). The vehicle license allocation also increased electric vehicle shares by more than three times. This is because people do not need to wait for a long time to obtain a NEV license and the NEVs are more attractive under the vehicle license allocations.

Table 1.10: Counterfactual 2: Impact on Vehicle Sales in Beijing

	License Lottery		No Allocations					
			No Subsidy or Tax		NEV Subsidy and Non-NEV Tax			
	Total	NEV Share	Total	NEV Share	NEV Share	Subsidy Rate	Tax Rate	Total Subsidy or Tax (billion Yuan)
2014	417,527	0.006	940,952	0.001	0.006	0.34	0.002	0.45
2015	422,323	0.032	1,003,305	0.002	0.032	0.35	0.005	1.56
2016	730,686	0.065	1,090,350	0.015	0.065	0.22	0.009	2.38
2017	497,452	0.092	1,168,578	0.022	0.092	0.21	0.013	4.29

Notes: The counterfactual simulations are based on demand estimation results from the top panel of Table1.5, where the implicit costs are assumed to be constant across years.

Table 1.11 reports the welfare change if there were no vehicle license allocation. Row 6 shows that the total consumer surplus would have increased by 26-52 billion Yuan. The consumer surplus increases due to two effects. First, the current buyers' utility increases because they do not have to wait several years to buy a car. The first two rows show that without the vehicle license allocation, the average compensating variation is around 30,000 Yuan, and the consumer surplus of the current buyers would have increased by 2.7-3.67 billion Yuan from 2014 to 2017. Second, there will be more vehicle sales, and more people can buy cars. Rows 3-4 suggest that the change in new buyers' consumer surplus would have been around 23.28-48.11 billion Yuan from 2014 to 2017, accounting for around 90 percent of the total consumer welfare change. This implies that the implicit cost of waiting has a nonnegligible impact on consumer welfare. My estimates of the consumer welfare loss by Beijing's lottery are slightly higher than the existing literature (e.g., Li 2018; Qin et al. 2021; Xiao et al. 2017). For example, Li (2018) estimates the vehicle license lottery in Beijing reduced consumer welfare by 33 billion Yuan in 2012.

Table 1.11: Counterfactual 2, Welfare Effects in Beijing

	2014	2015	2016	2017
CV: Current buyers (Yuan)	29,073	30,505	22,918	29,284
ΔCS: Current buyers (billion Yuan)	3.54	3.67	2.70	3.54
CV: New buyers (Yuan)	56,335	62,515	64,733	71,684
ΔCS: New buyers (billion Yuan)	29.49	36.32	23.28	48.11
Total ΔCS (billion Yuan)	33.03	39.99	25.98	51.65
15-year horizon:				
Δ External cost (billion Yuan)	32.67	36.08	21.28	40.65
Δ Net social welfare (billion Yuan)	0.36	3.91	4.69	11.00
10-year horizon:				
Δ External cost (billion Yuan)	24.30	26.84	15.83	30.24
Δ Net social welfare (billion Yuan)	8.73	13.15	10.15	21.41

Notes: The counterfactual simulations are based on demand estimation results from the top panel of Table1.5, where the implicit costs are assumed to be constant across years. All monetary variables are in 2017 Yuan. CV is the compensating variation from the original condition to the counterfactual condition. I assume the annual vehicle miles traveled is 16,350 km in Beijing and 18,000 km in Shanghai. The discount rate is 5 percent. The externalities include CO_2 emissions, local pollution, congestion, and traffic accidents. The external cost is 4.33 Yuan per liter of gasoline (in 2017 terms), of which the external cost of CO_2 emissions and local pollution account for 23 percent, or 1.01 Yuan/liter. Total change in consumer surplus equals the sum of CS change in current buyers and CS change in new buyers. Net social welfare equals the consumer surplus minus the external cost.

The second part of Table 1.11 shows the changes in externalities. Without vehicle license allocations, the total vehicle sales would have increased from 2014 to 2017, leading to a higher external cost. For example, assuming a 15-year vehicle life, the external cost would have increased by 40.65 billion Yuan in 2017. Since the total increase in consumer surplus is 51.65 billion Yuan, increasing externalities would offset about 80 percent of the consumer welfare gain by removing vehicle license allocations. Moreover, the net social welfare change would be about 11 billion Yuan.[3]

To better understand the vehicle license allocation's impact on electric vehicle adoption. I compare it with a NEV subsidy. Columns 6-9 of Table 1.10 show the results of a counterfactual simulation assuming no vehicle license allocation, but instead, the government taxes non-NEVs to subsidize NEVs. I assume the government is revenue neutral by using the tax collected from non-NEVs to subsidize NEVs. Moreover, the government aims at achieving the same NEV market shares under the no allocation condition as under vehicle license allocations. The simulation suggests that to achieve the same NEV share, the government would have had to subsidize 21-35 percent of the electric vehicle price from 2014 to 2017. In 2017, the government would have had to spend 4.29 billion Yuan to subsidize the NEV purchases without vehicle license allocations. These results suggest that vehicle license allocation is an efficient tool to promote NEV adoption.

Tables 1.12 and 1.13 show counterfactual simulation results for Shanghai. The vehicle license auction reduced new vehicle sales by 23-54 percent from 2013 to 2017, and increased NEV shares by about twice compared to the no allocation situation. To achieve the same NEV

[3] Li (2018) estimates the external cost by using estimates from Creutzig and He (2009). He assumes the marginal externality cost to be 9.7 Yuan/liter in Beijing, including externalities from CO2 emissions, local pollution, congestion and traffic accident, of which the pollution cost accounts for 80 percent. If I use the estimates from Creutzig and He (2009) and assume a 15-year vehicle life, the external cost will increase by 46.7-88.5 billion Yuan if we remove the vehicle license lotteries in Beijing. And the net social welfare loss will be 20.7-38.2 billion Yuan.

shares as observed under the current policy, the government would have had to subsidize about 40 percent of the electric vehicle price.

Table 1.12: Counterfactual 2: Impact on Vehicle Sales in Shanghai

	Auction		No Allocations					
			No Subsidy or Tax		NEV Subsidy and Non-NEV Tax			
	Total	NEV Share	Total	NEV Share	NEV Share	Subsidy Rate	Tax Rate	Total Subsidy or Tax (billion Yuan)
2013	244,602	0.001	483,090	0.000	0.001	0.43	0.0003	0.03
2014	241,791	0.032	530,829	0.009	0.032	0.44	0.011	1.30
2015	305,723	0.094	668,241	0.029	0.094	0.43	0.032	4.56
2016	574,187	0.041	741,956	0.014	0.041	0.42	0.023	3.23
2017	572,943	0.063	781,119	0.022	0.063	0.41	0.033	5.11

Notes: The counterfactual simulations are based on demand estimation results from the top panel of Table1.5, where the implicit costs are assumed to be constant across years.

Table 1.13 shows the welfare effects of Shanghai's auctions. Without auctions, consumer surplus would have increased by 25-36 billion Yuan from 2013 to 2017. The consumer welfare increase from no implicit waiting cost accounts for almost half of the total consumer welfare increase. Moreover, the government revenue would have decreased by 8-15 billion Yuan without vehicle license auctions. Removing the vehicle license auctions in Shanghai would have increased externalities by 10.3-22.87 billion Yuan, offsetting 35-68 percent of the consumer welfare gain given a 15-year vehicle life. However, we should treat those results for Shanghai with caution since there is no pre-policy period for Shanghai in my data.

Table 1.13: Counterfactual 2: Welfare Effects in Shanghai

	2013	2014	2015	2016	2017
CV: Current buyers (Yuan)	123,834	116,333	122,265	124,692	129,844
ΔCS: Current buyers (billion Yuan)	13.65	11.49	14.81	19.38	21.91
CV: New buyers (Yuan)	49,064	55,524	57,996	60,762	65,435
ΔCS: New buyers (billion Yuan)	11.70	16.05	21.02	10.19	13.62
Total ΔCS (billion Yuan)	25.35	27.54	35.83	29.58	35.53
Average bidding price (Yuan)	85,110	77,674	83,779	87,259	90,696
ΔAuction revenue (billion Yuan)	-9.38	-7.67	-10.15	-13.57	-15.30
15-year horizon:					
Δ External cost (billion Yuan)	15.25	18.66	22.87	10.30	12.83
Δ Net social welfare + ΔAuction revenue (billion Yuan)	0.72	1.20	2.82	5.72	7.40
10-year horizon:					
Δ External cost (billion Yuan)	11.35	13.89	17.01	7.66	9.54
Δ Net social welfare + ΔAuction revenue (billion Yuan)	4.62	5.98	8.67	8.35	10.68

Notes: The counterfactual simulations are based on demand estimation results from the top panel of Table1.5, where the implicit costs are assumed to be constant across years. All monetary variables are in 2017 Yuan. CV is the compensating variation from the original condition to the counterfactual condition. I assume the annual vehicle miles traveled is 16,350 km in Beijing and 18,000 km in Shanghai. The discount rate is 5 percent. The externalities include CO2 emissions, local pollution, congestion, and traffic accidents. The external cost is 4.33 Yuan per liter of gasoline (in 2017 terms), of which the external cost of CO2 emissions and local pollution account for 23 percent, or 1.01 Yuan/liter. Total change in consumer surplus equals the sum of CS change in current buyers and CS change in new buyers. Net social welfare equals the consumer surplus minus the external cost.

In the appendix, Tables A.5, A.6 and A.7 show the results for Counterfactual 2 if we allow the implicit cost to vary across years. The results are very similar to the results with time-invariant implicit cost. The vehicle license allocations in Beijing and Shanghai reduced the total vehicle sales and increased the NEV shares by more than three times in 2016 and 2017. The government would have had to subsidize 19-28 percent of the total NEV price to achieve the same NEV share if there were no license lotteries in Beijing. And the government would have had to subsidize about 40 percent of the total NEV price to achieve the same level of NEV share if there were no license auctions in Shanghai. Also, the vehicle license lottery reduced consumer welfare by 23-46 billion Yuan in Beijing, of which about 9 percent was due to the implicit cost of waiting.

The vehicle auction in Shanghai reduced consumer welfare by 20-35 billion Yuan in Shanghai, slightly lower than the results with time-invariant implicit cost. And the government would have lost revenues of 8-15.3 billion Yuan without the vehicle license auctions. The external cost would have increased by 21-41 billion Yuan in Beijing, offsetting more than 90 percent of the consumer welfare gain. The external cost would have increased by 10-23 billion Yuan in Shanghai, offsetting 37-90 percent of consumer welfare increases from 2013 to 2017.

1.8 Conclusion and Discussion

Many major cities in China use vehicle ownership restrictions to improve air quality and reduce traffic congestion. However, the welfare cost of vehicle license allocation policies is ambiguous. This paper investigates the impact of vehicle license allocation on electric vehicle adoption and reveals its welfare effects, focusing on two treated cities—Beijing and Shanghai. In recent years, to promote electric vehicle sales, Beijing added another lottery pool for NEV licenses in 2014, and Shanghai lifted the restrictions on NEV licenses in 2013. As a result, the wait time for a NEV license is much shorter, and thus the implicit waiting cost of NEV licenses is much lower than non-NEV licenses. This paper shows that the lower implicit cost of NEVs promotes electric vehicle adoption. Moreover, the implicit cost of waiting imposed by vehicle license allocations is nonnegligible and reduces consumer welfare significantly.

In the first part of this paper, I use the synthetic control approach to select two cities without vehicle license allocations. Adding cities without vehicle license allocations enables me to identify the implicit cost of waiting. Then, I use aggregated data from 2005 to 2017 to estimate a triple-difference model. The reduced-form estimation suggests that vehicle license allocations reduced vehicle sales by 61 percent in Beijing in 2011 and significantly encouraged electric vehicle sales in Beijing and Shanghai.

Second, I build up a structural model for vehicle demand and supply under the license allocations. In the demand model, the consumer's utility consists of the vehicle's mean utility from the vehicle attributes and the disutility from the total vehicle price and the implicit cost of waiting. All potential buyers are divided into two types: first-time buyers who need vehicle licenses and second-time buyers who do not need vehicle licenses. Only the first-time buyers are subject to the implicit cost caused by the vehicle license allocation and need to pay the bidding price for vehicle licenses. This demand model explains how the lower implicit cost of purchasing electric vehicles shifts people from non-NEVs to NEVs. The supply model explains the firm's pricing strategy under the vehicle license allocation and shows how to recover the marginal production cost.

In the third part of this paper, I use highly disaggregated data for the four cities from 2010 through 2017 to estimate the structural model. Because the total vehicle price and the implicit cost vary across vehicles and consumers, even if we assume common taste across consumers, there is still a part of utility that is individual-specific. Therefore, the mean utilities cannot be backed out analytically as in the standard Logit model. Therefore, I use the contraction mapping algorithm to recover the mean utilities. The nonlinear parameters are the price coefficients and the implicit costs, and are then estimated by GMM. The implicit costs are identified by comparing NEV shares in Beijing and Shanghai with other cities without the policy. The GMM estimations reveal that the average implicit cost of purchasing non-NEVs in Beijing is about 10 percent of the total vehicle price.

Finally, this paper compares the current policy with two counterfactuals—a counterfactual where there is one lottery for non-NEV and NEV licenses, and a counterfactual assuming no license allocation but the government taxes non-NEVs to subsidize NEVs. The counterfactual simulations find that compared with the one-lottery policy, the current policy increased the electric vehicle sales by three times in Beijing and twice in Shanghai. Also, the NEV share would have decreased by almost two-thirds without vehicle license allocations from 2013 to 2017. Moreover, the government would have had to subsidize 21-44% of the NEV price if there were no vehicle license allocations to achieve the same level of NEV market share as under the vehicle license allocation.

The vehicle license allocations reduce consumer welfare substantially because of the long wait time. One-lottery system would have reduced consumer welfare by 0.1 billion Yuan in 2017 and increased externalities by 0.36 billion Yuan due to lower NEV shares. Removing the vehicle license allocation would have increased consumer welfare by 26-52 billion Yuan in Beijing. The welfare increase is due to shorter waiting times and more vehicle sales, and the former accounts for around 10% of the total consumer welfare increase. However, without the policy, increasing vehicle sales would generate tremendous externalities, offsetting more than 80 percent of the consumer welfare gain.

This paper's findings have important policy implications for countries with a rapidly growing vehicle market. Some megacities in these countries also have vehicle ownership restrictions. This paper shows that vehicle ownership restrictions impose a high cost to consumers while successfully controlling vehicle ownership growth. This policy reduces consumer surplus not only because of fewer new vehicle transactions but also because of the high implicit cost of waiting.

Moreover, as the electric vehicle market has begun to take off in recent years, most countries still rely on subsidies to promote electric vehicles. However, EV subsidies induce high fiscal costs. As a result, many countries have sought regulation approaches to replace subsidies. This paper suggests that separating allocations of EV and non-EV licenses is an efficient instrument to promote electric vehicles, and compared to EV subsidies, it induces a much lower fiscal cost. Therefore, cities with vehicle license allocations should consider this approach to boost EV sales.

Future research could endogenize the supply side and investigate the vehicle license allocation's impact on a firm's pricing strategy and producer welfare. Endogenizing the supply side allows the firms to adjust their vehicle prices facing the vehicle license allocations, which will further affect the vehicle demand and affect the consumer welfare. Endogenizing the supply side will also enable the comparison between production subsidies with the vehicle license allocations to promote electric vehicles.

In the future, we could also allow heterogeneity in preferences across consumers. This will allow for more flexible substitution patterns between vehicles. Moreover, in recent years, many cities introduced a hybrid system where some licenses are allocated via lottery, and some licenses are sold via auctions. Further work can investigate people's participation decisions under this more complicated system and quantify its welfare consequences.

Chapter 2: Short-run Impact of China's Corporate Average Fuel Consumption Standard

2.1 Introduction

China has been the largest vehicle market for almost 14 years, and the total vehicle ownership in China has soared to 280 million by 2020. The rapid growth in vehicle ownership has put heavy pressure on the energy supply. For example, China's total oil consumption has reached 600 million tons, with a rate of oil import dependence as high as 70 percent. Transportation accounted for more than half of total oil consumption, of which passenger car fuel consumption contributed to about 90 percent of total gasoline consumption (about 20 percent of total oil demand). Also, the fast-growing vehicle ownership has led to severe air pollution and traffic congestion. The transportation sector accounts for 9 percent of China's total greenhouse gas emissions.

One approach to reduce fuel consumption and GHG emissions from the transportation sector is to increase the fuel economy of a single vehicle, and the other is to promote electric vehicles. In the first chapter of my dissertation, I discuss the second approach and focus on one policy to promote electric vehicles in China—vehicle license allocations. In this chapter, I will look at the first approach. China implemented passenger vehicle fuel consumption standards as early as in 2005. China's fuel economy standards were approved as one of the most effective efforts to improve fuel efficiency and energy management regulation. The standards were meant to reduce oil consumption and advance China's energy security.

Passenger vehicle fuel consumption standards in China have undergone five phases since 2005. Initially, the standard sets a limit on a single vehicle's fuel consumption. In 2012, China announced the corporate average fuel consumption (CAFC) policy. In 2018, China added a new NEV credits system to the existing CAFC credit system. This system is referred to as the "dual-credit" system.

In this paper, I focus on the CAFC standard in China and evaluate its impact on vehicle manufacturers' welfare using data from 2010 to 2017 for four populous cities in China: Beijing, Shanghai, Chongqing, and Suzhou. I show how manufacturers abate fuel consumption by sales-mixing strategies. The existing literature has discussed three strategies of manufacturers to reduce vehicle fuel consumption. The first strategy is sales mixing as explored by Goldberg (1998) and Jacobsen (2013). Manufacturers will push up prices of the fuel inefficient vehicles to shift demand from fuel inefficient vehicles to fuel efficient vehicles. This will increase the average fuel economy of the company. However, literature shows that the sales-mixing abatement strategy will generate considerable costs to consumers and firms.

The second strategy is to downsize the vehicles. Firms can tradeoff between fuel economy and other vehicle attributes, such as vehicle weight, size, and horsepower. Small and light cars usually have lower fuel consumption and will help achieve the corporate average fuel economy standards. Several studies have discussed the welfare effects of CAFE if firms trade off other vehicle attributes with fuel economy (Klier and Linn 2015; Knittel 2011). For example, Klier and Linn (2012) find that combining downsizing and sales mixing will reduce the firm's compliance costs by about 40 percent, from 9.07 billion dollars to 5.58 billion dollars per year. Ito and Sallee

(2018) shows that the weight-based regulation in Japan caused firms to increase vehicle weight, because heavier cars help to achieve the fuel economy target. Therefore, the attribute-based regulation leads to a substantial distortion in vehicle attributes.

The third strategy is technology adoption. Many studies have estimated the welfare effects of adopting new technology to abate emissions and fuel consumption (Klier and Linn 2016; Reynaert 2019). Reynaert (2019) quantifies the welfare effects of European emission standards, and finds that if firms adopt new technology to abate emissions, the total welfare effects of the regulation is 5 billion euros per year. However, if the firm only uses sales mixing strategy, the total welfare effects would be a yearly loss of 20 billion euros per year. These three strategies can be viewed as the firm's short-run, medium-run, and long-run reactions to the fuel economy standards, and will lead to different welfare consequences.

Few studies quantify the shadow cost of the policy directly. For example, Jacobsen (2013) finds that the CAFE standard imposes a significant shadow cost on US firms. A 1-mile-per-gallon increment in CAFE standards will reduce consumer and producer surplus by $20 billion per year. Anderson and Sallee (2011) quantifies the shadow cost imposed by the policy by exploring a loophole in the fuel economy standard. In contrast to the results of Jacobsen (2013), they find a very low shadow cost generated by the policy.

This paper estimates the short-run impacts of China's corporate average fuel consumption standard on vehicle producers. I use disaggregated data from 2010 through 2017 for four populous cities in China to estimate a structural model of vehicle demand and supply. I do not consider the medium-run or long-run effects of the CAFC standards because estimating the tradeoff between vehicle attributes and technological progress requires time-varying vehicle attributes data. However, unfortunately, the vehicle attributes remain unchanged across years in my data. In the short-run, the firm can only react to the standard by adjusting relative prices of fuel-efficient vehicles and fuel-inefficient vehicles. In the first part, I set up a structural model of vehicle supply under the CAFC standard. I assume the manufacturer will set a national vehicle price to maximize its profit from all cities subject to the CAFC standard requiring the firm's average fuel consumption to be lower than the target. The policy will generate a shadow cost to producers, which can be viewed as a subsidy to those firms with high fuel economy and a tax to firms with low fuel economy. I assume the vehicle set and marginal cost stay unchanged. The model explains how to recover the marginal production costs and how the CAFC standards will affect the firm's pricing strategy.

In the empirical estimation, first, I use one of the pre-policy years, the year 2011, to estimate the marginal production costs, based on the demand estimation in the second paper of my dissertation. Second, I do four simulations. In the first three scenarios, I simulate a policy equal to the CAFC standard with the Phase III fuel consumption target. This policy aims at a national average fuel consumption of 7 L/100 km by 2015. The first scenario does not allow the trading of CAFC credits between companies. In the second scenario, I allow a company to trade CAFC credits with its affiliated group corps. The third scenario allows free trading of CAFC credits. In the fourth simulation, I simulate a policy similar to the CAFC standard with the Phase IV fuel consumption target, assuming free trading of CAFC credits. Phase IV CAFC policy is more stringent than Phase III, aiming to achieve a national average fuel consumption of 5 L/100 km by 2020. The first three scenarios help to understand the impacts of allowing credit trading, and comparing the third and fourth simulations helps understand the impact of a more stringent policy.

My paper finds that the manufacturer's markup over marginal costs ranges from 19% to

24%. The Phase III CAFC standard will reduce the firm's profit by 1.07 billion Yuan, and the more stringent Phase IV CAFC standard will reduce the firm's profit by 4.66 billion Yuan. Moreover, allowing the trading of CAFC credits will bring down the compliance cost to producers substantially.

My paper contributes to the existing literature on evaluating the welfare effects of China's passenger vehicle fuel economy standards. Many literature quantifies the fuel economy standard's impact on the vehicle market structure, vehicle sales, and fuel consumption(Oliver et al. 2009;Wagner et al. 2009). Recently, many studies have estimated the impact of the "dual-credit" standard on electric vehicle adoption and compared the "dual-credit" standard with EV purchase subsidy (Ou et al. 2018;Li et al. 2018). However, few studies quantify the welfare consequences of China's fuel economy standards. My paper sets up a structural model of vehicle demand and supply that considers the vehicle license allocations in many China's megacities. Based on this structural model, I am able to quantify the welfare effects of fuel economy standards on producers. My paper helps to understand China's fuel economy standards' impact on producer surplus, and I show that this policy has generated substantial costs to producers.

My paper's findings have important policy implications. Corporate Average Fuel Economy standards have been widely used to reduce transportation emissions and fuel consumption. Many countries, including the US, Europe, Japan, and China, have such CAFC standards. In recent years, many developing countries with fast-growing vehicle markets have started to implement CAFC standards. China is one of the fast-growing vehicle markets. I show in this paper that although the more stringent CAFC standards in China have successfully reduced transportation emissions and fuel consumption, they also have induced nontrivial costs to vehicle producers.

2.2 Background and Data

2.2.1 Policy context

As vehicle ownership grows fast in China, oil consumption from the transportation sector increases rapidly, accounting for more than half of China's total oil consumption in 2017. Passenger car fuel consumption accounts for more than 90 percent of total gasoline consumption (iCET 2017). To reduce transportation fuel consumption, China introduced the fuel economy standard for light-duty passenger vehicles in 2005. Table 2.1 shows the timing of the fuel economy standards in China. The standard has undergone five phases. Initially, the policy set a limit for a single vehicle's fuel consumption, and only domestic cars were included in the regulation. In 2012, the third phase started and introduced the Corporate Average Fuel Consumption (CAFC) standard and included imported cars in the regulation. To promote new energy vehicles, China announced the dual-credit policy in September 2017, adding New Energy Vehicle (NEV) credits to the existing CAFC redits.

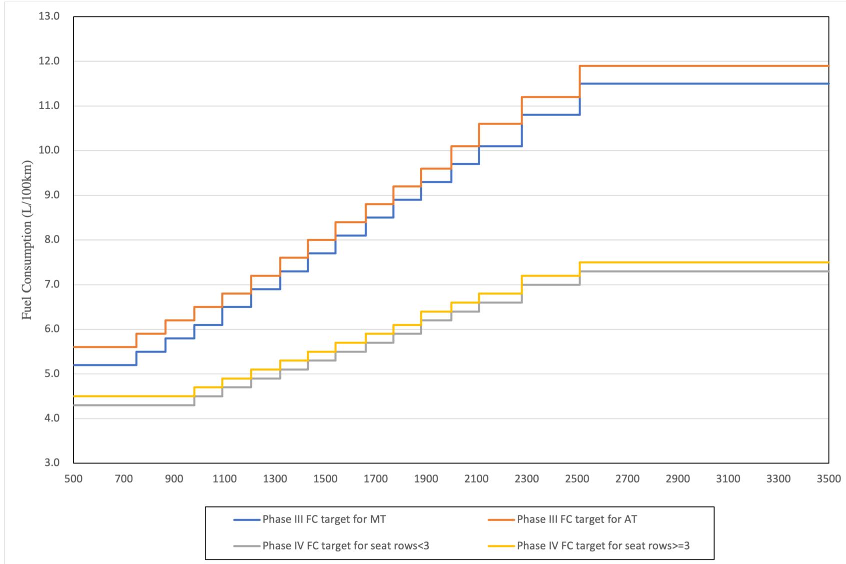
Table 2.1: China's Passenger Vehicle Fuel Economy Standards

Phase	Time Period	Policy Number	Comments
I	2005.07-2008.01 new models FC limit 2006.07-2009.01 in production models FC limit	GB19578-2004	Single vehicle fuel consumption limit;
II	2008.01-2012.07 new models FC limit 2009.01-2012.07 in production models FC limit	GB19578-2004	Imported cars not included.
III	2012.07-2015.12 FC limit similar to Phase II	GB19578-2004	Single vehicle FC limit and corporate average FC target;
	2012.07-2015.12 CAFC introduced	GB27999-2011	Imported vehicles included.
IV	2016.01-2020.12 new models FC limit 2018.01-2020.12 in production models FC limit	GB19578-2014	Single vehicle FC limit and corporate average FC target; Imported vehicles included.
	2016.01-2020.12 new CAFC target	GB27999-2014	
	2018.04-2020.12 Dual-credit policy introduced	GB27999-2014	Dual-credit policy that combines CAFC credits and NEV credits started in 2018.
V	2021.01-2025.12 new models FC limit 2023.01-2025.12 in production models FC limit	GB19578-2021	Single vehicle FC limit and corporate average FC target; Imported vehicles included; Dural-credit policy; Emission testing method is changed from NEDC to WLTC; FC target is linear in vehicle weight.
	2021.01-20205.12 Dual-credit policy	GB27999-2019	

China's CAFC sets a fuel consumption target for each vehicle, and requires that each passenger vehicle manufacturer's corporate average fuel consumption (CAFC) be lower than its corporate average fuel consumption target (T_{CAFC}). The fuel consumption target is attribute-based.

Before the fifth phase, China's CAFC fuel consumption target for a single vehicle is based on the vehicle's curb weight bins, different from the emission target in Europe which is linear in vehicle's weight. The fuel consumption target is different for vehicles with manual transmission and automatic transmission, and also varies across vehicles with different numbers of seat rows. Vehicles with the automatic transmission or more than two rows of seats have higher fuel consumption targets than other vehicles of the same weight. The standard requirement intensified with each phase. The target for the third phase implemented in 2012 is to achieve a national average fuel consumption of 7 L/100 km by 2015, which equals 167 grams of carbon dioxide per kilometer (g CO_2/km). The fourth phase introduced in 2016 becomes more stringent, aiming at reducing the national average fuel consumption to 5 L/100 km by 2020, or 120 g CO_2/km. In 2021, the fifth phase implemented is even more ambitious, aiming at a national average fuel consumption of 4 L/100 km by 2025, or 96 CO_2/km. Figure 2.1 shows how the CAFC fuel consumption targets vary across different vehicle weight bins in Phase III and IV. Phase III tightened the fuel consumption limits by more than 20 percent compared to those in Phase II, and the fourth phase's targets are 30-40% more stringent than those of the third phase.

Figure 2.1: China's CAFC Fuel Consumption Target



A manufacturer's CAFC is calculated according to the following equation:

$$CAFC = \frac{\sum_{i=1}^{N} FC_i \times V_i}{\sum_{i=1}^{N} V_i \times W_i} \tag{2.1}$$

where, i represents a vehicle produced by the manufacturer. FC is the fuel consumption of the vehicle (L/100 km), V is the production quantity (export volume not included) or import volume of the vehicle. W is the multiplier for each vehicle, which equals one for fossil fuel cars and is larger than one for new energy vehicles. Thus, producing more new energy vehicles will significantly lower a manufacturer's CAFC.

The corporate average fuel consumption target (T_{CAFC}) for a manufacturer is calculated according to the following equation:

$$T_{CAFC} = \frac{\sum_{i=1}^{N} T_i \times V_i}{\sum_{i=1}^{N} V_i} \tag{2.2}$$

where, the fuel consumption target for each vehicle, T, depends on the vehicle weight bins as shown in Figure 2.1.

The policy requires a manufacturer's CAFC to be lower than its $\mathrm{T_{CAFC}}$. And during the phase-in period a manufacturer's CAFC can be higher than its $\mathrm{T_{CAFC}}$, but the ratio of its CAFC to its $\mathrm{T_{CAFC}}$ must be smaller than a required value σ. The required ratio σchanges every year according to Table 2.2:

$$\frac{CAFC}{T_{CAFC}} \leq \sigma \tag{2.3}$$

Table 2.2: Required Ratio of CAFC to $\mathrm{T_{CAFC}}$

Year	Required σ(%)
2012	109
2013	106
2014	103
2015	100
2016	134
2017	128
2018	120
2019	110
2020—	100

A manufacturer's compliance credit equals the difference between its $\mathrm{T_{CAFC}}$ and CAFC. Before 2018 when the dual-credit policy started, the compliance credits could not be traded among manufacturers. After 2018, the CAFC credit deficit can be offset by previous years' CAFC credit surplus of the same company, CAFC credit surplus from affiliated group corp, NEV credit surplus produced in the same year by the same company, or purchasing NEV credit surplus. If the company cannot fulfill its CAFC target, the government will first issue a public notice of incompliant companies ("shaming" approach). Then, the incompliant companies need to rectify and notify the government of their rectification processes. If the company fails to meet the requirements after the rectification, the government will seize its vehicle production or importation, and suspend the issuance of new product certifications to the company.

2.2.2 Data

This paper uses four cities, Beijing, Shanghai, Chongqing, and Suzhou, as a sample to estimate the impact of passenger vehicle fuel economy standards on the vehicle market. Those four cities are the most populous cities in China and account for about 10 percent of China's total passenger car sales.

I use highly disaggregated data for the China market covering the years 2010 through 2017. Observations are by city, year-quarter, and vehicle. A unique vehicle is a unique model (nameplate), model year, origin (domestic or foreign), fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), engine displacement, and transmission configuration (manual or not). There are 81,056 observations in total, 1,396 unique vehicles and 99 unique manufacturers. The average quarterly sales for a vehicle in a city is about 136.

Another auxiliary data includes information on vehicle attributes. These attributes include price, fuel economy, engine displacement, length, width, height, wheelbase, curb weight, engine horsepower, number of doors, number of seats, number of cylinders, number of valves, drive type, number of gears, segment, and body type. The price includes the manufacturer suggested retail price, tax, and subsidies. In my dataset, vehicle's attributes won't change across city and time. Variations in price come from vehicle tax and subsidies as well as the bidding price. Variations in fuel cost are due to the energy price changes across cities and time.

Table 3.1 reports the sales-weighted average of vehicle attributes in each period. I divide the entire period into three parts: 1) 2010-2011, no CAFC period; 2) 2012-2015, CAFC standard started with Phase III fuel consumption target; 3) 2016-2017, more stringent CAFC standard with Phase IV fuel consumption target. The table shows that the sales-weighted average fuel consumption dropped from 7.72 L/100 km in the first period to 7.58 L/100 km in the second period. And in 2016 and 2017, the average fuel consumption decreased further to 7.08 L/100 km. The decreasing average fuel consumption might be explained by manufacturers making an effort to comply with the CAFC target. Also, the sales-weighted average vehicle horsepower, weight, and size increased from the first to the third period. Figure 2.2 shows the trend in the sales-weighted average of vehicle attributes from 2010 to 2017. This figure assumes that the vehicle's attributes do not change from 2010 to 2017. Therefore, it suggests how the changes in sales affected the average fuel consumption and other vehicle attributes. The decreasing average fuel consumption in the figure implies that manufacturers are very likely to adjust vehicle prices to attract people to buy low emission vehicles.

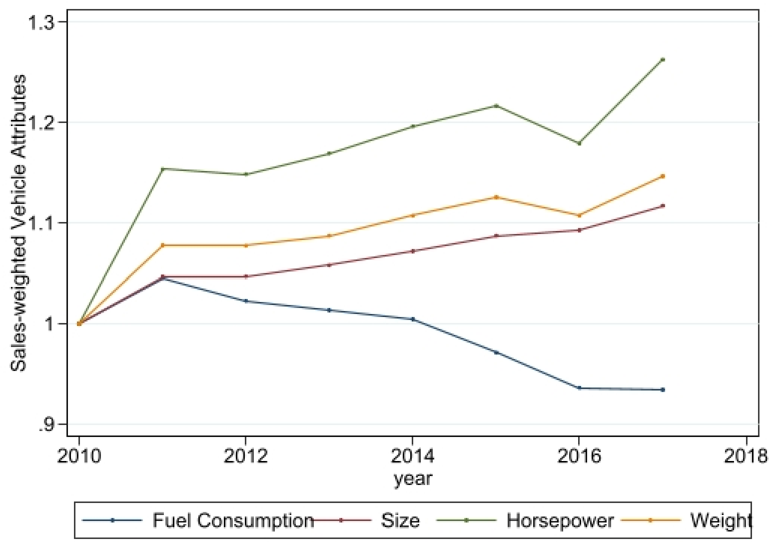
Besides the sales data and information on vehicle attributes, this paper also collects information on the vehicle license allocation policy in Beijing and Shanghai. Beijing uses lotteries and Shanghai uses auctions to allocate vehicle licenses. This data includes the number of applicants, quota amount, winning odds, average winning bid price, and lowest bid price in each treated city. The winning odds of non-NEV licenses in Beijing dropped rapidly, from 10% in 2011 to 0.1% in 2017. Shanghai's auctions have higher winning odds than lotteries in Beijing. However, the winning odds of non-NEV licenses in Shanghai also decreased a lot, from 40% in 2010 to 5% in 2017. The average winning bid increased from around 40,000 Yuan to 90,000 Yuan in 2017, accounting for about one-third of the total vehicle price.

Table 2.3: Summary Statistics

Variables	Period 1 2010–11	Period 2 2012–15	Period 3 2016–17
Quarterly sales by city	159.81	122.06	144.37
	(277.33)	(224.88)	(276.41)
Fuel consumption (L/100 km)	7.72	7.58	7.08
	(1.36)	(1.52)	(1.67)
Fuel cost (Yuan /100 km)	61.46	56.92	42.65
	(12.28)	(14.37)	(10.95)
Price (10,000 Yuan)	24.09	26.59	24.9
	(20.25)	(20.44)	(19.15)
Tax (10,000 Yuan)	2.22	2.31	1.88
	(1.86)	(1.85)	(1.71)
Horsepower (100 hp)	1.03	1.14	1.17
	(0.34)	(0.37)	(0.42)
Curb weight (ton)	1.39	1.48	1.51
	(0.26)	(0.27)	(0.28)
Size (cubic meters)	12.23	12.79	13.23
	(1.66)	(1.65)	(1.7)
Number of doors	4.31	4.42	4.55
	(0.49)	(0.53)	(0.53)
Manual	0.41	0.25	0.21
	(0.49)	(0.43)	(0.41)

Notes: The table reports the sales-weighted average of the attributes for the time periods indicated in the row heading, with standard deviations in parentheses.

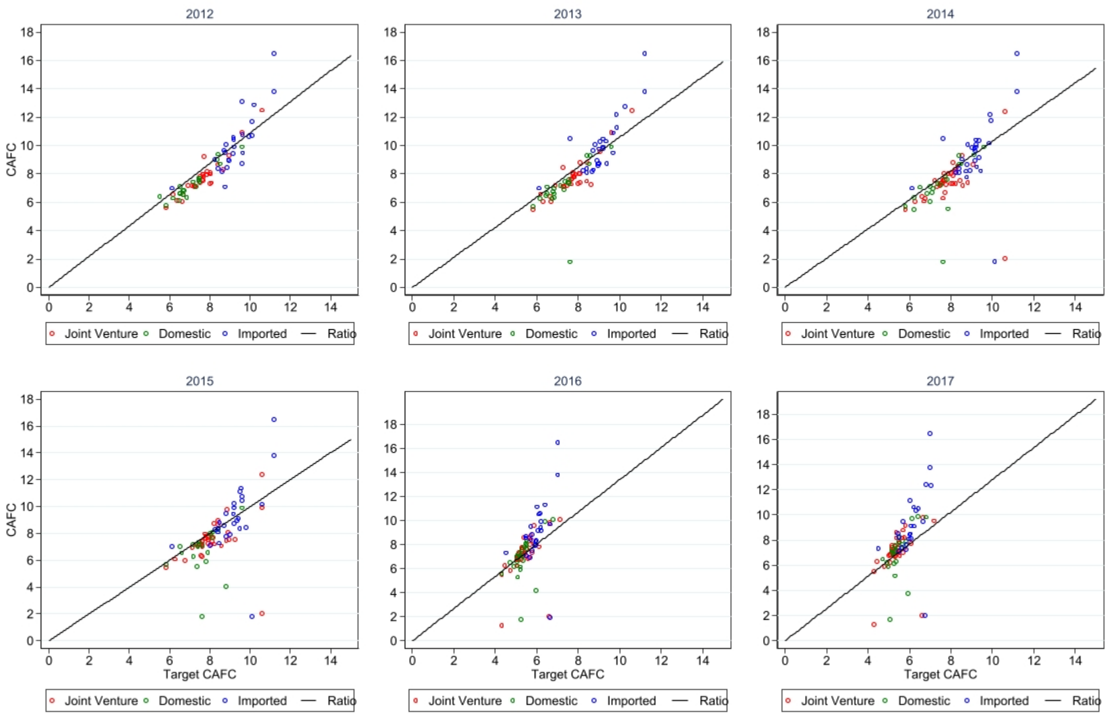
Figure 2.2: Trend in Vehicle Attributes (2010=1)



Notes: The figure shows the sales-weighted average of vehicle fuel consumption, size, horsepower, and weight from 2010 to 2017. It assumes that each vehicle's attributes unchanged from 2010 to 2017.

I also collected information on CAFC policy to calculate the CAFC and target CAFC for each vehicle manufacturer in each year. Figure 2.3 shows each manufacturer's CAFC and $T_{CAFC}$from 2012 to 2017. I assume that vehicle attributes have remained unchanged since 2010. Each point in the figure represents a manufacturer. The straight line represents each year's required ratio of CAFC to T_{CAFC} (σ). Manufacturers below the straight line are those that fulfilled the fuel economy standard, and manufacturers above the line failed to meet the standard. I divide all manufacturers into three types—joint venture, domestic manufacturer, and importer. The figure shows that importers' average fuel consumption is more likely to exceed the target average fuel consumption. Moreover, most companies are constrained by the CAFC policy. Only a few domestic manufacturers and joint ventures have very low CAFC and are thus not constrained by the policy. Also, the Phase IV requirement is more stringent than the Phase III since more manufacturers cannot meet the standard after 2016.

Figure 2.3: Manufacturer's CAFC and T_{CAFC}



Notes: Calculations of CAFC and T_{CAFC}assume that the fuel consumption remains unchanged from 2010 to 2017. The straight line represents each year's CAFC requirement. Points above the line are incompliant companies, and points below the line are compliant companies. The slope of the straight lines represents each year's required ratio of CAFC to $T_{CAFC}(\sigma)$. From 2012 to 2017, the ratios are 1.09, 1.06, 1.03, 1, 1.34, and 1.28.

2.3 Model of Firm's Profit Maximization under the CAFC Standard

In this section, first, I introduce the manufacturer's profit maximization when there is no CAFC policy. I will discuss how to recover the marginal cost from the first-order conditions of the profit maximization problem. Then I will explain the manufacturer's profit maximization under the CAFC policy. I assume that the policy imposes a shadow cost on each manufacturer. And I will explain how the policy affects the firm's pricing strategies.

2.3.1 Manufacturer's profit maximization without the CAFC standard

Assume a firm f sets the national vehicle priceP_r to maximize its profit from all cities in each year. The vehicle set of firm f in city m and quarter t is Θ_{fmt}. Let c_r denote the marginal cost of producing vehicle r. In this paper, I assume the marginal cost of production is the same across cities. N_{mt} denotes the market size, which is the total number of households in each city and time. The fuel consumption of each vehicle is M_r. $\tilde{P}_r$ represents the consumer's price for vehicle r. The market share of each vehicle in city m and quarter t, S_{rmt}, is determined by the vehicle price, the vehicle license bidding price B, the implicit cost of waiting imposed by the vehicle license allocations λ, and other vehicle attributes X. Then, the firm's profit maximization problem in each year is:

$$\max_{\{P_r\}} \pi_f = \sum_t \sum_m \sum_{r \in \Theta_{fmt}} (P_r - c_r) \cdot S_{rmt}(\tilde{P}_r, B_{vmt}, \lambda_{mt}, X_r; \theta) \cdot N_{mt} \tag{2.4}$$

First-order conditions w.r.t vehicle j's price is:

$$\sum_t \sum_m N_{mt} \{ S_{jmt} + \sum_{r \in \Theta_{fmt}} (P_r - c_r) \frac{\partial S_{rmt}}{\partial P_j} \} = 0 \tag{2.5}$$

Re-arrange the above equations into matrix format, we obtain:

$$Q(p) - \Omega(p)(P - c) = 0 \tag{2.6}$$

Where,

$$Q(P) = \begin{bmatrix} \sum_t \sum_m S_{1mt} N_{mt} \\ \sum_t \sum_m S_{2mt} N_{mt} \\ \vdots \\ \sum_t \sum_m S_{Jmt} N_{mt} \end{bmatrix}$$

$$\Omega(P) = - \begin{bmatrix} \sum_t \sum_m \frac{\partial S_{1mt}}{\partial P_1} N_{mt} & \sum_t \sum_m \frac{\partial S_{2mt}}{\partial P_1} N_{mt} & \dots & \sum_t \sum_m \frac{\partial S_{Jmt}}{\partial P_1} N_{mt} \\ \sum_t \sum_m \frac{\partial S_{1mt}}{\partial P_2} N_{mt} & \sum_t \sum_m \frac{\partial S_{2mt}}{\partial P_2} N_{mt} & \cdots & \sum_t \sum_m \frac{\partial S_{Jmt}}{\partial P_2} N_{mt} \\ \vdots & \vdots & & \vdots \\ \sum_t \sum_m \frac{\partial S_{1mt}}{\partial P_J} N_{mt} & \sum_t \sum_m \frac{\partial S_{2mt}}{\partial P_J} N_{mt} & \cdots & \sum_t \sum_m \frac{\partial S_{Jmt}}{\partial P_J} N_{mt} \end{bmatrix}$$

$$P = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_J \end{bmatrix}$$

$$c = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_J \end{bmatrix}$$

I can estimate the price elasticities after estimating the demand model. The derivatives of market shares with respect to vehicle prices can be computed using the following formulas. In cities with the vehicle license allocations, such as Beijing and Shanghai, the demand changes with respect to the consumer price changes are:

$$\frac{\partial S_{rmt}}{\partial \tilde{P}_{jmt}} = \begin{cases} \rho_{0mt}[\rho_{1mt} \cdot \rho_{2mt} \cdot S^{(1)}_{jmt}(1 - S^{(1)}_{jmt}) \cdot \frac{\alpha}{\tilde{P}_{jmt}+B_{v(j)mt}} + (1-\rho_{1mt})S^{(2)}_{jmt}(1 - S^{(2)}_{jmt}) \cdot \frac{\alpha}{\tilde{P}_{jmt}}], r = j \\ \rho_{0mt}[\rho_{1mt} \cdot \rho_{2mt} \cdot S^{(1)}_{jmt} S^{(1)}_{rmt} \frac{-\alpha}{\tilde{P}_{jmt}+B_{v(j)mt}} + (1-\rho_{1mt})S^{(2)}_{jmt} S^{(2)}_{rmt} \cdot \frac{-\alpha}{\tilde{P}_{jmt}}], r \neq j \end{cases} \tag{2.7}$$

where ρ_{0mt} is the probability that a consumer wants a new car; ρ_{1mt} is the probability that the new car buyer does not have a vehicle license; ρ_{2mt} is the winning odds of vehicle license lotteries/auctions. α is the price coefficient from the demand estimation. P is the vehicle price, and B is the vehicle license bidding price in Shanghai. $S^{(1)}_{jmt}$ and $S^{(2)}_{jmt}$ are the purchase probabilities conditional on the consumer is a the first-time buyers or the second-time buyers. Therefore, the price elasticity is a weighted average of the price elasticities of the first- and second-time new car buyers.

The conditional purchase probabilities $S^{(1)}_{jmt}$ and $S^{(2)}_{jmt}$ can be computed by using the following formula after we estimate the demand and obtain the preference parameters. λ represents the implicit cost of waiting imposed by the vehicle license allocations on consumers. δ represents the mean utility from buying the vehicle.

$$S^{(1)}_{jmt} = \frac{exp[\alpha log(P_{jmt} + B_{mt}) + \lambda_{mt} + \delta_{jmt}]}{\sum_j^{J_1} exp[\alpha log(P_{jmt} + B_{mt}) + \lambda_{mt} + \delta_{jmt}] + \sum_r^{J_2} exp[\alpha log(P_{rmt} + B_{mt}) + \lambda_{mt} + \delta_{rmt}]} \tag{2.8}$$

$$S_{jmt}^{(2)} = \frac{exp(\alpha logP_{jmt} + \delta_{jmt})}{\sum_r^{J_1+J_2} exp(\alpha logP_{rmt} + \delta_{rmt})} \tag{2.9}$$

In cities without the vehicle license allocations, the demand changes with respect to price changes are:

$$\frac{\partial S_{rmt}}{\partial \tilde{P}_{jmt}} = \begin{cases} \alpha \cdot \rho_{0mt} \cdot S_{jmt}(1 - S_{jmt}) \cdot \frac{1}{\tilde{P}_{jmt}}, r = j \\ \\ -\alpha \cdot \rho_{0mt} \cdot S_{jmt} S_{rmt} \cdot \frac{1}{\tilde{P}_{jmt}}, r \neq j \end{cases} \tag{2.10}$$

where the probability that a consumer i chooses a vehicle j is:

$$S_{jmt} = \frac{exp(\alpha logP_{jmt} + \delta_{jmt})}{\sum_r^{J_1+J_2} exp(\alpha logP_{rmt} + \delta_{rmt})} \tag{2.11}$$

The demand changes with respect to the MSRP thus are:

$$\frac{\partial S_{rmt}}{\partial P_r} = \frac{\partial S_{rmt}}{\partial \tilde{P}_{jmt}} \frac{\partial \tilde{P}_{jmt}}{\partial P_r} \tag{2.12}$$

After estimating the demand model, we can compute the price elasticities and calculate the matrix Ω. We can then recover the vehicle production marginal costs c from the first-order conditions according to equations 2.6.

2.3.2 Manufacturer's profit maximization under the CAFC standard

Assume a firm f sets the national vehicle price P_r to maximize its profit from all cities in each year. Now, the firm faces another constraint imposed by the CAFC standard. The target fuel consumption for each vehicle is A_r, and the ratio of the corporate average fuel consumption (CAFC) and the target corporate average fuel consumption (T_{CAFC}) is required to be no larger than σ. Then, the firm's profit maximization problem in each year now becomes:

$$\max_{\{P_r\}} \pi_f = \sum_t \sum_m \sum_{r \in \Theta_{fmt}} (P_r - c_r) \cdot S_{rmt}(\tilde{P}_r, B_{vmt}, \lambda_{mt}, X_r; \theta) \cdot N_{mt} \tag{2.13}$$

$$s.t. \quad \frac{CAFC}{T_{CAFC}} = \frac{\frac{\sum_t \sum_m \sum_r M_r S_{rmt} N_{mt}}{\sum_t \sum_m \sum_r S_{rmt} N_{mt}}}{\frac{\sum_t \sum_m \sum_r A_r S_{rmt} N_{mt}}{\sum_t \sum_m \sum_r S_{rmt} N_{mt}}} \leq \sigma \tag{2.14}$$

(2.15)

We can re-write the constraint as:

$$\sum_t \sum_m \sum_r (\sigma A_r - M_r) S_{rmt} N_{mt} \geq 0 \tag{2.16}$$

where, $\sigma A_r - M_r$ represents the distance between vehicle r's actual fuel consumption and its target fuel consumption.

The lagrangean function of this profit maximization problem is:

$$
\begin{aligned}
L &= \sum_t \sum_m \sum_{r \in \Theta_{fmt}} (P_r - c_r) S_{rmt} N_{mt} + \mu \sum_t \sum_m \sum_r (\sigma A_r - M_r) S_{rmt} N_{mt} \\
&= \sum_t \sum_m \sum_{r \in \Theta_{fmt}} [(P_r - c_r) + \mu(\sigma A_r - M_r)] S_{rmt} N_{mt}
\end{aligned} \tag{2.17}
$$

where μ represents a shadow cost imposed by the CAFC policy on the manufacturer. It measures the cost of deviating one unit from the standard. The shadow cost can be viewed as a subsidy to manufacturers whose corporate average fuel consumption is far below the target, and a tax on manufacturers whose CAFC exceeds the target. Before 2018 China did not allow manufacturers to trade CAFC credits, I thus assume the shadow cost μ to firm-specific. Moreover, manufacturers whose CAFC are much higher than the target will face more pressure from the policy and be subject to higher shadow costs.

Solve the first-order conditions with respect to vehicle prices for this problem and we can obtain:

$$
\sum_t \sum_m N_{mt} \{ S_{jmt} + \sum_{r \in \Theta_{fmt}} [(P_r - c_r) + \mu(\sigma A_r - M_r)] \frac{\partial S_{rmt}}{\partial P_j} \} = 0 \tag{2.18}
$$

Comparing equation 2.18 with equation 2.5, we will find that the shadow cost will change the manufacturer's pricing strategy and the firms will adjust relative prices of high and low fuel consumption vehicles to meet the standard. If a vehicle is more fuel-consuming than the target, $\sigma A_r - M_r < 0$, the firm will perceive that this vehicle has a higher cost. To maximize its profit, the firm will therefore increase this vehicle's price and shift demands of this vehicle to other vehicles. How much the firms will change the vehicle prices depends on the demand elasticities.

2.4 Estimation of marginal cost

In the above section, I discuss how to recover marginal costs from the first-order conditions of the manufacturer's profit maximization problem. This section uses one of the pre-policy years, 2011, to estimate each vehicle's marginal production cost. Re-arrange the equation 2.6, and marginal cost can be estimated by the following equation:

$$c = P - \Omega(p)^{-1}Q(p) \tag{2.19}$$

In 2011, there were 505 unique vehicles and 62 unique manufacturers. The manufacturer's sales-weighted average markup over marginal cost ranges from 19% to 24%. Table 2.4 selects the 15 companies with the largest sales in 2011, accounting for 76% of the total sales. The average manufacturer suggested retail price (MSRP) are the highest for importers, and the lowest for domestic manufacturers. And the average price-marginal cost markup over marginal cost for the top 15 companies is around 21.6%. The vehicle model's markup over marginal cost ranges from 19% to 32%, with an average of 21%. Table 2.5 shows the estimated markups for 15 vehicle models with the largest sales in 2011.

Table 2.4: Estimated Markups and Variable Profits: Top 15 Maunufacturers in 2011

Manufacturer	Firm Type	Market Shares	MSRP (10,000 Yuan)	Marginal Cost (10,000 Yuan)	Markup over MC	Variable Profit (billion Yuan)
SAIC Volkswagen	JV	0.17	17.83	14.41	0.244	3.66
FAW Volkswagen	JV	0.15	29.04	23.59	0.243	4.90
SAIC General Motors	JV	0.14	18.21	14.84	0.233	2.99
Dongfeng Nissan	JV	0.09	17.55	14.47	0.215	1.78
Beijing Hyundai	JV	0.08	14.75	12.17	0.214	1.21
Changan Ford	JV	0.05	17.86	14.81	0.207	0.99
FAW Toyota	JV	0.05	23.15	19.21	0.207	1.20
Dongfeng Peugeot Citroen	JV	0.05	14.43	11.97	0.206	0.72
BMW	Importer	0.04	67.15	55.80	0.205	2.57
GAC Honda	JV	0.03	19.80	16.48	0.203	0.72
Dongfeng Yueda Kia	JV	0.03	14.06	11.69	0.204	0.5
Mercedes Benz	Importer	0.03	78.48	65.28	0.205	2.65
GAC Toyota	JV	0.03	26.59	22.15	0.201	0.80
Dongfeng Honda	JV	0.03	21.91	18.25	0.201	0.66
BYD	Domestic	0.03	6.90	5.74	0.202	0.18

Notes: Total sales is the total sales in Beijing, Shanghai, Chongqing and Suzhou in 2011. MSRP, marginal cost, and variable profit are in 2017 Yuan.

Table 2.5: Estimated Markups and Variable Profits: Top 15 Vehicle Models in 2011

Make Model	Total Sales	MSRP (10,000 Yuan)	Marginal Cost (10,000 Yuan)	Markup over MC	Variable Profit (bilion Yuan)
Volkswagen Lavida	23,150	14.84	11.96	0.24	0.67
Buick Excelle	19,387	13.48	10.88	0.24	0.50
Cheyrolet Cruze	18,891	14.46	11.80	0.23	0.50
Ford Focus	17,494	14.33	11.86	0.21	0.43
Skoda CC	16,417	15.33	12.33	0.24	0.49
Volkswagen Tiguan	15,469	28.95	23.74	0.22	0.81
Nissan Teana	15,089	24.84	20.57	0.21	0.64
Audi A6L	15,076	49.95	41.08	0.22	1.34
Toyota Corolla	14,393	14.62	12.07	0.21	0.37
Volkswagen Polo	14,270	12.15	9.66	0.26	0.36
Volkswagen Bora	13,659	13.55	10.68	0.27	0.39
Hyundai Celesta	12,704	11.78	9.69	0.22	0.27
Audi A4L	12,560	39.38	32.29	0.22	0.89
Volkswagen Sagitar	11,747	17.08	13.58	0.26	0.41
Buick Lacrosse	11,645	27.32	22.47	0.22	0.56

Notes: Total sales is the total sales in Beijing, Shanghai, Chongqing and Suzhou in 2011. MSRP, marginal cost, and variable profit are in 2017 Yuan.

2.5 Impact of Corporate Average Fuel Consumption Standards

In the above section, I have estimated the marginal production costs based on 2011 data. In this section, I assume the marginal production costs and the vehicle set remain the same as in 2011, and I simulate the impact of CAFC on the producer's surplus.

2.5.1 Simulation set-up

I will run four different policy simulations. In the first three scenarios, I simulate a policy equal to the CAFC standard with the Phase III fuel consumption target. This policy aims at a national average fuel consumption of 7 L/100 km by 2015. In the first scenario, I do not allow the trading of CAFC credits between companies, exactly as China's CAFC policy before 2018. Therefore, the shadow cost imposed by the policy will be manufacturer-specific. In the second scenario, I allow a company to trade CAFC credits with its affiliated group corp. This is similar to the requirements of the dual-credit policy started in 2018, which allows trading credits within an affiliated group corp. Hence, the shadow costs vary across affiliated groups. In the third scenario, I allow free trading of CAFC credits. At the equilibrium, every company's shadow cost must be the same. In the last simulation, I simulate a policy similar to the CAFC standard with the Phase IV fuel consumption target, assuming free trading of CAFC credits. Phase IV CAFC policy is more stringent than Phase III, aiming to achieve a national average fuel consumption of 5 L/100 km by 2020.

I will compare the impacts of CAFC on companies' profits, vehicle price, and fuel consumption under different scenarios. The first three scenarios help to understand the impacts of allowing credit trading, and comparing scenarios 3 and 4 helps understand the impact of a more stringent policy.

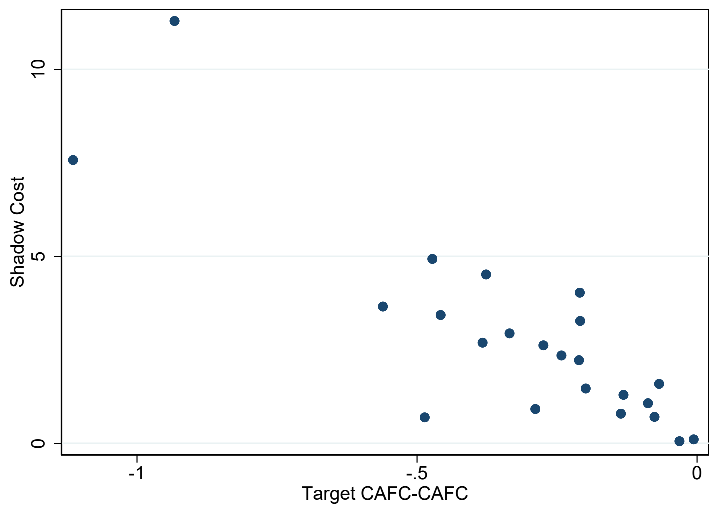
The assumption for the simulations is that the vehicle set and vehicle attributes remain the same as in the pre-policy year 2011. Moreover, there is no technological progress, and thus, the only way for companies to comply with the policy is by adjusting relative prices of vehicles and shifting demands to more fuel-efficient vehicles.

The estimation procedure is that, first, starting with a guess of shadow costs, based on the marginal costs estimated from 2011 data, I can use the first-order conditions to solve for vehicle prices. Next, I can compute the vehicle market shares and the corporate average fuel consumption and target CAFC for each company. Then, I will check whether the CAFC equals the target CAFC for each company. If it does not, I will update the guess for shadow cost. The shadow costs and vehicle prices will be solved when both the first-order conditions in equation 2.18 are satisfied and the CAFC constraints in equation 2.16 are binding.

2.5.2 Simulation Results

Figure 2.4 shows the relation between the estimated shadow costs and the stringency of the CAFC policy from the first simulation. The first simulation is the baseline simulation. In Scenario 1, the simulated policy equals the 2012-2015 Phase III CAFC standard. I define a manufacturer-specific stringency of the policy, which equals the difference between the target CAFC and the actual CAFC at the beginning of the policy (the year 2011). If the difference is positive, then the company is more fuel-efficient than required, and its shadow cost should be negative, implying that the CAFC policy acts as a subsidy for it. If the difference is negative, then the company is subject to the policy, implying a positive shadow cost. And the CAFC policy will act as a tax. Moreover, for a specific company, the larger its difference is, the more stringent the policy is. The shadow cost for companies facing a more stringent policy should be higher than it for companies facing a less stringent policy. Figure 2.4 shows a negative relation between the shadow cost and the difference between target CAFC and CAFC, suggesting a positive trend between the shadow cost and the policy's stringency, which is as expected. Companies that satisfy the standard have zero shadow costs, while incompliant companies are subject to positive shadow costs. Also, a less fuel-efficient company faces a more stringent policy and is subject to a higher shadow cost.

Figure 2.4: Scenario 1: Shadow Cost and Stringency of CAFC



Notes: The horizontal axis represents the difference between the target CAFC and the actual CAFC. This figure only includes companies that are subject to the CAFC standards. The more negative the difference is, the more stringent the standard is.

Table 2.6 reports the fuel consumption rate and the estimated shadow costs by fuel type. In the data, diesel cars have the highest fuel consumption rate, which is about 9.47 L/100 km, and electric vehicles have the lowest average fuel consumption rate, which is about 1.7 L/100 km. The average fuel consumption of gasoline cars is 7.54 L/100 km. In the first simulation, the estimated shadow cost for gasoline cars is 14,400 Yuan, higher than the shadow cost for diesel cars, which is about 800 Yuan. This implies that gasoline cars are more constrained by the Phase III CAFC standard.

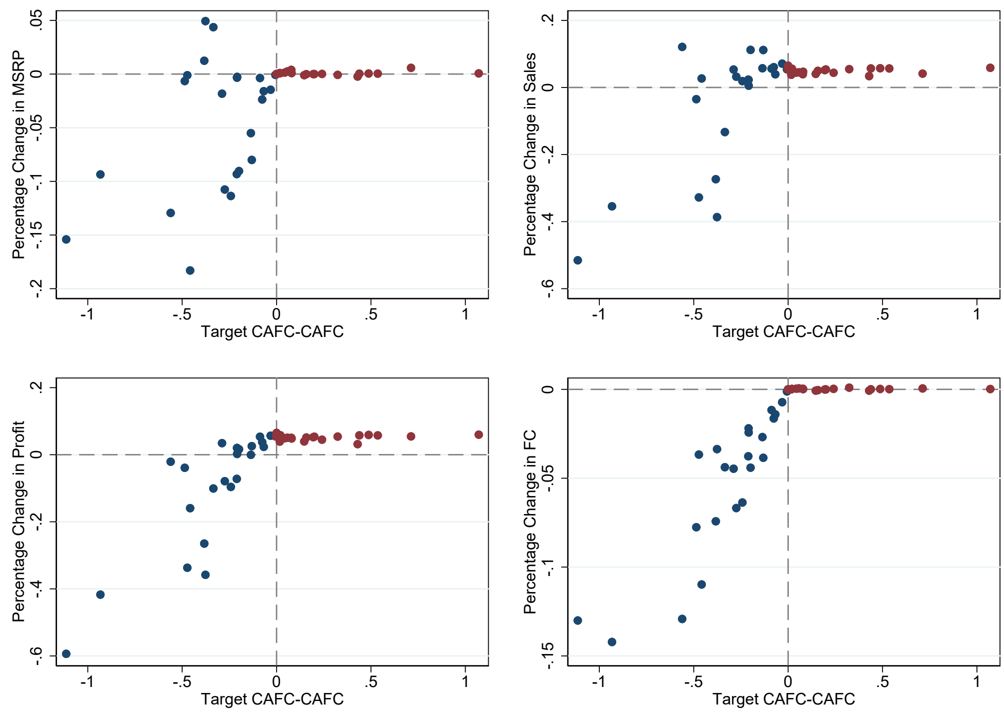
Table 2.6: Scenario 1: Fuel Consumption Rate and Shadow Costs by Fuel Type

Fuel Type	Period 1 2010-11	Period 2 2012-15	Period 3 2016-17	Total 2010-17	Shadow Cost (10,000 Yuan)
EV	1.39	1.65	1.72	1.7	0
	(0)	(0.2)	(0.25)	(0.24)	(0)
Hybrid		5.45	5.2	5.3	
		(1.13)	(1.33)	(1.26)	
Diesel	9.22	10.21	7.78	9.47	0.08
	(1.55)	(1.3)	(0.93)	(1.61)	(0.22)
Gasoline	7.71	7.65	7.32	7.54	1.44
	(1.35)	(1.38)	(1.28)	(1.35)	(2.11)

Notes: The table reports the sales-weighted average of the fuel consumption rate by fuel type in each time period. The shadow cost is estimated by using vehicles in 2011. In 2010 and 2011, there is only one electric vehicle and no hybrid electric vehicle on the market.

Figure 2.5 shows the relations between policy stringency and its impacts on the vehicle price, sales, profit, and fuel consumption, from the results of the first simulation. I divide all firms into two types: unconstrained firms with zero shadow costs, and constrained firms with positive shadow costs. Red points in the figure represent the unconstrained firms and blue points represent the constrained firms. The horizontal axis represents the policy stringency. From right to left, the difference between the target CAFC and CAFC becomes more negative, and the policy stringency increases. The figure shows that how the policy affects the manufacturer's pricing strategy, sales, and profit is ambiguous, depending on the demand elasticities. However, the policy is likely to have more considerable impacts on the less fuel-efficient companies. Fuel-inefficient companies face a more stringent policy, and their average vehicle price, sales, and profit are more likely to decrease. Moreover, the most fuel-efficient companies (unconstrained companies) seem to steal sales from the most fuel-inefficient companies (constrained companies), and their profits are more likely to increase. In terms of fuel consumption, the compliant companies are very likely to reduce their fuel efficiency while the incompliant companies will significantly increase their fuel efficiency.

Figure 2.5: Scenario 1: Stringency and Impacts of CAFC



Notes: The horizontal axis represents the difference between the target CAFC and the actual CAFC. This figure includes both companies that are subject to the CAFC standards (blue points, Target CAFC - CAFC <0) and companies that are not subject to the standards (red points, Target CAFC - CAFC ≥ 0).

Table 2.7 reports the impacts of the Phase III CAFC standards on the constrained and unconstrained companies. The CAFC standards reduce the total profit of the constrained firms by 2.09 billion Yuan while increase the total profit of the unconstrained firms by 1.02 billion Yuan. On average, the vehicle prices of the constrained firms will decrease and the vehicle prices of the unconstrained firms will increase. The markups of the constrained firms drop by 2.5% while the markups of the unconstrained firms do not change a lot. As expected, the average fuel consumption of the constrained firms decreases significantly.

Table 2.7: Scenario 1: Impacts of CAFC on Constrained and Unconstrained Firms

Firm Type	Change in Total Profits (billion Yuan)	Change in Sales-weighted Average MSRP (10,000 Yuan)	Change in Sales-weighted Average Fuel Consumption (L/100km)	Change in Sales-weighted Markup over MC
Unconstrained	1.02	0.12	0.01	0.001
Constrained	-2.09	-1.77	-0.58	-0.025
All	-1.07	-0.80	-0.28	-0.01

Notes: The change in the markup over marginal cost is the fraction change not the percentage change.

Table 2.8 compares the results of the four simulations described in the above section. In Scenario 1, which equals the 2012-2015 Phase III CAFC standard, the total profit of manufacturers decreases by 1.07 billion Yuan. And the sales-weighted average MSRP decreases by 8,000 Yuan. The sales-weighted average fuel consumption drops by 0.28 L/100 km, as expected. On average, the markup over marginal cost is reduced by 1%. This shows that the policy has significant negative impact on producer's surplus. Scenario 2 allows CAFC credit trading within an affiliated group. Scenario 3 allows free trading of CAFC credits. Comparing Scenarios 1, 2, and 3, we can find that allowing trading of credits will mitigate the negative impacts of the CAFC standards on vehicle manufacturers. The shadow cost measures the cost of deviating one unit from the standard. The average firm-specific shadow cost equals 14,100 Yuan for a CAFC standard without trading, and decreases to 6,900 Yuan if we allow free trading of CAFC credits.

The fourth and fifth columns of Table 2.8 compare the Phase III and Phase IV CAFC standards. Phase IV CAFC standard is tightened and will reduce the average fuel consumption by 0.84 L/100 km. However, it will cause a huge negative effect on manufacturers, reducing manufacturer's total profit by 4.66 billion Yuan.

Table 2.8: Impact of CAFC on Manufacturers under Different Policy Scenarios

	Phase III CAFC Standard			Phase IV CAFC Standard
Credits Trading Mechanism	No Trading	Trading between Affiliated Group Corps	Free Trading	Free Trading
Change in total profits (billion Yuan)	-1.07	-1.02	-0.49	-4.66
Change in sales-weighted average MSRP (10,000 Yuan)	-0.80	-0.75	-0.42	-3.29
Change in sales-weighted average fuel consumption (L/100km)	-0.28	-0.28	-0.18	-0.84
Change in sales-weighted markup over MC	-0.01	-0.008	-0.005	-0.07
Average shadow cost μ(10,000 Yuan)	1.41	1.85	0.69	2.39

Notes: The change in the markup over marginal cost is the fraction change not the percentage change.

Table 2.9 shows the CAFC standard's impact on 15 vehicle manufacturers with the largest sales. Companies with higher shadow costs, such as Dongfeng Peugeot Citroen and GAC Toyota, have more significant decreases in their profits. In contrast, unconstrained companies such as Dongfeng Nissan and Beijing Hyundai, have a significant increase in their profit. However, the impacts of the CAFC standards on profit, vehicle prices, and sales are not determined. For example, FAW Toyota was constrained by the standard, with a positive shadow cost. However, its profit increases under the CAFC standards because its sales increase by 11 percent even if its vehicle prices drop by 9 percent.

Table 2.9: Simulation 1: Impact of CAFC on Top 15 Manufacturers

Manufacturer	Shadow Cost (10,000 Yuan)	T_{CAFC}-CAFC	Percent Change in MSRP	Percent Change in Sales	Percent Change in Profit	Change in Profit (billion Yuan)	Change in Fuel Consumption (L/100 km)
SAIC Volkswagen	0.00	0.08	0.004	0.04	0.051	0.185	0.003
FAW Volkswagen	0.00	0.71	0.006	0.04	0.055	0.268	0.004
SAIC General Motors	3.43	-0.46	-0.183	0.03	-0.159	-0.476	-0.896
Dongfeng Nissan	0.00	0.06	0.002	0.05	0.051	0.090	0.004
Beijing Hyundai	0.00	0.04	0.001	0.04	0.049	0.059	0.003
Changan Ford	2.94	-0.33	0.044	-0.13	-0.101	-0.100	-0.350
FAW Toyota	1.47	-0.20	-0.090	0.11	0.016	0.020	-0.355
Dongfeng Peugeot Citroen	4.93	-0.47	-0.001	-0.33	-0.337	-0.244	-0.285
BMW	4.03	-0.21	-0.003	0.02	0.020	0.052	-0.200
GAC Honda	1.30	-0.13	-0.080	0.11	0.026	0.018	-0.300
Dongfeng Yueda Kia	0.71	-0.08	-0.024	0.06	0.038	0.019	-0.118
Mercedes Benz	3.66	-0.56	-0.129	0.12	-0.021	-0.055	-1.260
GAC Toyota	7.58	-1.11	-0.154	-0.52	-0.594	-0.476	-1.238
Dongfeng Honda	0.11	-0.01	-0.001	0.05	0.055	0.036	-0.009
BYD	0.00	0.16	0.000	0.05	0.051	0.009	-0.003

2.6 Conclusions

The rapid growth in vehicle ownership has put heavy pressure on the energy supply and has led to severe air pollution and traffic congestion. In this paper, I look at the one method to mitigate fuel consumption and emissions from the transportation sector—fuel economy standard. China's passenger vehicle fuel consumption standards have undergone five phases since 2005. Initially, the standard sets a limit on a single vehicle's fuel consumption. In 2012, China announced the corporate average fuel consumption policy. In 2018, China added a new NEV credits system to the existing CAFC credit system, referred to as the "dual-credit" system.

This paper uses data from 2010 through 2017 for four populous cities to estimate the welfare effect of China's CAFC standard on manufacturers. First, I set up a structural model of vehicle supply under the CAFC standard. Second, I use one of the pre-policy years, 2011, to estimate the marginal production costs. Third, I run four simulations to explore the impacts of China's CAFC standards on the firm's profit, vehicle prices, fuel consumption, and sales. I find that the Phase III CAFC standard will reduce the producer's profit by 1.07 billion Yuan per year. Moreover, I compare the outcomes of the Phase III standard and the Phase IV standard, finding that the more stringent Phase IV standard reduces the producer's profit five times as much as the Phase III standard. Also, allowing the trading of CAFC credits will improve the producer surplus.

My paper's findings have important policy implications. Corporate Average Fuel Economy standards have been widely used to reduce transportation emissions and fuel consumption. Many countries, including the US, Europe, Japan, and China, have such CAFC standards. In recent years, many developing countries with fast-growing vehicle markets have started to implement CAFC standards. China is one of the fast-growing vehicle markets. I show in this paper that although the more stringent CAFC standards in China have successfully reduced transportation emissions and fuel consumption, they also have induced nontrivial costs to vehicle producers.

In this paper, I assume that firms will only use the sales-mixing strategies to abate fuel consumption. However, firms can also use other abatement strategies such as adopting new technology or trading off between fuel economy and other vehicle attributes. In the future, I will run simulations assuming some exogenous rate of technological improvement and compare the impacts of CAFC standards allowing the technology adoption with the impacts of CAFC standards only allowing sales mixing.

Future work could also explore how the CAFC standards affect the production of electric vehicles. China's CAFC standards give preferences to electric vehicles, and producing electric vehicles will significantly reduce the firm's average fuel consumption. Therefore, in the future, I will use more recent data, which includes more electric vehicles, to estimate the CAFC standards' impact on electric vehicle production.

Existing literature argues that in the absence of other market failures, fuel economy regulations are less efficient than fuel taxes. Hence, in the future, I will compare the CAFC standards with market-based policies such as fuel tax to reduce transportation fuel consumption.

Chapter 3: Environmental Regulation and Product Attributes: The Case of European Passenger Vehicle Greenhouse Gas Emissions Standards

3.1 Introduction

This paper considers the welfare consequences of regulating one of multiple attributes in a differentiated product market. Many consumer durable products, such as home appliances and passenger vehicles, are subject to energy efficiency or environmental standards. Such regulations introduce a shadow cost on energy consumption or emissions, which incentivizes firms to improve energy efficiency or discount energy efficient versions of their products (e.g., Goldberg 1998; Jacobsen 2013; Durrmeyer and Samano 2018). In the absence of other market failures, the regulations are less efficient than emissions taxes because they distort utilization and scrappage decisions (Jacobsen and Van Benthem 2015). However, if consumers systematically undervalue energy cost savings when choosing a product, standards may be more efficient than taxes by correcting that market failure (Allcott and Greenstone 2012; Leard et al. 2017a). An extensive literature has examined whether consumers undervalue energy cost savings, finding mixed results (e.g., Busse et al. 2013; Houde 2018; Leard et al. 2017a)

For many products, consumers value not just the regulated attribute, such as a refrigerator's energy efficiency, but also unregulated attributes, such as storage space. A few studies have considered the effect of regulation on an unregulated attribute that is related technologically to the regulated attribute. For example, a manufacturer can modify a vehicle's power train to trade off performance for fuel economy and emissions. Consequently, tightening fuel economy or emissions standards causes manufacturers to reduce performance to reduce fuel consumption and emissions (Knittel 2011; Klier and Linn 2015; Reynaert 2019).

The literature has focused narrowly on attributes that are linked technologically to the regulated attribute. We argue that regulating one attribute can affect virtually any other attribute because of demand and supply linkages across the attributes. We demonstrate this point theoretically, and then we test it empirically as part of the first retrospective analysis of Europe's carbon dioxide emissions standards for new passenger vehicles. The standards have reduced emissions and consumption of gasoline and diesel fuel, but changes in other vehicle attributes offset at least 26 percent of those welfare gains. This unintended consequence of the standards is a similar magnitude to the inefficiencies of the standards mentioned above.

More specifically, the first part of this paper provides a general framework for environmental regulation of differentiated product markets. We consider a firm that sells a differentiated product and chooses the price and attributes of the product to maximize profits.

The firm chooses three types of attributes. The first is the attribute that is directly regulated, such as a new vehicle's fuel economy or an air conditioner's energy efficiency. The second type includes attributes that are linked technologically to the regulated attribute, as in the fuel economy—performance example above. The third type includes any other attribute, such as those the firm chooses jointly with the regulated attribute when designing the product. While the literature on fuel economy regulation has considered the first and second types, we are not aware of analysis of the third type—either for passenger vehicles or for any other product.

The model yields two predictions. First, regulation of a particular product attribute may affect any other attribute either positively or negatively, depending on the structure of demand and supply constraints affecting attribute choice. For example, on the demand side of the market, a regulation that reduces a vehicle's fuel costs could increase consumer demand for cargo space if the lower fuel costs cause the consumer to take extended vacations. On the supply side, design constraints may cause the firm to trade off attributes for one another. For example, suppose a firm has a fixed budget for redesigning a vehicle and that it is costly to redesign the vehicle and reduce its emissions or improve its seating comfort. In that case, regulating lower emissions could cause the firm to invest more research and development in reducing emissions and less in improving seating comfort.[1]

Second, standards could increase or decrease private welfare, depending on whether the unregulated market over- or underprovides attributes. Intuitively, in the absence of regulation, if consumer demand for the regulated attribute is negatively correlated with the value of a second attribute (such as exterior styling), the firm may choose low levels of both attributes to help segment the market. That is, giving a vehicle a "sporty" styling could increase demand for horsepower (to help show off the vehicle's look) while reducing demand for fuel economy. In this case, the unregulated market could underprovide attributes, and regulation could raise consumer welfare (Fischer (2010) and Houde and Spurlock (2015) also raise this possibility).

In the empirical part of the paper, we test whether Europe's carbon dioxide emissions standards for passenger vehicles have affected product attributes. European road transportation accounts for about 20 percent of Europe's carbon dioxide emissions, and Europe's carbon dioxide

[1] Porter and Van der Linde (1995) and the ensuing "Porter Hypothesis" literature suggest that tighter regulation could induce innovation that either reduces the direct costs of meeting the regulation or reduces the cost of improving product attributes that are not directly related. The mechanism we discuss in this paper is distinct, because it arises from demand and cost relationships among attributes.

emissions standards are the primary policy aiming to reduce these emissions. In Europe, about 15 million new vehicles are sold annually, and these vehicles represent roughly one-quarter of all the vehicles sold globally that are subject to fuel economy or greenhouse gas standards. Legally binding standards were finalized in 2009 and began to apply in 2012. Although manufacturers have achieved the standards partly by designing vehicles to meet the test cycles rather than reducing on-road emissions (Reynaert and Sallee 2019), the standards have substantially reduced on-road emissions (Tietge et al. 2017); tested emissions declined by about 29 percent between 2005 and 2017. The fact that efficiency improvements of gasoline and diesel-powered vehicles explain most of that decline motivates our focus on emissions and attribute changes for those vehicles.

The model highlights three effects of the standards on manufacturer price and attribute choices: adjusting the relative prices of vehicles to encourage customers to obtain vehicles with lower emissions; trading off emissions for performance or weight; and adjusting other attributes because of product design or demand linkages. We test for these effects using highly disaggregated data for the European market covering the years 2005 through 2017. The data include the eight countries with the largest markets in Europe, which collectively account for about 90 percent of all new vehicle sales in Europe. Observations are by country, year, and vehicle, where a vehicle is a unique model (nameplate), trim, body type, engine and transmission configuration, fuel type and drive type—such as the BMW 320 four-door sedan with a four-cylinder diesel-powered engine, an eight-speed automatic transmission, and rear-wheel drive.

Because the theory suggests that regulation can affect virtually any attribute, we devise a two-stage empirical strategy that allows us to estimate the effects of the standards on any attribute–even unobserved ones. First, we estimate consumer demand for observable vehicle attributes. The main observed attributes include size; fuel economy, which is directly affected by the regulation (because fuel economy is inversely related to carbon dioxide emissions); and horsepower and weight, which are related technologically to fuel economy. We use the term *residual quality* to characterize the combined WTP for all attributes of the vehicle that are not observed, such as safety, reliability, and cargo space. Quality is a residual in that it excludes WTP for attributes that are directly affected by the regulation or that are linked technologically to fuel economy (quality also excludes other observed attributes, such as the vehicle's physical dimensions). Importantly, quality includes any attribute that may be affected indirectly by the regulation via the design process. Whereas previous research has examined the effects of standards on fuel economy, weight, and horsepower, we are not aware of previous analysis of quality.

We estimate WTP for each observed attribute and quality with a nested logit model that uses a vehicle's market segment and country of origin to define the nests. The estimation accounts for endogeneity of vehicle prices and within-nest market shares by using instruments based on the physical size and engine size of other vehicles in the market. We estimate own-price elasticities of demand and consumer WTP for fuel economy and horsepower that are broadly consistent with the European vehicle demand literature (for example, Grigolon et al. 2017; Reynaert 2019). Having estimated the demand parameters, we recover quality as a residual.

In the second stage, we test whether the European carbon dioxide standards have affected quality, horsepower, weight, and price. We identify the effects of the standards on vehicle quality and other attributes using a shift-share (i.e., Bartik) approach. We define three time periods to match the timing of the regulations: 2005—8 (no standards); 2009—11 (standards proposed but not enacted); and 2012—7 (standards enacted). We interact the overall shift in regulatory pressure over time with cross-sectional variation in the pressure that the standards apply to each firm (Klier and Linn 2016); the theoretical analysis motivates the functional form.

We find that the standards reduced quality and have had small effects on performance, weight, and vehicle prices. Whereas Klier and Linn (2016) show that the standards slightly reduced horsepower and weight in the beginning of the second period (2007 through 2010), we find that horsepower may have increased subsequently. The results are robust across a range of tests, although we note that tests for common pre-policy trends suggest caution for the horsepower results and that the timing of the regulations make it impossible to rule out the possibility that the economic recession also affected vehicle quality. The estimates imply that vehicle manufacturers preferred sacrificing quality rather than horsepower, which is consistent with the demand estimation and Klier and Linn (2016). We note that although the theoretical model emphasizes demand-side connections among attributes, the estimation results may also reflect supply-side considerations. For example, maintaining a constant quality while increasing fuel economy may be more costly than maintaining constant horsepower.

We make back-of-the-envelope calculations of the welfare implications of the quality reduction by comparing the quality change with the fuel cost savings and carbon dioxide emissions benefits of marginally tightening the standards. For a hypothetical 1 percent tightening of the standards, the attribute changes offset 26 percent of the fuel cost and carbon dioxide benefits of the standards.[2] The welfare effects of the quality changes are much larger than the welfare effects of other observed attribute changes, including weight and horsepower. We note that the welfare

[2] Mock et al. (2014), Tietge et al. (2015), and Reynaert and Sallee (2019) conclude that vehicle manufacturers have designed vehicles to perform well on the tests used to assess compliance with the standards. Such gaming is distinct from outright cheating, such as what occurred in the Volkswagen emissions scandal. Because of this gaming, on-road fuel consumption and emissions reductions have been roughly half as large as the reductions in tested fuel consumption and emissions. For that reason, we consider the percent change reported in the text to be a lower bound of the share of fuel cost and greenhouse gas benefits offset by attribute changes. Responding to the apparent gaming, Europe has recently adopted a new testing procedure.

calculations do not include manufacturer profits, which lie outside the scope of our analysis.

Our paper contributes to the existing literature in several ways. First, we generalize the treatment of differentiated product regulation. Fischer (2010) shows that fuel economy regulation can improve private consumer welfare if a subset of consumers undervalue fuel economy. We show that product attribute regulation can affect a large set of other attributes that are linked to the regulated attribute via demand or supply channels, generalizing Houde and Spurlock (2015). Whereas Buchanan (1969) and Fowlie et al. (2016) analyze the implications of output distortions for introducing a carbon price to an imperfectly competitive market with a homogeneous product (such as cement), we consider the implications of market failures in attribute choices for differentiated products.

Second, we conduct the first retrospective analysis of the European passenger vehicle standards. Klier and Linn (2016) use data through 2010 and Reynaert (2019) uses data through 2011, which is just prior to the period in which the standards take effect. Moreover, whereas those papers consider performance and vehicle price changes, we provide the first evidence on the effect of passenger vehicle fuel economy and carbon dioxide standards on vehicle quality. Reynaert (2019) anticipates that the benefits of the standards would be lower than the costs, and our analysis confirms the low benefits of the standards.

Third, we contribute to the literature on attribute-based fuel economy and greenhouse gas standards. The European standards, like most others, depend on a vehicle attribute; the European standards depend on a vehicle's weight. Ito and Sallee (2018) show that attribute-based standards may affect the attribute on which the standard is based. We highlight the possibility that standards may affect attributes other than the attribute on which the standard is based. Although Ito and Sallee (2018) find that Japan's weight-based standards distorted vehicle weight, we do not find evidence that the European standards have affected weight. The difference may arise from the fact that the European standards are linear in weight and the Japanese standards vary discretely with weight.

Finally, we analyze new vehicle markets, and Brucal and Roberts (2019) and Houde and Spurlock (2015) analyze product quality in home appliance markets. An important difference between our analysis and theirs is that whereas they identify the effects from time series variation in the standards, we combine time series variation in aggregate standards with cross-sectional variation in the stringency of the standards. This allows us to control for potentially confounding factors that may have coincided with the adoption of the standards, such as the 2008-9 economic recession.

3.2 Regulating Emissions from Differentiated Product Markets

We consider a market in which firms sell differentiated products to consumers. We begin with a case in which the product attribute is exogenous, and subsequently we endogenize the attribute. We represent the standard as a shadow price that a regulator imposes on the endogenous attribute and conduct comparative statics of a non-marginal change in the shadow price. With an endogenous regulated attribute, increasing the stringency of regulation could cause the firm to increase or decrease other attributes.

3.2.1 Case 1: Exogenous regulated attribute

The market contains J products and each consumer chooses the product j that maximizes utility (for simplicity we abstract from the decision to forgo purchasing any product); we normalize the number of consumers to 1 for convenience. Each consumer, i, has utility that is linear in the price of the product j, p_j, and other attributes of the product. The consumer values two attributes: m_j and x_j. The attribute m_j may be subject to regulation, such as the vehicle's fuel economy. For the moment, both attributes are exogenous. The utility function is

$$U_{ij} = \alpha p_j + m_j \beta^m + x_j \beta^x + \varepsilon_{ij}. \tag{3.1}$$

The parameter $\alpha < 0$ is the disutility of forgone income, the parameters β are the utility from the corresponding product attributes, and ε_{ij} is a household-specific utility shock. Making a distributional assumption for ε_{ij} (for example, extreme value) and integrating over the error term yields a function for the product's market share

$$s_j = s(p_j, m_j, x_j; \alpha, \beta). \tag{3.2}$$

The market share depends on the product's price and attributes as well as the preference parameters. Note that the share depends on prices and attributes of other vehicles in the market; we omit these terms to simplify the notation.

The market includes $n > 1$ firms, and for simplicity we focus on a single firm that produces one type of product, j. The attribute m_j is exogenous and the firm maximizes profits by choosing the product's price,

$$\max_{p_j}(p_j - c_j)s_j - \nu F(m_j)s_j, \tag{3.3}$$

where c_j is the exogenous marginal cost of producing the product. For each unit of the product that the firm sells, a regulation introduces a cost on the product attribute $\nu F(m_j)$. The regulation function $F(m_j)$ characterizes the form of regulation. For energy efficiency and greenhouse gas standards, $F(m_j)$ decreases with m_j. For example, if m_j is the vehicle's fuel economy (miles per gallon) and the regulator imposes a fuel consumption rate tax, $F(m_j) = 1/m_j$ and ν is the tax rate; a lower fuel economy implies a higher tax. Note that for emissions rate or fuel economy standards, $F(m_j)$ is negative if the vehicle's fuel economy or emissions rate exceeds the standards.

The first-order condition for the product price is

$$\frac{\partial s_j}{\partial p_j}(p_j - c_j - \nu F) + s_j = 0. \tag{3.4}$$

Equation (3.4) is a variation of the standard monopoly markup equation. The greater the price sensitivity of demand (that is, $\frac{\partial s}{\partial p}$), the lower the equilibrium price. The regulation distorts the optimal price. For example, a fuel consumption tax raises the equilibrium price inversely with the vehicle's fuel economy.

3.2.2 Case 2: Endogenous attributes with technological or design trade-off

In this subsection, the attributes m_j and x_j are endogenous. The vehicle is endowed with levels of m_j and x_j, denoted by m_{j0} and x_{j0}. Initially, we interpret x_j an attribute that is linked technologically to the regulated attribute. For example, considering the market for refrigerators, a manufacturer can improve energy efficiency (m_j) by adding insulation, which may decrease storage space (x_j). In that case, there is a technological relationship between energy efficiency and storage space.

The firm chooses levels of m_j and x_j simultaneously with price. There is a trade-off between the two attributes, and if the firm selects a level of m_j that is greater than m_{j0}, the firm must reduce x_j below x_{j0}. We characterize this relationship by expressing the attributes x_j as a function of m_j: $x_j - x_{j0} = x(m_j - m_{j0})$, where $\frac{\partial x_j}{\partial m_j} < 0$.[3] Importantly, trading off these attributes does not affect marginal costs.[4]

The first-order condition for m_j is

$$[\frac{\partial s_j}{\partial m_j} + \frac{\partial s_j}{\partial x_j}\frac{\partial x_j}{\partial m_j}](p_j - c_j - \nu F) - \nu F' s_j = 0. \tag{3.5}$$

F' is the derivative of the regulation function with respect to the product attribute. The price first-order condition is the same as in equation (3.4).

To interpret equation (3.5), it is useful to begin by assuming that there is no regulation ($\nu = 0$). Combining equations (3.4) and (3.5) yields

[3] We assume a monotonic relationship between the attributes for simplicity. In practice, the relationship could be non-monotonic.

[4] The assumption that the derivative of the function is negative is consistent with evidence for passenger vehicles (e.g., Knittel 2011; Klier and Linn 2012; EPA and NHTSA 2016).

$$\frac{W^m}{W^x} = -\frac{\partial x_j}{\partial m_j}, \tag{3.6}$$

where $W^m = \frac{-\frac{\partial s_j}{\partial m_j}}{\frac{\partial s_j}{\partial p_j}}$ is the marginal WTP for m_j and similarly for W^x. Equation (3.6) shows that the firm equates the ratio of marginal WTP with the technological trade-off between the two attributes. If consumers have declining marginal WTP for both attributes, an increase in the marginal WTP for one attribute causes the firm to decease the other attribute.

If there is regulation and $\nu > 0$, the first-order conditions can be combined to yield

$$W^m + W^x \frac{\partial x_j}{\partial m_j} = \nu F'. \tag{3.7}$$

As noted above, F' is typically negative, as would be the case for an emissions tax. If $\nu > 0$, the right-hand side of the equation is negative, which causes the firm to trade off x_j for m_j. More stringent regulation causes the shadow price (ν) to increase, and the firm responds by increasing the regulated attribute at the expense of the unregulated attribute.

Appendix Figure B.1 provides the intuition for equations (3.6) and (3.7). The curve labeled $x(m)$ represents the technological tradeoff between the regulated attribute (x) and the unregulated attribute (m). The curve is analogous to a production possibilities frontier, in that it describes the maximum level of x for any level of m, given the endowments of the two attributes. The curve $\frac{W^m}{W^x}$ is the ratio of the WTP for the two attributes (we assume that WTP for each attribute is decreasing in the corresponding attribute). Point A shows that without regulation the firm chooses levels of the two attributes such that the technology and WTP curves are tangent to one another. The regulation causes the firm to choose a point along the frontier such that the WTP ratio is steeper than the tradeoff; the firm substitutes the unregulated for the regulated attribute and chooses point B.

Thus far, we have interpreted x_j an attribute that is linked technologically to the regulated attribute and that the manufacturer can trade off the two attributes costlessly. A second interpretation of x_j is that the manufacturer can pay a fixed cost to choose both x_j and m_j. The fixed cost depends on the level of the attributes and their initial values. The cost function $D(m_j - m_{j0}, x_j - x_{j0})$ is increasing in both arguments, and the cost represents the cost of redesigning the vehicle to improve x_j and m_j. For simplicity, c_j remain exogenous.

In addition, we assume that there is a maximum cost that the firm can incur during the design stage, $\overline{D}$. This maximum cost captures capital market or time constraints that the firm faces, such as the need to update a refrigerator model during a regular product cycle. Provided that this constraint binds, the equation $D(m_j - m_{j0}, x_j - x_{j0}) = \overline{D}$ implicitly defines x_j as a function of m_j. Given this relationship, we write $x_j = D(m_j; \overline{D}, m_{j0}, x_{j0})$. In other words, the technological tradeoff from the previous example, $x_j - x_{j0} = x(m_j - m_{j0})$, has been replaced by a relationship arising from product design constraints.

This situation yields an equilibrium condition that is identical to the one above:

$$W^m + W^x \frac{\partial x_j}{\partial m_j} = \nu F', \tag{3.8}$$

Thus, regulation can affect attributes that are chosen during product designs, such as cargo space. The intuition is that the regulation causes the manufacturer to increase the resources devoted to designing the vehicle and increasing the regulated attribute, leaving fewer resources available for improving the unregulated attribute.

In the cases considered so far, increasing ν causes the firm to reduce x_j , but this need not hold generally when the product has more than two attributes. Consider an extension of this model that includes three attributes: m_j; x_j, which is linked technologically to m_j; and z_j, which is chosen jointly with m_j and x_j. Suppose further that z_j affects W^x. For example, redesigning a vehicle's exterior to have a sporty look (z_j) could increase a consumer's marginal WTP for horsepower (x_j). Under these assumptions, increasing ν could cause the firm to increase z_j and reduce the extent to which the firm trades off x_j for m_j. The intuition is that if here is no product regulation, and WTP for m_j is positively correlated with WTP for z_j, the firm may find it optimal to offer low levels of m_j and z_j, relative to the levels of attributes chosen by other firms. For example, for home appliances, consumer preferences for energy efficiency (m_j) may be positively correlated with preferences for overall product quality (z_j). In such a situation, the firm may offer a low-quality product that also has low energy efficiency because doing so helps the firm segment the market and attract the consumers with low demand for the two attributes.

Starting from this equilibrium, hypothetically regulating m_j has a similar effect on the firm's attribute choices as if consumer demand for m_j were to increase. This can be seen by comparing equations (3.6) and (3.7), which show that $\nu > 0$ has the same effect on attribute choices as an increase in demand for m_j. Essentially, the regulation reduces the positive correlation between m_j and z_j, reducing the firm's incentive to offer a low level of z_j. More generally, whether increasing ν causes z_j to increase or decrease depends on the magnitudes of the derivatives in equations (3.7) and (3.8) as well as the cross partial derivatives of the marginal WTP for each attribute with respect to the other attributes.

We conclude this section by noting a few simplifying assumptions. First, the model is static, and it abstracts from the timing of vehicle price and attribute decisions. Because manufacturers adjust prices more frequently than other attributes, and some attributes such as exterior styling are changed infrequently, a change in regulation that occurs in one year may affect product attributes in future years. We allow for this possibility in the empirical analysis that follows. Second, firms sell multiple products, which we allow for in the demand estimation.

Third, in practice, marginal costs depend on vehicle attributes (Klier and Linn 2012). We could endogenize marginal costs as in Klier and Linn 2012. Specifically, the marginal costs can increase with the level of technology (for example, the product's energy efficiency), where a higher level of technology allows the firm to increase one attribute without affecting the other attributes; consumers do not directly value the technology, but only the attribute improvements that a higher level of technology enables. Having chosen the technology, the firm can trade off attributes without affecting marginal costs. The conclusion that standards can affect other attributes is not affected by endogenizing marginal costs in this way. As Sections 3.4.2 and 3.5.1 explain, the estimation strategies for estimating the demand parameters and quality do not depend on this assumption.

3.3 Background and Data

The conclusions from Section 3.2 motivate an empirical analysis of whether regulating one product attribute can affect a broad set of other attributes. The remainder of the paper focuses on the European carbon dioxide emissions standards, and this section describes the policy context and the data.

3.3.1 Policy context

In Europe, passenger cars contribute the majority of transportation emissions, and Europe's carbon dioxide emissions standards are the central policy aiming to reduce those emissions. Traditionally, European countries have taxed fuels more heavily than have other countries (Parry and Small 2005). In 1995, the European Parliament and the Council formulated an objective of reaching an average emissions rate of 120 grams of carbon dioxide per kilometer (g CO_2/km) by 2010 (COM 1995; a gasoline-powered vehicle that emits 120 g CO_2/km achieves about 45 miles per gallon). However, the emissions target was voluntary, and by the mid-2000s, it was apparent that the actual emissions rate would far exceed the target (EC 2009).

Therefore, in 2007, the Commission proposed a legislative framework mandating passenger vehicle emissions reductions. For each vehicle, the carbon dioxide emissions target E_j depends on the vehicle's weight w_j, and is determined according to the formula: $E_j = 130 + 0.0457 \cdot (w_j - w_0)$, where, w_0 equals 1372 kg from 2012 to 2015 and 1392.4 kg after 2015.

A manufacturer's emissions target is the sales-weighted average of the vehicle-specific targets. Therefore, a manufacturer selling heavy vehicles has a higher target than does a manufacturer selling light vehicles. The framework included a phase-in period that began in 2012, and by 2015 each manufacturer had to attain an average carbon dioxide emissions rate for new passenger cars of 130 g CO_2/km (EC 2009).[5] The European standards do not allow compliance credit trading across firms. The framework also set a target of 95 g CO_2/km to be met by 2020,

[5]Between 2012 and 2014, the standards were phased in by including a subset of the manufacturer's sales when computing its sales-weighted emissions rate: 65 percent in 2012, 75 percent in 2013, and 80 percent in 2014. Between 2012 and 2015, cars with emissions rates less than 50 g CO_2/km (which are mainly electric vehicles) earned more than 1 credit: 3.5 in 2012 and 2013, 2.5 in 2014, and 1.5 in 2015. In certain situations, the target for vehicles capable of using fuel with high ethanol content was different from that reported in the text.

which was delayed.

Since 2012, a manufacturer whose sales-weighted average emissions rate exceeds its target must pay fines that increase with the degree of the manufacturer's noncompliance. When the manufacturer exceeds its target by no more than 1 g CO_2/km, the fine is 5 euros per g CO_2/km per car. The fine increases to 15 euros from 1 to 2 g CO_2/km, to 25 euros from 2 to 3 g CO_2/km, and to 95 euros above 3 g CO_2/km.

Because each manufacturer must meet the standard and manufacturers cannot trade compliance credits with one another, the shadow price of the regulation may vary across manufacturers, ν_m. Therefore, the regulation function from the previous section is given by $F(m_j) = \nu_m(k_f/m_j - E_j)$, where k_f is the carbon content of the fuel (which varies by fuel type). The regulation creates an implicit tax on a vehicle if $k_f/m_j > E_j$, and it creates an implicit subsidy otherwise.

3.3.2 Data

The main data were obtained from IHS Markit. For the eight EU countries with the largest car markets in Europe (Austria, Belgium, France, Germany, Italy, the Netherlands, Spain, and the United Kingdom), the data include registrations by month and vehicle from 2005 through 2017. A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), and drive type (front-, rear-, or all-wheel). For each vehicle, the data also include the vehicle's length, height, width, gross vehicle weight, size, fuel consumption rate, carbon dioxide emissions rate, engine horsepower, number of engine cylinders, engine size (that is, displacement), and number of transmission speeds, as well as the retail price.[6] The data are similar to those used in Klier and Linn (2015), except that our data extend through 2017, whereas theirs ended in 2010.

We construct a categorical variable labeled *origin* that takes one of three values: whether the car is produced by a domestic manufacturer, a foreign European or US manufacturer, or an Asian manufacturer. We calculate the vehicle purchase tax, ownership tax, and fuel tax using the annual European Automobile Manufacturers Association (ACEA) Tax Guide. We also construct the vehicle's per-kilometer fuel price by multiplying the fuel consumption rate (liters of fuel per kilometer) by the fuel price (2005 euros per liter). Monthly prices for gasoline (petrol) and diesel fuel are obtained from the Weekly Oil Bulletin and are converted to 2005 euros using consumer price indexes from Eurostat.

We drop vehicles with weight greater than 3,500 kilograms because they are not subject to the carbon dioxide emissions rate standards for passenger cars, and we drop vehicles with prices exceeding 59,537 euros, which is the 99th percentile of the price distribution (nearly all vehicles above this threshold use gasoline or diesel fuel). In the final data set, a unique observation is a vehicle by country by year. The data set contains 341,725 observations and 68,089 unique vehicles.

Table 3.1 provides summary statistics by time period. The table defines three policy regimes that are used in the empirical analysis below. During the first period (2005—8), the standards were voluntary and there were no fines for noncompliance. During the second period (2009—11), manufacturers knew that mandatory standards would be imposed starting in 2012. During the third period (2012—17), the standards were phased in and firms were assessed fines

[6]There is far less negotiation between consumers and car dealers in Europe than in the United States. Most of the literature on European new car markets uses retail prices rather than transaction prices (e.g., Reynaert 2019).

for noncompliance.

The second row shows the average carbon dioxide emissions rate, indicating a 28 percent decline between the first and third periods. The average price is stable across the periods, and the average tax decreases substantially. The tax includes the purchase tax and the present discounted value of future registration taxes, although it excludes the Value Added Tax (which we control for in the demand estimation). The tax varies across vehicles and countries because of variation in tax structure over countries and years, as well as variation in vehicle attributes. For example, purchase taxes in France depend on a vehicle's carbon dioxide emissions rate. Annual registration taxes in the United Kingdom also depend on emissions rates, and the tax rates varied over time.[7] The average fuel consumption rate, fuel costs, and carbon dioxide emissions rate decrease across the three periods, which is consistent with the fact that the carbon dioxide standards tightened during the sample. The market share of plug-in vehicles increased from zero in the first period to about 1 percent in the third period. The small market share in the third period implies that efficiency improvements for gasoline and diesel fuel vehicles explain most of the observed emissions decrease.

[7]See Linn (2019) and Cerruti et al. (2019) for more information on the tax variation. We do not summarize the tax variation further in this paper because as we show below, there is insufficient tax variation to separately identify consumer responses to vehicle prices and taxes.

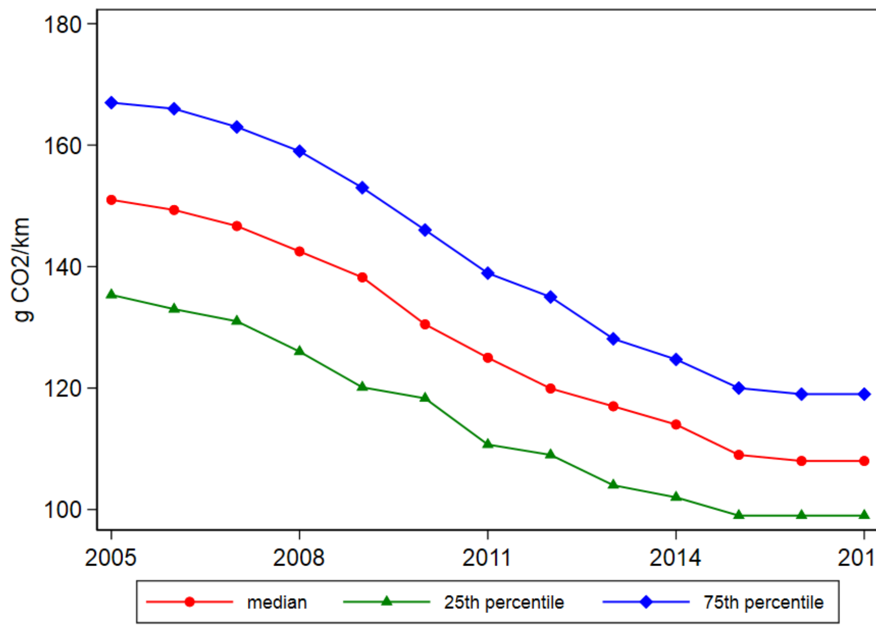
Table 3.1: Summary Statistics

Variable	Period 1 2005—8	Period 2 2009—11	Period 3 2012—17
Annual registrations of each vehicle in each country	336.15	295.08	212.28
	(1099.48)	(1044.79)	(687.06)
CO_2 emissions rate (g CO_2/km)	174.42	154.32	125.60
	(37.91)	(33.76)	(27.16)
Price (1,000 2005 euros)	25.78	25.94	26.46
	(11.19)	(11.70)	(11.53)
Tax (1,000 2005 euros)	3.88	3.30	3.14
	(5.25)	(4.69)	(4.83)
Engine horsepower	139.36	143.64	144.90
	(54.03)	(59.08)	(60.57)
Gross vehicle weight (metric tons)	1.86	1.87	1.88
	(0.27)	(0.29)	(0.29)
Size (cubic meters, m^3)	11.26	11.33	11.36
	(1.43)	(1.47)	(1.41)
Fuel cost (2005 euros/100 km)	8.31	7.21	6.10
	(2.46)	(2.06)	(1.92)
Fuel consumption rate (liters/100 km)	7.02	6.26	5.15
	(1.71)	(1.51)	(1.23)
Number of engine cylinders	4.34	4.25	4.01
	(0.84)	(0.80)	(0.71)
Market share of plug-in vehicles	0	0.001	0.013
		(0.0007)	(0.014)
Number of observations	101,389	74,709	165,627

Notes: The table reports means of the attributes for the time periods indicated in the row headings, with standard deviations in parentheses. See text for details on data construction.

Figure 3.1 shows the median carbon dioxide emissions rate as well as the 25th and 75th percentiles of the emissions rate across vehicles. By the end of the sample, the average emissions rate was far below the target of 130 g CO_2/km, which likely is explained by manufacturers' efforts to comply with the target of 95 g CO_2/km by the early 2020s.

Figure 3.1: CO_2 Emissions Trend



Notes: The figure shows the median, 25th percentile, and 75th percentile of CO_2 emissions rate by year, weighted by registrations.

Appendix Table B.1 motivates the nested logit structure that we adopt in the next section. France and Germany have the largest markets in Europe, and the table shows the market shares in France and Germany of the top three French and German brands. The table indicates a strong home bias, such that the French brands have substantially higher market shares in France than they do in Germany, and vice versa for the German brands.

3.4 Estimating Preferences and Vehicle Quality

Section 3.2 showed that regulation can affect product attributes that are not directly targeted. Moreover, regulation could either increase or decrease other attributes, depending on the structures of demand and costs. These findings motivate our investigation of the effects of Europe's CO_2 regulations on vehicle attributes. In principle, we could use a structural model of the vehicle market to simulate the standards, which would require specifying both the demand and supply sides of the market. However, modeling the supply side is particularly problematic, since, as Section 3.2 illustrated, we would need to characterize technological and design tradeoffs across attributes. Instead, we employ a strategy in which we estimate only the demand side of the market and analyze consumer welfare consequences of marginal changes in the standards.

In this section, we implement a method similar to that of Houde and Spurlock (2015) to estimate consumer preferences and vehicle quality. The first two subsections describe the demand model and empirical strategy, and the third subsection reports the estimation results.

3.4.1 Demand model

A market corresponds to a country c and year y, and each country has M_{cy} consumers who are considering purchasing a vehicle. Each consumer can choose a new or a used vehicle, where $j = 0$ indicates a used vehicle and $j = \{1, \ldots, J\}$ indexes the new vehicles. As is customary in the vehicle choice literature (e.g., Berry et al. 1995), consumer i's utility is linear in vehicle attributes and an idiosyncratic preference shock:

$$U_{ijcy} = \alpha p_{jcy} + X_{jcy}\beta + \xi_{jcy} + \varepsilon_{ijcy} \tag{3.9}$$

The retail price of the vehicle is p_{jcy}, and X_{jcy} includes the vehicle's tax, fuel costs, log of the ratio of horsepower and weight, log weight, and log size (the product of width, length, and height). We include the vehicle's price and tax separately in the utility function to allow for the possibility that consumers respond differently to taxes than prices, because of salience or other factors (Cerruti et al. 2019). Fuel costs are the price of fuel per 100 km of travel, as constructed for Table 3.1, and fuel costs are proportional to the present discounted value of fuel costs over the vehicle's lifetime assuming that the current price equals the expected future real price. This measure of fuel costs is commonly used and is consistent with existing evidence of consumer fuel price expectations (Anderson et al. 2013). The log of the ratio of horsepower and weight is included because it is directly related to the vehicle's acceleration (Leard et al. 2017a), and it is a commonly used proxy for performance. ξ_{jcy} represents the mean utility across all consumers of the vehicle arising from all attributes except price and the attributes in X_{jcy}. For example, ξ_{jcy} includes cabin comfort and cargo space. Finally, ε_{ijcy} is the household's preference shock.

We use a nested logit structure to capture preference heterogeneity across consumers. Appendix Figure B.3 illustrates the structure. First, the consumer decides whether to purchase a new or used vehicle. If the consumer decides to purchase a new vehicle, the consumer then chooses a market segment, where segments are denoted A through F and correspond roughly to vehicle size (for example, A indicates mini cars and B indicates small cars). Having chosen a segment, the consumer chooses an origin (domestic, other European or US, or Asian) and a specific vehicle. We differentiate between foreign and domestic cars to capture the home bias indicated in Table B.1. The nesting structure implies that $\varepsilon_{ijcy} = \eta_{ig(j)cy} + (1 - \sigma_g)\nu_{ijcy}$, where $\eta_{ig(j)cy}$ represents consumer i's specific taste for group $g(j)$, and ν_{ijcy} is an independently and identically distributed variable with Type 1 extreme value distribution.

The probability of choosing vehicle j, P_j, is

$$P_j = P_{j|so} \cdot P_{o|s} \cdot P_s, \tag{3.10}$$

where $P_{j|so}$ is the probability of choosing vehicle j conditional on choosing segment s and origin o, $P_{o|s}$ is the probability of choosing origin o conditional on choosing segment s, and P_s is the probability of choosing segment s. The nesting structure and assumptions on the error term yield

$$P_{m_l|j_{l-1}} = \frac{exp(\frac{\lambda_{m_l} IV_{m_l}}{\lambda_{j_{l-1}}})}{\sum_{k \in \Theta_{j_{l-1}}} exp(\frac{IV_{k_l} \lambda_{k_l}}{\lambda_{j_{l-1}}})} \tag{3.11}$$

$$IV_{m_l} = log[\sum_{p \in \Theta_{m_l}} exp(\frac{\delta_{p_{l+1}}}{\lambda_{m_l}})], \tag{3.12}$$

where the subscript l represents a particular level in the choice tree, the subscript $l-1$ represents the choice level above, and subscript $l+1$ refers to the choice level below (McFadden 1981; Goldberg 1995). The subscript m_l represents a specific alternative m at the choice level l. $P_{m_l|j_{l-1}}$ is the probability that a consumer chooses alternative m at the choice level l conditional on the consumer having chosen j at the higher choice level $l-1$. The inclusive value IV_{m_l} measures the expected utility of the choice subset given the choice m on level l. The dissimilarity coefficients are λ_{m_l} and $\lambda_{j_{l-1}}$, which measure the dissimilarity of consumer utility for choices belonging to the same nest. Consistency of equation (3.11) with random utility maximization requires that $\lambda_{m_l}, \lambda_{j_{l-1}} \in [0, 1]$. Moreover, vehicles belonging to the same nest at level l are more similar on average to vehicles belonging to the nest at level $l-1$. For example, segment A (mini) cars sold by French brands in France are more similar to one another than are all segment A cars sold in France. This assumption implies that $0 < \lambda_{m_l} < \lambda_{j_{l-1}} < 1$. When λ approaches 1, the distribution of ε_{ij} approaches an independently and identically distributed extreme value distribution, and the nested logit model degenerates to a logit model.

Combining equations (3.10) and (3.11) yields the market-level equation

$$logS_{jcy} - logS_{0cy} = \alpha p_{jcy} + X_{jcy}\beta + \sigma_{so} logS_{j|so,cy} + \sigma_s logS_{o|s,cy} + \xi_{jcy}, \tag{3.13}$$

where S_{jcy} and S_{0cy} are market shares for vehicle j and the outside option (used car). The similarity parameters are $\sigma_{so} = 1 - \lambda_{so}$ and $\sigma_s = 1 - \lambda_s$.

3.4.2 Strategy for estimating preference parameters and quality

Equation (3.13) is the basis for estimating preference parameters and vehicle quality. We decompose the error term in the equation into four components: $\xi_{jcy} = \delta_{mb(j)} + \delta_{sy} + \delta_{cy} + \mu_{jcy}$. The first component includes a fixed effect for each model and body type, such as the hatchback version of the Volkswagen Golf, as distinct from the station wagon version of the Golf. The second component includes fixed effects for each segment by year. The third component includes a fixed effect for each market, which includes the average utility from the outside option; including this variable avoids the need for data on the outside option (that is, because of the third component, the choice of the outside option does not affect the estimated parameters). The final term is a mean zero error term.

This decomposition of the error term in equation (3.13) yields the estimation equation

$$logS_{jcy} - logS_{0cy} = \alpha p_{jcy} + X_{jcy}\beta + \sigma_{so} logS_{j|so,cy} + \sigma_s logS_{o|s,cy} + \delta_{mb(j)} + \delta_{sy} + \delta_{cy} + \mu_{jcy}. \tag{3.14}$$

Estimating equation (3.14) by ordinary least squares (OLS) would yield biased parameter estimates because the vehicle's price and the within-nest shares are likely to be correlated with μ_{jcy}. Following Berry et al. (1995) we use the sum of attributes of other vehicles in the market to instrument for price and market shares. The intuition supporting the relevance of the instruments is that the profit-maximizing price of vehicle j depends on attributes of other competing vehicles in the market, and that an increase in the number of competing vehicles reduces the firm's price. A similar intuition applies to the endogenous market shares, because the equilibrium market share is likely to be correlated with attributes of other vehicles. The relevance of the instruments arises from the firm's profit-maximizing price choices.

The exclusion restriction is satisfied if attributes of competing vehicles are uncorrelated with μ_{jcy}. Vehicle manufacturers typically make major redesigns of vehicles at regular intervals, during which they may make substantial changes to the vehicle's power train, architecture, and components. In between redesigns, manufacturers make more modest changes, such as modifying the power train to adjust fuel economy or horsepower. Consequently, μ_{jcy} is particularly likely to be correlated with attributes of other vehicles that vary between redesigns. The correlation between μ_{jcy} and other vehicle attributes may be weaker for attributes that are typically changed only during redesigns. Based on this reasoning, we use as instruments the physical dimensions (length, width, and height) of other vehicles, as well as the number of engine cylinders, because these attributes change only during major redesigns.

After estimating the preference parameters in equation (3.14), we recover the vehicle's residual quality as $\widehat{\xi}_{jcy} - \widehat{\delta}_{cy} = \widehat{\delta}_{mb(j)} + \widehat{\delta}_{sy} + \widehat{\mu}_{jcy}$. The variable varies by vehicle, country, and year. We exclude the country-year fixed effects from quality because they include the mean utility from the outside option. We normalize quality by the disutility of the vehicle price, $\widehat{Q}_{jcy} = -(\widehat{\xi}_{jcy} -$

$\widehat{\delta}_{cy})/\widehat{\alpha}$, to express quality in 2005 euros. Quality includes WTP for all attributes other than those included in equation (3.14). For example, quality includes the vehicle's seating comfort and infotainment options.

Note that in the demand estimation, we assume that unobserved attributes (that is, quality) are exogenous to observed attributes. This assumption is consistent with nearly all of the vehicle demand literature (e.g., Berry et al. 1995). A few papers, such as Whitefoot et al. (2017), have relaxed this assumption partially and instrumented for a subset of observed attributes, but in our case unfortunately the available data do not yield plausible instruments for observed attributes. Because we interpret quality as an attribute of the vehicle chosen by the manufacturer, the main threat to identification would be any component of quality that is correlated with fuel economy, horsepower, or weight. This situation could cause the attribute coefficients to absorb components of quality correlated with the attributes. Below, we report evidence consistent with this interpretation of quality, in particular showing specifications that take different approaches to controlling for omitted demand shocks.

3.4.3 Results

3.4.3.1 Preference parameters

Columns 1 and 2 of Table 3.2 report estimates of a logit model to compare with column 3, which is the preferred nested logit model. Parameters are estimated by OLS in column 1 and by IV in columns 2 and 3, using attributes of other vehicles as instruments. Standard errors are clustered by model and trim to allow for correlation within trims. All regressions include fixed effects for model by body type, country by year, and segment by year. The appendix reports the first-stage estimates for the IV models. The Sanderson-Windmeijer multivariate F-test of the excluded variables reduces concerns about weak instruments bias and rejects the null assumption that the model is underidentified.

The price coefficient is negative and statistically significant at the 1 percent level for all three demand models. The magnitude of the price coefficient is larger using IV than OLS, which is consistent with expectations because the IV strategy corrects for the positive correlation between price and the error term. The top panel of Table 3.3 shows that the OLS estimates yield implausibly small own-price elasticities.[8] The preferred IV estimates in column 3 yield own-price elasticities that typically lie between -5.9 and -9.0, which is consistent with the fact that the price sensitivity parameter is identified by variation across highly disaggregated vehicles. The estimates are somewhat larger than, but broadly similar to, other estimates that use disaggregated European data (e.g., Grigolon et al. 2017).

[8]The elasticity of choice probability for vehicle j with respect to attribute $X^{(n)}$ is

$$\frac{\partial P_j/P_j}{\partial X_j^{(n)}/X_j^{(n)}} = [\frac{1-P_{j|so}}{\lambda_{so}} + \frac{(1-P_{o|s})P_{j|so}}{\lambda_s} + (1-P_s)P_{o|s}P_{j|so}]\beta^{(n)}X_j^{(n)}, \tag{3.15}$$

where λ_s is the dissimilarity of alternatives belonging to the same segment but having different origins, and λ_{so} is the dissimilarity of alternatives belonging to the same segment and having the same origin. The elasticity increases with the preference coefficient and decreases with the dissimilarity parameters.

Table 3.2: Estimated Preference Parameters

	(1)	(2)	(3)
	Logit	Logit	Nested logit
Estimated by	OLS	IV	IV
Price (1,000 2005 euros)	-0.040***	-0.280***	-0.088***
	(0.003)	(0.047)	(0.015)
Log within segment-origin share			0.774***
			(0.018)
Log share of origin in segment			0.498***
			(0.029)
Tax (1,000 2005 euros)	-0.063***	0.028	-0.006
	(0.003)	(0.018)	(0.006)
Fuel cost (2005 euros/100 km)	-0.277***	-0.329***	-0.086***
	(0.008)	(0.014)	(0.006)
Log horsepower/weight (hp/kg)	0.027	2.511***	0.909***
	(0.077)	(0.502)	(0.155)
Log weight (tonnes)	-1.392***	5.681***	2.176***
	(0.251)	(1.408)	(0.436)
Log size (m^3)	8.587***	7.920***	1.8***
	(0.379)	(0.426)	(0.202)
First-stage summary			
F-test of excluded instruments for price		20.08	16.55
F-test of excluded instruments for within-origin share			50.58
F-test of excluded instruments for share of origin in segment			58.37
Number of observations	341,725	341,725	341,659

Notes: The table reports coefficient estimates with standard errors in parentheses, clustered by model and trim. All regressions include country—year fixed effects, model—body type fixed effects, and segment—year fixed effects. Column 1 is estimated by ordinary least squares, and columns 2 and 3 are estimated by instrumental variables, using width, length, height, and number of engine cylinders as instruments (see text). We use the Sanderson-Windmeijer multivariate F-test of excluded instruments to account for clustering of the standard errors. Column 3 contains 68,089 unique vehicles and 429 unique models.

Table 3.3: Estimated Own-Price Elasticities, Willingness to Pay and Valuation Ratio

	Logit OLS	Logit IV	Nested logit IV
Estimated own-price elasticities			
Median	-0.77	-5.41	-7.51
Mean	-0.77	-5.39	-7.46
Standard deviation	0.09	0.62	0.88
5th percentile	-0.92	-6.49	-9.02
95th percentile	-0.60	-4.24	-5.87
Willingness to pay for 1 percent change (2005 euros)			
Fuel cost decrease	441	75	62
Horsepower/weight increase	7	90	103
Weight increase	-348	203	247
Size increase	2,147	283	205
Quality increase	5,868	760	564
Valuation ratio			
15 years, r = 0.06	4.74	0.80	0.67
15 years, r = 0.03	3.97	0.67	0.56
10 years, r = 0.06	6.25	1.06	0.88

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table 3.2. Own-price elasticities are calculated using equation (3.15). The elasticities are weighted by registrations. Valuation ratio is the willingness to pay for a 1 percent reduction in fuel costs divided by the present discounted value of the fuel cost savings. These calculations assume that each vehicle is driven 14,700 kilometers each year and that the future real price of fuel equals the average real price of fuel in the estimation sample. The calculations use the vehicle lifetime and real discount rate indicated in the row heading.

Coefficients on the within-group shares represent the similarity parameters for vehicles within the same group. Both estimates are significant at the 1 percent level and lie between 0 and 1. The similarity parameter for the share of origin within segment is less than the within-origin-segment share, which is consistent with the assumed nesting structure.

The tax coefficient in Table 3.2 is negative (as expected), but it is not statistically significant. The lack of significance may reflect the strong correlation between taxes and prices after including model—body type fixed effects. The estimated own-price elasticities are similar if we add the tax to the price, as in Grigolon et al. (2017).

In column 3, the estimates of the fuel cost and log of the ratio of horsepower and weight coefficients are statistically significant, and they have the expected signs. The coefficient on weight is positive and statistically significant. The coefficient reflects consumer preferences for performance, safety, and components such as speakers, all of which are correlated positively with weight. Finally, the vehicle size coefficient is statistically significant and positive, as expected.

The second panel of Table 3.3 provides an economic interpretation of the coefficients on fuel costs, performance, weight, and size. For comparability with the literature, it reports the mean willingness to pay for 1 percent changes in the indicated attributes. The three columns correspond to the three demand models reported in Table 3.2. On average, consumers are willing to pay 62 euros for a 1 percent reduction in fuel costs and about 103 euros for a 1 percent increase in performance. These estimates are similar to those reported in Leard et al. (2017b) for the US market.

The bottom panel of Table 3.3 provides a second interpretation of the willingness to pay for fuel cost savings. We define the valuation ratio as the willingness to pay for a 1 percent reduction in fuel costs divided by the present discounted value of the fuel cost savings over the vehicle's lifetime. A valuation ratio of 1 implies full valuation, where consumers pay 1 euro for 1 euro of present discounted fuel cost savings; a ratio less than 1 implies undervaluation. Making this calculation requires assumptions on future fuel prices, kilometers traveled, and the real discount rate. The first row shows the valuation ratio under the same assumptions as in Grigolon et al. (2017). Our estimated valuation ratio, 0.67, implies a modest amount of undervaluation (similar to Allcott and Wozny 2014), which is smaller than the estimate in Grigolon et al. (2017) of 0.91.

Our undervaluation is consistent with the discrepancy between real-world and laboratory tested fuel consumption. As mentioned in the Introduction, real-world fuel consumption has exceeded estimated fuel consumption from laboratory testing of passenger vehicles in Europe. The fuel cost variable in our data is constructed from laboratory test data rather than real-world consumption. Consequently, if consumers knew about the difference between the two measures, they would undervalue fuel cost savings implied by laboratory test results. Note that other papers on European vehicle demand use data that largely predates the growing discrepancy between tested and real-world consumption, which could explain why our results differ somewhat from theirs.

3.4.3.2 Quality

After estimating the preference parameters, we compute the quality in euros as described at the end of Section 3.4.2. Appendix Figure B.4 plots the unweighted mean quality by country and year, for each of the three demand models estimated in Table 3.2. In this figure and for the remainder of the paper we normalize estimated quality by the negative of the vehicle price coefficient (α), and quality is measured in 2005 euros. For each country, quality may vary over time because of within-vehicle changes in quality as well as entry and exit of vehicles. The vertical dashed lines indicate the three regimes of the standards.

The figure indicates that for most countries, quality increased more quickly during the first period (before the standards took effect) than in the second and third periods (after the standards were announced and as they were phased in). This pattern provides suggestive evidence that the standards caused quality to increase less quickly than in the first period, or even decrease. Of course, other factors may have contributed to the slowing quality growth, such as the economic recession; the empirical analysis in the next section aims to disentangle the effects of the carbon dioxide standards from other factors.

Appendix Table B.2 shows that estimated residual quality varies with observed vehicle attributes that are not included in the demand model. Plug-in vehicles and vehicles with large engines tend to have higher estimated quality than other vehicles. Quality also varies across body types in plausible ways. Because quality includes vehicle attributes that are not shown in the table, we do not interpret the correlations among quality and observed attributes as causal relationships. Instead, we interpret the table as showing intuitive correlations among quality, fuel type, engine size, and body type.

Because residual quality is derived from the demand model, we report a number of alternative demand model specifications in the Appendix Section B.8. The appendix also includes a brief discussion of these results.

3.5 Estimating the Effects of the Standards on Quality and Other Attributes

The first subsection describes the empirical strategy for estimating the effects of the carbon dioxide standards on vehicle quality, horsepower, weight, and vehicle price. The second subsection reports the point estimates, discussing statistical significance and potential sources of bias.

3.5.1 Empirical strategy

The objective is to estimate the effects of the standards on equilibrium quality and observed attribute choices. Motivated by the model in Section 3.2 and following Klier and Linn (2015), we construct a measure of stringency that is analogous to a shift-share or Bartik-style estimation (Bartik 1991). Equations (3.7) and (3.8) show that the standards affect vehicle attribute choices in proportion to the shadow price of the regulation, ν, which varies across firms. We assume that the shadow price is proportional to the amount the firm has to reduce the average emissions of its fleet, and define stringency as

$$Stringency_f = ln(e_f) - ln(E_f), \tag{3.16}$$

where e_f is the registration-weighted average emissions rate of the firm's vehicles, and E_f is the registration-weighted emissions rate target. We use the emissions rate, weight, and registrations of vehicles during the first year of the sample to compute $Stringency_f$. Therefore, $Stringency_f$ does not vary over time, and it measures the amount that the firm has to reduce emissions between 2005 and 2017.

Because of the timing of the regulation, we expect $Stringency_f$ to affect attributes by different amounts in the three periods: (1) 2005—8, pre-standard period; (2) 2009—11, announcement period; and (3) 2012—17. Standards did not apply between 2005 and 2008, and we do not expect stringency to affect quality during these years. In periods 2 or 3, however, stringency may affect quality. Thus, by constructing stringency as a proxy for the shadow price of the standards and interacting the variable with time period fixed effects, we can estimate the average effects of the standards on the dependent variables, despite the fact that the firm's shadow price is not observed.

We interact the stringency variable with fixed effects for the three time periods, and the estimation equation is

$$Y_{jcy} = \gamma_1 + \gamma_2 Stringency_f * I_y^{(2)} + \gamma_3 Stringency_f * I_y^{(3)} + \delta_j + \delta_{sy} + \delta_{cy} + \varepsilon_{jcy}, \quad (3.17)$$

where Y_{jcy} is the dependent variable (quality, $ln(horsepower/weight)$, log weight, or log price); $I_y^{(l)}$ is an indicator for period l; δ_j, δ_{sy} and δ_{cy} are vehicle, segment by year and country by year fixed effects; ε_{jcy} is an error term; and γ are coefficients to be estimated. Because the equation includes vehicle and country-year fixed effects, we omit the main effects of $Stringency_f$ and time period fixed effects. The dependent variables for quality, $ln(horsepower/weight)$, and log weight are normalized by $-\alpha$, and we interpret the variables as the WTP for quality, horsepower, and weight.

The key coefficients γ_2 and γ_3 are identified by cross-sectional stringency variation interacting with time periods. For example, γ_2 would be negative if vehicles sold by firms with high stringency experience larger quality decreases between the first and second periods compared with vehicles sold by firms with low stringency. We test whether the coefficients γ_2 or γ_3 are different from zero, and we interpret the coefficients as the market-wide average effects of the standards on the dependent variables during the corresponding periods.

We estimate equation (3.17) by OLS, and the vehicle fixed effects and definition of the stringency variable support our interpretation of the coefficients γ_2 and γ_3 as the supply-side response of quality to the standards. Recall that, in principle, estimated quality may include both demand- and supply-side components. For example, a small car's quality may change over time if the manufacturer improves unobserved attributes such as seating comfort or if preferences for small cars change over time. Our objective is to estimate the effects of the standards on the former type rather than the latter type of quality change. The vehicle fixed effects control for the cross-sectional correlation between stringency and the dependent variable, and the country by year fixed effects control for country-level demand or supply shocks to the dependent variable. For example, the vehicle fixed effects control for the possibility that high-quality vehicles typically are heavier or have higher carbon dioxide emissions rates.

The stringency variable helps identify the supply-side effect of standards on quality by isolating quality changes that are correlated with a firm's stringency. A causal interpretation relies on a parallel trends assumption: in the absence of the standards, temporal variation of the dependent variables would not be correlated with $Stringency_f$. A violation of this assumption amounts to an omitted variable that is correlated cross-sectionally with stringency and that varies over time. More specifically, omitted demand shocks, either in equation (3.14) or (3.17), would yield biased or spurious estimates of the stringency coefficients. In the robustness analysis below, we test for pre-policy trends and provide evidence that demand shocks appear to be uncorrelated with a firm's stringency, which support our interpretation of γ_2 and γ_3.

Because carbon dioxide emissions rates are strongly correlated with fuel consumption rates, it might seem that demand for fuel cost savings would be correlated with $Stringency_j$, which would bias the estimates. However, this is not a significant concern because quality is a residual estimated from the demand model, which purges the variable of consumer WTP for fuel cost savings.

3.5.2 Results

Table 3.4 reports the estimates of equation (3.17). The dependent variables are quality, $ln(horsepower/weight)$, log weight, and log price. In columns 1 through 3, the coefficients on the stringency variables are the change in WTP (in thousands of 2005 euros) for the dependent variable caused by a 1 percent change in stringency during the relevant period. All regressions include fixed effects for vehicle, segment by year, and country by year. Standard errors are bootstrapped to account for the fact that the stringency variable is computed after estimating equation (3.14).[9]

Column 1 shows that the standards reduced quality in periods 2 and 3. According to the estimates, a 1 percent increase in stringency in period 2 reduced quality by 55 (= 5.5*1,000*0.01) euros, which is statistically significant at the 1 percent level.

The timing of the stringency effect is consistent with the timing of the policy announcement, which occurred in 2007. Manufacturers often make major redesigns of their vehicles every 5-7 years, and sometimes more frequently (Klier and Linn 2016). Redesigns are staggered across a manufacturer's vehicles; a subset of its vehicles are in the midst of a redesign in any particular year. Consequently, the policy announcement could affect quality during period 2. The results suggest that manufacturers responded to the standards within one redesign cycle, which is consistent with the observation that emissions began to level off after 2012.[10] Appendix Table B.25 provides additional results regarding the timing of the effect of the standards on quality.

[9]Standard errors are clustered by model and trim. Appendix Table B.4 shows that clustering standard errors by firm has small effects on the standard errors.

[10]Vehicles are designed to allow manufacturers to easily swap certain components without substantially redesigning the vehicle. Because some of these components may affect quality, manufacturers may be able to adjust quality in between major redesigns,

The largest effects occurred between 2009 and 2012, and the effects tend to be negative but not statistically significant after 2012.

The stringency coefficient for period 3 is negative, but it is not statistically significant and the magnitude is smaller than the period 2 coefficient. We consider two explanations for this result. First, recall that emissions decreased sharply in period 2 but were flat in period 3 (see Figure 3.1). The leveling off of emissions reflects the fact that most manufacturers' emissions were below the corresponding standards.Although the shadow price is not observed, the fact that emissions were below the standard for this period could imply that the shadow price was zero in period 3. A second interpretation is that the tradeoff between quality and emissions became less severe over time. We leave for future research an investigation of these possible explanations.[11]

Table 3.4: Effects of the Standards on Quality, Performance, Weight, and Price

	(1)	(2)	(3)	(5)
Dependent Variable	Quality	Log (Horsepower/Weight)	Log Weight	Log Price
Stringency Variable	firm-level	firm-level	firm-level	firm-level
Period 2 x Stringency	-5.512***	1.854***	-0.085	0.087**
	(1.782)	(0.446)	(0.289)	(0.036)
Period 3 x Stringency	-2.921	0.192	0.41	0.025
	(2.363)	(0.705)	(0.413)	(0.051)
Joint F—test	5.562	16.932	1.999	5.439
P Value	0.004	0.000	0.136	0.004
Number of Observations	339,065	345,033	345,033	359,445
Adjusted R-squared	0.815	0.967	0.986	0.992

Notes: Each regression is weighted by registrations and includes vehicle fixed effects, country fixed effects, year fixed effects, country by year fixed effects and segment by year fixed effects. All columns use the firm-level stringency variable. Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. The dependent variable in columns 1 through 3 is normalized by $-\alpha$, and the variables are measured in thousands of 2005 euros. The number of observations varies across columns because of missing vehicle attributes.

[11] Section 3.2 suggests that stringency may reduce quality because of correlation between demand for fuel economy and quality. Although marginal costs were exogenous in that model, in practice cost-side considerations could explain why the standards caused manufacturers to reduce quality but not horsepower; that is, the cost of reducing quality may have been low.

The standards slightly increased performance in period 2 and did not affect weight. In contrast, Klier and Linn (2016) find that the standards slightly reduced horsepower and weight at the end of the 2000s. Our results suggest that although Klier and Linn (2016) find that the standards initially affected performance, we find that this effect did not persist into the enforcement period. The fact that performance did not decrease in period 2 is consistent with the consumer preference estimates reported in the previous section. Recall that manufacturers can trade off horsepower for fuel economy, but doing so reduces consumer WTP for the vehicle if the consumers value the horsepower more highly than the fuel economy. The estimate preferences suggest that such a trade-off would substantially reduce WTP for the vehicle, and by more than the quality reduction reported in Table 3.4.[12] Thus, the performance results are consistent with profit maximization.[13]

Column 4 shows a positive effect of stringency on prices in period 2, although the effect is small in magnitude. The small effect likely reflects three forces that roughly cancel one another. First, an increase in stringency causes the firm to adopt fuel-saving technology that reduces emissions, which raises production costs and vehicle prices. Second, the lower quality reported

[12]More specifically, consider a 1 percent stringency increase. Estimates from Klier and Linn (2016) imply that the manufacturer could achieve the new standard by reducing performance by about 5 percent. Based on our demand estimates from the previous section, the lower performance would reduce WTP for the vehicle by about 500 euros. In contrast, the lower quality implied by the estimates in Table 3.4 reduces WTP by about 55 (using the point estimate from period 2). Thus, reducing emissions by lowering quality causes WTP to fall by less than would reducing emissions by lowering performance. Note that this calculation omits any changes in fixed costs associated with these attribute changes, and estimating the fixed costs lies outside the scope of the paper.

[13]Unfortunately, data are not available to assess whether the weight results are consistent with profit maximization. On the one hand, the weight coefficient in the demand estimation makes it even more unlikely that manufacturers would reduce emissions by reducing weight than by reducing performance, because reducing weight by 1 percent lowers WTP for the vehicle twice as much as reducing performance by 1 percent. Thus, given the demand estimates combined with estimated tradeoffs between weight and emissions estimated in Klier and Linn (2016), the lack of a weight response is consistent with profit maximization. On the other hand, manufacturers can reduce weight by removing components and safety features or by light-weighting (substituting heavy materials such as steel for lighter materials such as aluminum). Each of these choices would have different consumer welfare implications. Specifically, removing components or safety features would reduce WTP for the vehicle, whereas light-weighting would increase costs (since lighter materials tend to be more expensive and light-weighting requires some fixed costs to redesign the vehicle), without affecting WTP. Because costs of light-weighting are unobserved, it is not possible to determine whether the lack of a weight response in Table 3.4 is consistent with profit maximization

in column 1 indicates a decline in demand, which reduces the price. Third, an increase in stringency causes manufacturers to reduce prices to encourage consumers to purchase vehicles with lower stringency. Reynaert (2019) finds that manufacturers did not pursue this strategy before 2012, which is consistent with our results.

Next, we assess the robustness of the estimates of equation (3.17). Identification rests on the assumption that quality for low-stringency vehicles and high-stringency vehicles would have followed parallel trends in the absence of the standards. Because we have data prior to the standards, we can test whether quality followed a common trend during the pre-policy period. Appendix Table B.14 reports the same specification as in Table 3.4, except that the sample includes only the years 2005 through 2008 and we interact the stringency variable with a linear time trend. We observe that quality, weight, and price have parallel trends during the pre-policy period, supporting the identifying assumption. Moreover, the data reject large pre-trends. However, the stringency coefficient is positive and statistically significant for the performance regression, which causes us to treat the performance results in Table 3.4 with some caution.

Above we noted that the main threat to identification would be an unobserved demand shock correlated with the stringency variable in the cross section and that varies over time. Appendix Section B.11 reports several approaches to modifying the estimation equation and controling for such omitted variables. Appendix Section B.11 also includes three additional checks on outliers and construction of the sample. Overall, the estimated effects of the standards on quality do not appear to be biased substantially by omitted variables bias or affected by outliers and construction of the sample.

3.6 Welfare Implications for Consumers

We use the estimation results to quantify the consumer and social welfare effects of increasing stringency by 1 percent for each vehicle sold in the last year of our sample. We focus on consumer and social benefits, and abstract from compliance costs, which is outside the scope of the paper.

We consider a hypothetical 1 percent stringency increase for all manufacturers. We assume that manufacturers reduce emissions by reducing the fuel consumption rate of gasoline and diesel fuel vehicles. This assumption is consistent with the fact that reducing emissions rates of these vehicles, rather than introducing new plug-in vehicles, has accounted for nearly all of the emissions reductions observed through the end of the sample (see Table 3.1). Under this assumption, the higher stringency reduces fuel consumption rates and fuel costs by 1 percent.

The first row of Table 3.5 reports the consumer benefits of the lower fuel costs using two approaches to value the savings, which we use to bound the consumer benefits. First, we use estimated willingness to pay from the demand model. This is the appropriate welfare measure if the undervaluation reported in Table 3.3 arises from hidden costs, as discussed above. In that case, the undervaluation includes the disutility from the technologies or differences between tested and on-road fuel consumption, and using the estimated preference parameters accounts for these hidden costs.

Table 3.5: Consumer and Social Welfare Effects of a 1 Percent Stringency Increase (2005 euros per vehicle)

	Benefits from fuel cost savings and lower emissions	
Method	Fuel savings computed using preference estimates	Fuel savings computed using full value
Fuel cost savings	62.20	93.15
Social value of lower GHG emissions	7.39	
	Willingness to pay for changes in attributes and quality	
WTP for the quality change	-42.17	
WTP for the performance change	9.29	
WTP for the weight change	3.54	
Price change	2.90	
Sum	-26.44	

Notes: The table reports the consumer and social welfare effects of increasing stringency by 1 percent. We use two methods to compute the benefits from fuel cost savings and the social value of lower emissions. The first method uses the estimated preference parameters, and the second uses the present discounted value of the fuel cost savings. The social value of the lower emissions uses the same assumptions on vehicle lifetimes and driving as those used to compute fuel cost savings, a 3 percent discount rate, and the US Environmental Protection Agency estimates of the social cost of carbon. To compute the WTP for changes in attributes and quality due to a 1 percent increase in stringency, we use the average of the two stringency coefficients in the corresponding column of Table 3.4, and similarly for the price and other attribute changes.

The second approach is to assume that undervaluation reflects a consumer mistake, and that consumers incorrectly undervalue the fuel cost savings. In this case, consumers benefit from the full value of the fuel cost savings (see Train 2015). The second column of the table uses the value of fuel cost savings computed in Table 3.3, and with the same assumptions as in the first row of that table.

The second row reports the social benefits of the lower greenhouse gas emissions. The calculation uses the same assumptions on vehicle lifetimes and driving as those used for the fuel cost calculations. We use the US Environmental Protection Agency's estimates of the social cost of carbon, counting the global benefits and using a 3 percent discount rate.

The second panel reports changes in WTP for performance, weight, and quality, as well as the price change. Note that the weight and price changes are not statistically significant, but the point estimates are included in the welfare calculations. The net welfare change is -26 euros, which is 26 percent of the combined fuel cost and emissions benefits in the first panel.

These calculations assume that a 1 percent stringency increase translates to a 1 percent reduction in on-road fuel consumption and emissions. However, Mock et al. (2014), Tietge et al. (2015), and Reynaert and Sallee (2019) conclude that on-road fuel consumption reductions have been just half as large as the reductions in tested emissions rates because of gaming of the emissions tests. Accounting for this effect means that the quality reduction caused by tighter standards offsets 52 percent of the consumer and social benefits in Table 3.5.[14]

As a caveat, we note that these welfare calculations include the estimated consumer welfare and GHG changes. Because we do not explicitly model supply-side responses to the standards, the welfare estimates do not include the effects of standards on manufacturer profits. Nonetheless, we observe that marginally tightening standards affects vehicle quality, which has substantial effects on consumer welfare.

3.7 Conclusions

In this paper, we have investigated the effects of regulating product attributes on other attributes and social welfare, focusing on the European passenger vehicle carbon dioxide emissions standards. We used a static model of a differentiated product market to derive two general results. First, regulating one product attribute may affect a wide range of other attributes. Whereas the

[14]As calculated above, changes in quality, performance, weight, and price offset 26 percent of the combined fuel cost and emissions benefits assuming that the on-road fuel consumption reduction is the same as the tested fuel consumption reduction. If the on-road reductions have been half as large as the tested reduction, the fuel cost savings and social value of GHG reductions would be (93.15 + 7.39)/2 = 50.27. Therefore, the changes in quality, performance, weight, and price offset 52 (=100*26.44/50.27) percent of the fuel cost savings and value of GHG reductions.

literature on passenger vehicle fuel economy regulation has considered attributes that are technologically related to fuel economy, such as horsepower, we showed that many other attributes may be affected because of trade-offs in the product design process and demand correlations across attributes.

Second, we showed that in an imperfectly competitive market, firms can under or over provide attributes. Therefore, regulating one attribute could increase welfare by causing firms to increase other attributes. Because the consumer welfare effects of regulation depend on changes in all product attributes, estimating welfare effects of regulations requires accounting for all these changes.

The remainder of the paper focuses on European carbon dioxide emissions standards for passenger vehicles. A major challenge to welfare analysis of the standards is that many product attributes that consumers value are unobserved, such as seating comfort. To address this challenge, we defined the residual quality of the vehicle as the consumer WTP for the vehicle excluding fuel costs, performance, and size. We estimated quality and willingness to pay for other attributes using a nested logit demand model, and we found that the standards have substantially reduced quality. In particular, the attribute changes offset at least 26 percent of the fuel cost and greenhouse gas benefits of the standards. Future work may explore the manufacturer response further, such as the extent to which market segmentation causes manufacturers to under-provide attributes (Fischer 2010 and Houde and Spurlock 2015). Future work may also determine whether demand or supply-side considerations explain the results.

For context, there is an extensive literature on two inefficiencies of the standards: rebound and vintage differentiated regulation (e.g., Jacobsen and Van Benthem 2015). The rebound effect refers to the increase in driving caused by the fact that the standards reduce per-mile fuel costs, which undermines some of the greenhouse gas and fuel consumption benefits. Moreover, because the standards apply to new but not existing vehicles on the road, the standards are a form of vintage differentiated regulation and can delay scrappage of older and higher-emitting vehicles. The estimated welfare effects of attribute changes are comparable to the magnitude of the rebound or scrappage effects reported in the literature. Future research could investigate the underlying sources of quality changes or consider whether standards in other countries have affected quality.

Appendix A: Appendix Chapter 1

A.1 Timing of regulations

Figure A.1: Timing of Regulations

Year-quarter	Beijing	Shanghai	Guangzhou	Tianjin	Hangzhou	Shenzhen
Allocation system:						
non-NEVs	Lottery	Auction	Lottery & auction	Lottery & auction	Lottery & auction	Lottery & auction
NEVs	Lottery	Free	Lottery	Lottery	Free	Lottery
Timing of regulatory action:						
1986		Allocation start				
.						
.						
.						
2011q1	Allocation start					
.						
.						
.						
2012q3			Allocation start			
.						
.						
.						
2013q1		Free NEV-license pilot				
2013q2						
2013q3						
2013q4						
2014q1	Lottery for NEV-license start	Free NEV-license start		Allocation start		
2014q2					Allocation start	
2014q3						
2014q4						
2015q1						Allocation start
2015q2						
.						
.						
.						
2017q4						

A.2 Zero market shares

In this part, I explain the methods to deal with the zero market shares in detail. I follow the method by Li (2016) closely. I assume the sale of each vehicle in each city by quarter K_{jmt} is a draw from a binomial distribution with N_{mt} trials and purchase probability s^0_{jmt}. Where the subscript m represents the city, the subscript t represents the year-quarter, and the subscript j represents the vehicle. N_{mt} is the total vehicle sales in a city by quarter. I assume the purchase probabilities s^0_{jmt} are drawn from a Beta prior distribution with hyperparameters λ_{1jmt} and λ_{2jmt}.

$$K_{jmt} \sim Binomial(N_{mt}, s^0_{jmt}) \tag{A.1}$$

$$s^0_{jmt} \sim Beta(\lambda_{1jmt}, \lambda_{2jmt}) \tag{A.2}$$

Therefore, the posterior distribution of the purchase probabilities s_{jmt} is also a Beta distribution:

$$s_{jmt} \sim Beta(\lambda_{1jmt} + K_{jmt}, \lambda_{1jmt} + N_{mt} - K_{jmt}) \tag{A.3}$$

The posterior mean is given by:

$$\hat{s}_{jmt} = \frac{\lambda_{1jmt} + K_{jmt}}{N_{mt} + \lambda_{1jmt} + \lambda_{2jmt}} \tag{A.4}$$

For each city m, I first construct a similar city group Θ_m which includes 15 cities that have the closest income per capita and population size to the city. Then, for each vehicle j in city m in year-quarter t, I use the sales of the same vehicle in its similar city group (Θ_m) at the same time to estimate the beta-binomial model in equation A.3. The hyperparameters λ_{1jmt} and λ_{2jmt} are estimated by maximizing the following likelihood function:

$$L(K_{jlt}, l \in \Theta_m | \lambda_{1jmt}, \lambda_{2jmt}) = \prod_{l \in \Theta_m} \binom{K_{jlt}}{N_{lt}} \frac{\Gamma(\lambda_{1jmt} + \lambda_{2jmt})\Gamma(\lambda_{1jmt} + K_{jlt})\Gamma(N_{lt} - K_{jlt} + \lambda_{2jmt})}{\Gamma(\lambda_{1jmt})\Gamma(\lambda_{2jmt})\Gamma(\lambda_{1jmt} + \lambda_{2jmt} + N_{lt})} \tag{A.5}$$

After estimating the above MLE, I obtain a pair of hyperparameters $\hat{\lambda}_{1jmt}$ and $\hat{\lambda}_{2jmt}$ for each vehicle j in city m in year-quarter t. Then I construct the posterior mean estimate of the purchase probabilities as $\hat{s}_{jmt} = \frac{\hat{\lambda}_{1jmt}+K_{jmt}}{N_{mt}+\hat{\lambda}_{1jmt}+\hat{\lambda}_{2jmt}}$.

The third part in Table A.1 summarizes the observed market shares and the imputed market shares. The means of the observed and imputed market shares are very similar, 0.001064 and 0.001068, respectively.

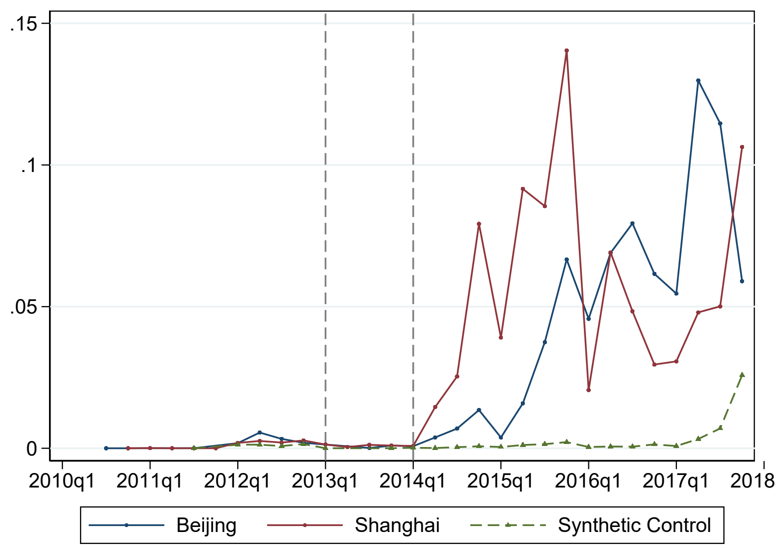
Table A.1: Market Shares of NEVs and non-NEVs

	Mean	Std. Dev.	Min	Max	5%	25%	50%	75%	95%	N	Share of zeroes	Unique vehicles
							Non-NEVs					
Total	135.73	247.05	1	4920	1	11	45	150	570	79,408	0.00	1347
2010	230.58	370.53	1	4591	4	31	95	262.5	934.5	5,000	0.00	336
2011	113.43	178.34	1	2352	1	15	47	138	435	7,600	0.00	504
2012	134.26	228.60	1	3383	1	13	47	153	547.5	8,420	0.00	559
2013	121.60	218.37	1	3310	1	9	38	135	526	9,588	0.00	638
2014	121.09	215.40	1	2513	1	9	40	137	527	10,416	0.00	705
2015	115.46	217.75	1	3280	1	8	37	120	504	11,536	0.00	779
2016	160.47	287.73	1	3348	1	11	51	178	697.5	13,220	0.00	898
2017	128.59	246.86	1	4920	1	10	42	136	542	13,628	0.00	890
							NEVs					
Total	129.67	442.86	0	4837	0	0	2	33	713	1,648	0.40	49
2011	1.13	1.25	0	3	0	0	1	1	3	8	0.38	1
2012	36.13	40.13	0	131	0	0	27	53	121	52	0.35	4
2013	16.17	25.35	0	82	0	0	1	11	71	52	0.40	4
2014	74.84	378.28	0	4046	0	0	0.5	15.5	209.5	140	0.50	11
2015	137.30	562.52	0	4837	0	0	2	26	581	312	0.39	22
2016	158.66	467.90	0	3973	0	0	1	33	1124	452	0.46	33
2017	136.88	405.27	0	3925	0	0	3	44	745	632	0.34	44
Observed market share	0.0011	0.0041	0	0.063	0	0	0.000018	0.00029	0.0059	1648	0.40	49
Posterior market share	0.0011	0.0041	3.47E-07	0.063	4.47E-06	9.75E-06	0.000018	0.00029	0.0059	1648	0.00	49

A.3 More results from the reduced-form estimation

A.3.1 Trends in Electric vehicle sales

Figure A.2: Trends in the Electric Vehicle Market Shares: Treated Cities vs. Synthetic Control



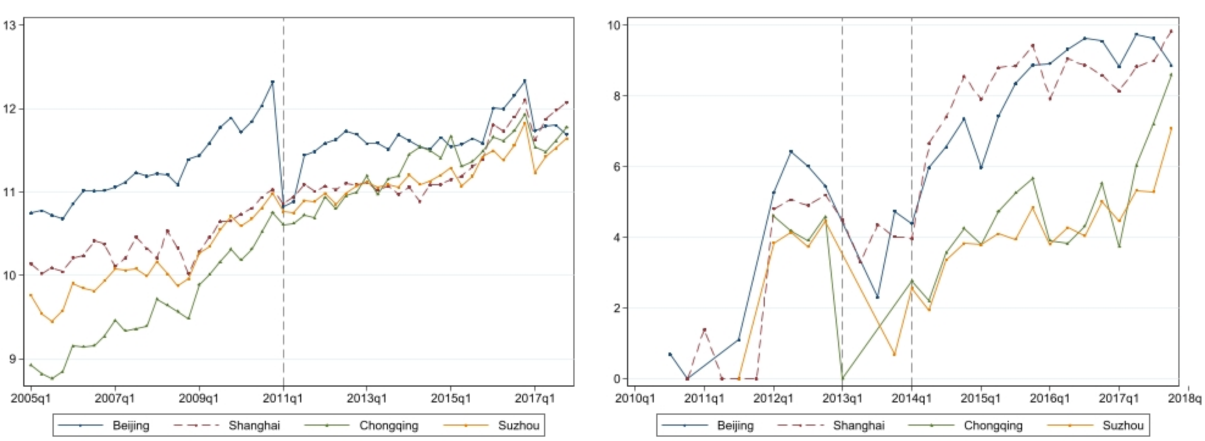
Notes: The dependent variable is the market share of EVs in each city and year-quarter. The dashed vertical lines represent the removal of EV license auctions in Shanghai in 2013 and the separation of EV license lotteries and non-EV license lotteries in Beijing in 2014.

A.3.2 Synthetic control matching based on other outcome variables

Figure A.3: Trends in Other Variables: Treated Cities vs. Synthetic Control

Notes: This figure shows the trends in sales-weighted vehicle attributes for treated cities and synthetic control group.

Figure A.4: Trends in Non-NEV and NEV Sales



Notes: This figure shows the trends in log of vehicle sales in Beijing, Shanghai, Chongqing, and Suzhou. The left graph is for non-NEV sale and the right graph is for NEV sale. The dashed lines in the graph represents the time when the policy changed (Jan 2011, 2013 and 2014).

A.3.3 Common trend test

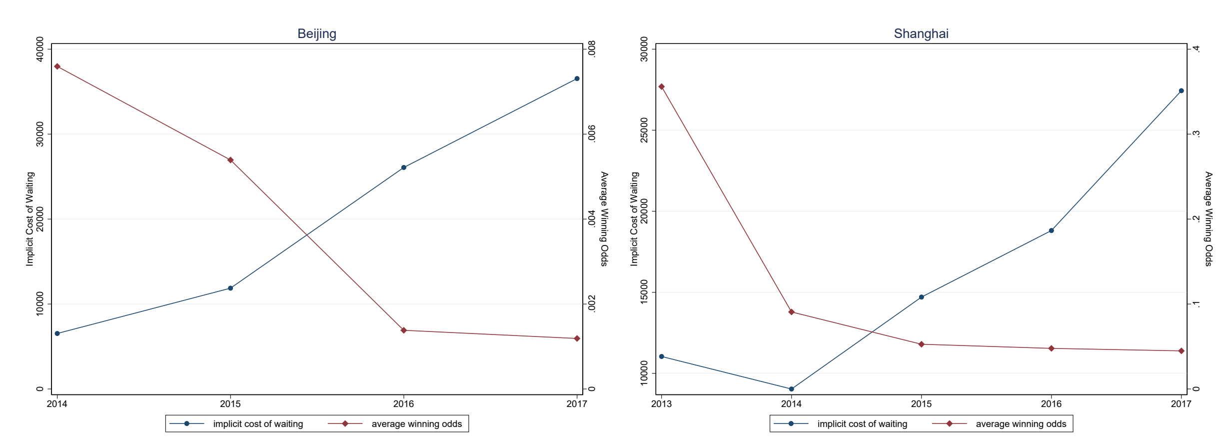
Table A.2: Common Trend Test for Vehicle Sales

	(1)	(2)
Beijing x 2006	-0.1785	-0.2103
	(0.1881)	(0.2194)
Beijing x 2007	-0.0306	-0.1312
	(0.1564)	(0.1876)
Beijing x 2008	-0.0507	-0.1778
	(0.1568)	(0.1905)
Beijing x 2009	-0.0036	-0.2113
	(0.1852)	(0.2022)
Beijing x 2010	-0.0035	-0.2388
	(0.2183)	(0.2587)
City fixed effects	X	X
Year-quarter fixed effects	X	X
Specific time trend for Shanghai		X
Number of observations	96	96
Adjusted R-squared	0.9607	0.9748

Notes: This regression uses data in the pre-policy period only (2005-2010). Dependent variable is log of vehicle sales per household by city and year-quarter. All regerssions include city and year-quarter fixed effects. Columns 2 allows a specific time trend for Shanghai since all data belongs to the post-treatment period of Shanghai. Standard errors are clustered by city and year.

A.4 Trends in average winning odds and estimated implicit cost of waiting

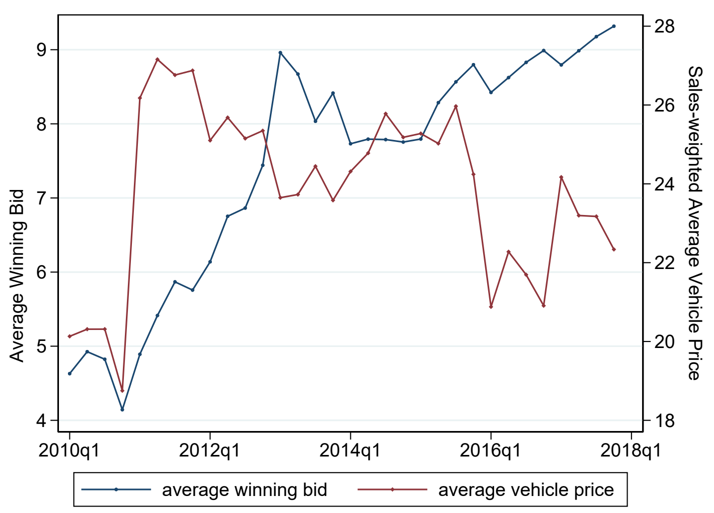
Figure A.5: Trends in the Average Winning Odds and the Estimated Implicit Costs of Waiting



Notes: The implicit costs are in 1 Yuan.

A.5 Trends in the average winning bid and the average vehicle price

Figure A.6: Trends in the Average Winning Bids and the Sales-weighted Average Vehicle Price



Notes: The average winning bids and the average vehicle price are in 10,000 Yuan.

A.6 More results from counterfactual simulations

Table A.3: Counterfactual 1, Time-varying Implicit Cost: Impact on Vehicle Sales in Beijing

	Separate Systems				One System			
	Total	Non-NEV	NEV	NEV Share	Total	Non-NEV	NEV	NEV Share
2014	417,527	414,816	2,711	0.006	417,527	417,150	377	0.001
2015	422,323	408,892	13,431	0.032	422,323	420,785	1,538	0.004
2016	730,686	682,995	47,691	0.065	730,686	716,904	13,782	0.019
2017	497,452	451,862	45,590	0.092	497,452	486,692	10,760	0.022

Notes: The counterfactual simulations are based on demand estimation results from the bottom panel of Table1.5, where the implicit costs are assumed to be varying across years.

Table A.4: Counterfactual 1, Time-varying Implicit Cost: Welfare in Beijing

	2014	2015	2016	2017
CV (Yuan)	-4	-36	-314	-857
ΔCS (billion Yuan)	-0.001	0.00	-0.04	-0.10
15-year horizon:				
External cost of separate lotteries (billion Yuan)	5.91	5.82	9.31	6.44
External cost of one lottery (billion Yuan)	5.94	5.95	9.65	6.82
Δ External cost (billion Yuan)	0.03	0.13	0.35	0.38
Δ Net social welfare (billion Yuan)	-0.03	-0.13	-0.38	-0.48
Δ Net social welfare / Δ NEV sales (Yuan)	10,946	10,981	10,251	10,849
10-year horizon:				
External cost of separate lotteries (billion Yuan)	4.40	4.33	6.92	4.79
External cost of one lottery (billion Yuan)	4.42	4.43	7.18	5.07
Δ External cost (billion Yuan)	0.02	0.10	0.26	0.28
Δ Net social welfare (billion Yuan)	-0.02	-0.10	-0.30	-0.38
Δ Net social welfare / Δ NEV sales (Yuan)	8,143	8,169	7,626	8,071

Notes: The counterfactual simulations are based on demand estimation results from the bottom panel of Table1.5, where the implicit costs are assumed to be varying across years. All monetary variables are in 2017 Yuan. CV is the compensating variation from the original condition to the counterfactual condition. I assume the annual vehicle miles traveled is 16,350 km in Beijing and 18,000 km in Shanghai. The discount rate is 5 percent. The externalities include CO_2 emissions and local pollution, and the external cost is 1.01 Yuan per liter of gasoline (in 2017 Yuan). Total change in consumer surplus equals the sum of CS change in current buyers and CS change in new buyers. Net social welfare equals the consumer surplus minus the external cost.

Table A.5: Counterfactual 2, Time-varying Implicit Cost: Impact on Vehicle Sales

	Lottery/Auction		No Allocations					
			No Subsidy or Tax		NEV Subsidy and Non-NEV Tax			
	Total	NEV Share	Total	NEV Share	NEV Share	Subsidy Rate	Tax Rate	Total Subsidy or Tax (billion Yuan)
				Beijing				
2014	417,527	0.006	940,952	0.001	0.006	0.25	0.001	0.34
2015	422,323	0.032	1,003,305	0.004	0.032	0.28	0.004	1.25
2016	730,686	0.065	1,090,350	0.016	0.065	0.19	0.008	2.11
2017	497,452	0.092	1,168,578	0.020	0.092	0.21	0.013	4.20
				Shanghai				
2013	244,602	0.001	483,090	0.0003	0.001	0.39	0.0003	0.03
2014	241,791	0.032	530,829	0.011	0.032	0.39	0.010	1.16
2015	305,723	0.094	668,241	0.032	0.094	0.39	0.029	4.16
2016	574,187	0.041	741,956	0.013	0.041	0.39	0.022	3.02
2017	572,943	0.063	781,119	0.017	0.063	0.40	0.033	5.00

Notes: The counterfactual simulations are based on demand estimation results from the bottom panel of Table1.5, where the implicit costs are assumed to be varying across years.

Table A.6: Counterfactual 2, Time-varying Implicit Cost, Beijing: Welfare

	2014	2015	2016	2017
CV: Current buyers (Yuan)	4,684	9,367	17,040	32,874
ΔCS: Current buyers (billion Yuan)	0.57	1.13	2.01	3.98
CV: New buyers (Yuan)	50,203	54,401	58,037	63,211
ΔCS: New buyers (billion Yuan)	26.28	31.61	20.87	42.42
Total ΔCS (billion Yuan)	26.85	32.73	22.88	46.40
15-year horizon:				
Δ External cost (billion Yuan)	32.66	36.04	21.26	40.73
Δ Net social welfare (billion Yuan)	-5.81	-3.31	1.62	5.67
10-year horizon:				
Δ External cost (billion Yuan)	24.30	26.81	15.82	30.30
Δ Net social welfare (billion Yuan)	2.55	5.92	7.06	16.10

Notes: The counterfactual simulations are based on demand estimation results from the bottom panel of Table1.5, where the implicit costs are assumed to be varying across years. All monetary variables are in 2017 Yuan. CV is the compensating variation from the original condition to the counterfactual condition. I assume the annual vehicle miles traveled is 16,350 km in Beijing and 18,000 km in Shanghai. The discount rate is 5 percent. The externalities include CO2 emissions, local pollution, congestion, and traffic accidents. The external cost is 4.33 Yuan per liter of gasoline (in 2017 terms), of which the external cost of CO2 emissions and local pollution account for 23 percent, or 1.01 Yuan/liter. Total change in consumer surplus equals the sum of CS change in current buyers and CS change in new buyers. Net social welfare equals the consumer surplus minus the external cost.

Table A.7: Counterfactual 2, Time-varying Implicit Cost, Shanghai: Welfare

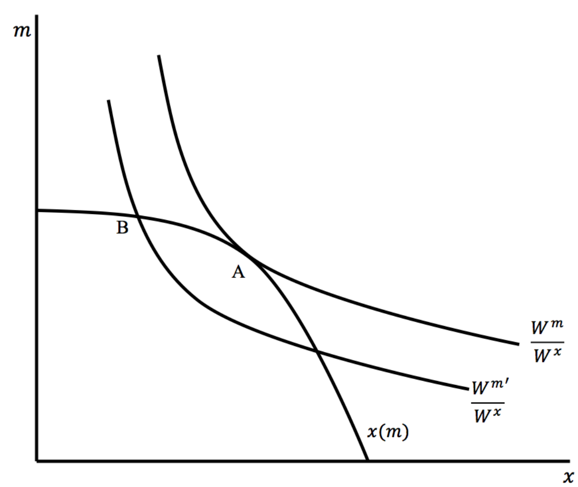
	2013	2014	2015	2016	2017
CV: Current buyers (Yuan)	99,613	89,032	102,271	111,561	129,718
ΔCS: Current buyers (billion Yuan)	10.98	8.79	12.39	17.34	21.89
CV: New buyers (Yuan)	38,435	41,608	48,591	54,797	61,167
ΔCS: New buyers (billion Yuan)	9.17	12.03	17.62	9.19	12.73
Total ΔCS (billion Yuan)	20.14	20.82	30.00	26.54	34.62
Average bidding price (Yuan)	85,110	77,674	83,779	87,259	90,696
ΔAuction revenue (billion Yuan)	-9.38	-7.67	-10.15	-13.57	-15.30
15-year horizon:					
Δ External cost (billion Yuan)	15.19	18.57	22.76	10.28	12.87
Δ Net social welfare + ΔAuction revenue (billion Yuan)	-4.43	-5.42	-2.91	2.69	6.45
10-year horizon:					
Δ External cost (billion Yuan)	11.30	13.82	16.93	7.65	9.57
Δ Net social welfare + ΔAuction revenue (billion Yuan)	-0.54	-0.67	2.92	5.33	9.74

Notes: The counterfactual simulations are based on demand estimation results from the bottom panel of Table1.5, where the implicit costs are assumed to be varying across years. All monetary variables are in 2017 Yuan. CV is the compensating variation from the original condition to the counterfactual condition. I assume the annual vehicle miles traveled is 16,350 km in Beijing and 18,000 km in Shanghai. The discount rate is 5 percent. The externalities include CO_2 emissions, local pollution, congestion, and traffic accidents. The external cost is 4.33 Yuan per liter of gasoline (in 2017 terms), of which the external cost of CO_2 emissions and local pollution account for 23 percent, or 1.01 Yuan/liter. Total change in consumer surplus equals the sum of CS change in current buyers and CS change in new buyers. Net social welfare equals the consumer surplus minus the external cost.

Appendix B: Appendix Chapter 3

B.1 Firm's profit maximization

Figure B.1: Firm's Profit Maximization



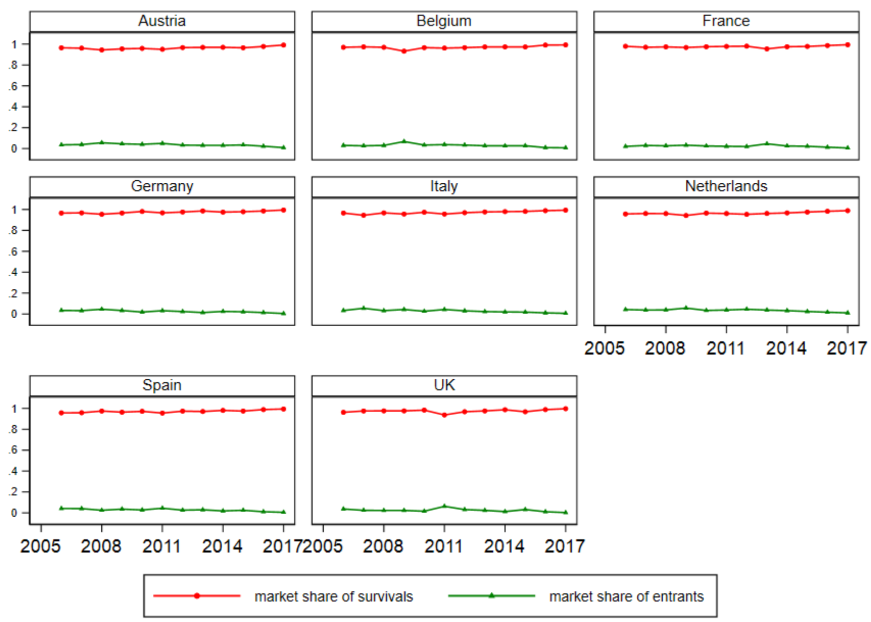
Notes: The vertical axis represents the attribute m_j that is subject to regulation, and the horizontal axis represents the attribute x_j that is linked technologically to the regulated attribute. The curve $x(m)$ represents the technological tradeoff function: $x_j - x_{j0} = x(m_j - m_{j0})$. The curve $\frac{W^m}{W^x}$ is the ratio of the marginal WTP for the two attributes. The point A shows the firm's profit maximization without regulation (equation 3.6). Point B shows the firm's profit maximization under regulation (equation 3.7).

B.2 Data construction

Our main data were obtained from IHS Markit. The data include registrations by month and vehicle, and we aggregated the data to country-year level for estimation. A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric) and drive type (front-, rear-, all-wheel).

In the data, the names of models, body type, fuel type, and drive type are sometimes inconsistent across countries and years. We harmonize these variables across countries and years. Figure B.2 shows the market shares of survivals and entrants after harmonizing the model names. Market shares of surviving vehicles are typically above 95 percent, and market shares of entering vehicles are typically less than 5 percent. Note that one of the demand specifications that we consider in the robustness analysis includes model by year fixed effects, which controls for changes in unobserved attributes due to entry and exit.

Figure B.2: Market Shares of Surviving and Entering Models



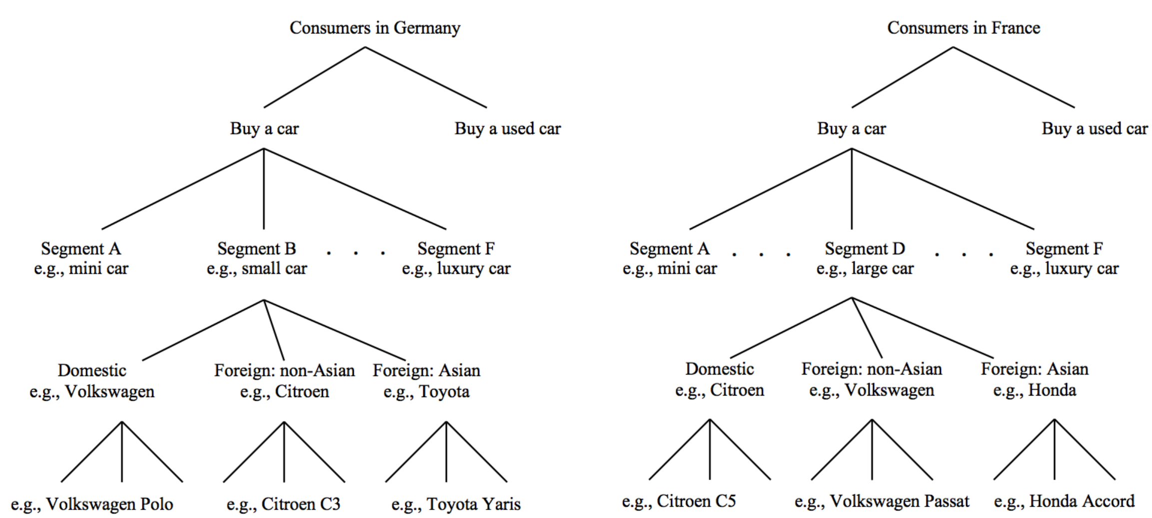
B.3 Home Bias

Table B.1: Home Bias in Vehicle Market Shares

Brand	Origin	Market share in France	Market share in Germany
Citroen	France	0.13	0.02
Renault	France	0.21	0.04
Peugeot	France	0.20	0.03
Volkswagen	Germany	0.08	0.20
Audi	Germany	0.04	0.10
BMW	Germany	0.03	0.09

B.4 Nested logit structure

Figure B.3: Nested Logit Structure of Vehicle Choice



B.5 Mean quality by vehicle attribute

Table B.2: Mean Quality by Vehicle Attribute

Fuel type	Mean	Number of engine cylinders	Mean	Body type	Mean
Diesel	57	$\leq$4	56	Convertible	60
Electric or plug-in hybrid	61	5/6	60	Coupe	59
Gasoline / hybrid	56	$\geq$7	71	Wagon	56
				Hatchback	57
				Sedan	54

Notes: The table reports the sales-weighted mean quality by the indicated attribute. Quality is divided by the negative of price coefficient and is measured in thousands of 2005 euros.

B.6 First-stage results

Table B.3: First-Stage Estimation Results for Preferred Nested Logit Model

	Price	Log share within segment-origin	Log origin share within segment
Sum length (same firm, different segments)	-3.00E-06***	-3.20E-07	-8.80E-07***
	(7.7e-07)	(4.1e-07)	(1.1e-07)
Sum length (different firm, same segment)	8.80E-06***	6.10E-06***	-3.90E-06***
	(2.2e-06)	(1.4e-06)	(4.3e-07)
Sum width (same firm, different segments)	-2.10E-06	-3.70E-07	-7.40E-08
	(2.3e-06)	(1.0e-06)	(3.4e-07)
Sum width (different firm, same segment)	-4.40E-05***	8.70E-06	1.30E-05***
	(7.8e-06)	(5.3e-06)	(1.9e-06)
Sum height (same firm, different segments)	9.40E-06***	6.40E-07	2.90E-06***
	(2.2e-06)	(1.0e-06)	(3.1e-07)
Sum height (different firm, same segment)	1.20E-05*	-2.00E-05***	-8.40E-06***
	(6.4e-06)	(4.9e-06)	(2.0e-06)
Sum engine cylinder (same firm, different segments)	1.20E-03***	2.40E-04*	-1.30E-05
	(2.5e-04)	(1.2e-04)	(3.5e-05)
Sum engine cylinder (different firm, same segment)	5.70E-03***	-3.50E-03***	1.90E-03***
	(1.5e-03)	(8.5e-04)	(4.5e-04)
Sum length (same firm, different origins)	-7.80E-06***	-6.10E-06***	4.10E-06***
	(2.2e-06)	(1.4e-06)	(4.0e-07)
Sum width (same firm, different origins)	4.60E-05***	-8.70E-06	-1.20E-05***
	(7.8e-06)	(5.3e-06)	(1.8e-06)
Sum height (same firm, different origins)	-1.90E-05***	2.10E-05***	8.30E-06***
	(6.2e-06)	(4.8e-06)	(2.0e-06)
Sum length (different firms, same origin)	-1.40E-06**	1.90E-06***	-4.50E-07***
	(5.8e-07)	(3.3e-07)	(1.6e-07)
Sum width (different firms, same origin)	-8.50E-06***	3.50E-06***	-8.40E-07**
	(1.8e-06)	(7.7e-07)	(3.8e-07)
Sum height (different firms, same origin)	1.30E-05***	-7.30E-06***	3.80E-07
	(1.6e-06)	(8.2e-07)	(4.2e-07)
Sum engine cylinders (same firm, different origins)	-5.60E-03***	3.20E-03***	-2.50E-03***
	(1.6e-03)	(8.5e-04)	(4.3e-04)
Sum engine cylinders (different firms, same origin)	7.10E-04***	-1.40E-03***	8.70E-04***
	(2.6e-04)	(1.2e-04)	(8.7e-05)

Table 10: *(Continued)*

	Price	Log share within segment-origin	Log origin share within segment
Tax (1,000 2005 euros)	4.00E-01***	-7.10E-02***	-7.00E-03***
	(7.8e-03)	(3.7e-03)	(6.7e-04)
Fuel cost (2005 euros/100 km)	-2.10E-01***	-2.60E-01***	-4.60E-03***
	(1.2e-02)	(7.6e-03)	(7.5e-04)
Log horsepower (hp)	1.00E+01***	-4.30E-01***	4.80E-02***
	(1.7e-01)	(6.9e-02)	(7.8e-03)
Log weight (tonnes)	3.00E+01***	-2.50E+00***	-6.90E-02*
	(7.0e-01)	(2.4e-01)	(3.7e-02)
Log size (m^3)	-2.60E+00***	8.30E+00***	5.30E-01***
	(6.5e-01)	(4.1e-01)	(9.0e-02)
Constant	4.10E+01***	-2.50E+01***	-1.60E+00***
	(1.6e+00)	(9.9e-01)	(2.1e-01)
First-stage summary			
F-test of excluded instruments for price		20.08	16.64
F-test of excluded instruments for within-origin share			51.1
F-test of excluded instruments for share of origin in segment			58.82
Number of observations	341,659	341,659	341,659

Notes: The table reports the first-stage estimation results for our preferred demand estimation (Column 1 in Table 3.2). The Sanderson-Windmeijer multivariate F-test of the excluded variables concerns about weak instruments bias and underidentification in the case of multiple endogenous regressors and clustered standard errors.

B.7 Clustered Standard Errors by Firm

Table B.4: Cluster Standard Errors by Firm

	(1)	(2)	(3)	(5)
Dependent Variable	Quality	Log (Horsepower/Weight)	Log Weight	Log Price
Stringency Variable	firm-level	firm-level	firm-level	firm-level
Period 2 x Stringency	-5.512***	1.854***	-0.085	0.087
	(1.592)	(0.600)	(0.437)	(0.058)
Period 3 x Stringency	-2.921	0.192	0.41	0.025
	(3.451)	(1.259)	(0.735)	(0.062)
Joint F—test	6.271	13.069	2.722	1.179
P Value	0.010	0.001	0.098	0.334
Number of Observations	339,065	345,033	345,033	359,445
Adjusted R-squared	0.816	0.967	0.986	0.992

Notes: Each column corresponds to the column in Table 3.4. The standard errors are clustered at firm level.

B.8 Demand: Alternative specifications

Because residual quality is derived from the demand model, we report a number of alternative demand model specifications in this appendix section. Appendix Table B.5 shows the main parameter estimates using alternative nesting structures. The two subsequent tables show that the estimated own-price elasticities and WTP are similar for the other nesting assumptions.

In Appendix Table B.8 we return to the preferred nesting structure from Table 3.2. Column 1 repeats the estimates from that model, and columns 2 through 4 include additional fixed effects for model trim and time, which account for potential unobserved factors at the trim level. The estimated own-price elasticities and WTP vary somewhat across these specifications.

The nested logit model, as with other discrete choice models derived from a linear utility model with an additive error term, can yield biased estimates of own-price elasticities because of implicit assumptions on the cross-vehicle variation of unobserved product attributes (Ackerberg and Rysman 2002; Berry and Pakes 2007). One approach to address this problem is to control for the number of products in the same segment and to control for the similarity of observed attributes across products. Column 5 of Appendix Table B.8 follows Houde and Spurlock (2015) and adds these two variables to the preferred model.

In our baseline demand estimation, we drop luxury cars whose prices are above the 99th percentile of the price distribution. To check the effect of dropping luxury cars, instead of dropping those luxury cars, we generate a dummy variable for them and include it in the demand estimation (see column 6 of Appendix Table B.8). The price coefficient is smaller than the baseline, which implies less elastic demand and a higher valuation ratio.

To address the possibility that WTP for fuel costs or weight varies over time, we reestimate the consumer demand model and allow the preference parameters to vary each year (see column 7, which reports the mean across years). The average of the preference coefficients is similar to our baseline estimates.

Appendix Figure B.5 plots the quality index by year for different demand estimations. The quality index estimated by the alternative models has similar patterns to the preferred estimation. Because the estimated preference parameters vary across the demand specifications reported in the appendix, in robustness analysis below we report results using quality estimated from the alternative specifications.

Table B.5: Alternative Nesting Structures

	Dependent variable is log market share			
	(1)	(2)	(3)	(4)
Nests	Segment and origin	Segment	Origin	Segment by origin
Price (1,000 2005 euros)	-0.088***	-0.106***	-0.079***	-0.147***
	(0.015)	(0.018)	(0.014)	(0.025)
Log within-segment share		0.743***		
		(0.023)		
Log within-origin share			0.818***	
			(0.020)	
Log within segment-origin share	0.774***			0.608***
	(0.018)			(0.019)
Log share of origin within segment	0.498***			
	(0.029)			
Tax (1,000 2005 euros)	-0.006	0.001	0.011**	0.006
	(0.006)	(0.007)	(0.005)	(0.009)
Fuel cost (2005 euros/100 km)	-0.086***	-0.097***	-0.068***	-0.144***
	(0.006)	(0.008)	(0.007)	(0.008)
Log horsepower	0.909***	1.062***	0.774***	1.453***
	(0.155)	(0.186)	(0.145)	(0.257)
Log weight (tonnes)	2.176***	2.62***	1.813***	3.428***
	(0.436)	(0.521)	(0.393)	(0.710)
Log size (m^3)	1.8***	1.869***	1.795***	3.28***
	(0.202)	(0.233)	(0.190)	(0.237)
Number of observations	341,659	341,659	341,659	341,659

Notes: The table reports estimation results for different nesting structures. Column 1 is repeated from column 3 in Table 3.2. Column 2 assumes a single nest corresponding to market segments, column 3 assumes a single nest corresponding to origin, and column 4 assumes a single nest corresponding to market segment by origin. Columns 2 through 4 are otherwise identical to column 1. Standard errors are in parentheses, clustered by model and trim.

Table B.6: Estimated Own-Price Elasticities: Alternative Nesting Structures

	(1) Segment and origin	(2) Segment	(3) Origin	(4) Segment by origin
Median	-7.51	-7.94	-8.37	-7.21
Mean	-7.46	-7.90	-8.33	-7.16
Standard deviation	0.88	0.92	0.97	0.84
5th percentile	-9.02	-9.53	-10.04	-8.65
95th percentile	-5.87	-6.23	-6.55	-5.63

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table B.5. The calculations are otherwise identical to those in Table 3.3.

Table B.7: Willingness to Pay and Valuation Ratio: Alternative Nesting Structures

	(1) Segment and origin	(2) Segment	(3) Origin	(4) Segment by origin
Willingness to pay for 1 percent change (2005 euros)				
Fuel cost decrease	62	58	55	62
Horsepower/weight increase	103	100	98	99
Weight increase	247	247	229	233
Size increase	205	176	227	223
Valuation ratio				
15 years, r = 0.06	0.67	0.63	0.59	0.67
15 years, r = 0.03	0.56	0.52	0.49	0.56
10 years, r = 0.06	0.88	0.83	0.78	0.88

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table B.5. The calculations are otherwise identical to those in Table 3.3.

Table B.8: Demand: Alternative Specifications

	Dependent variable is log market share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price (1,000 2005 euros)	-0.088***	-0.116***	-0.072***	-0.122***	-0.095***	-0.043***	-0.087***	-0.088***
	(0.015)	(0.031)	(0.023)	(0.019)	(0.017)	(0.013)	(0.016)	(0.004)
Log within segment-origin share	0.774***	0.767***	0.762***	0.773***	0.582***	0.744***	0.763***	0.774***
	(0.018)	(0.024)	(0.019)	(0.019)	(0.029)	(0.021)	(0.019)	(0.005)
Log share of origin within segment	0.498***	0.516***	0.507***	0.492***	0.515***	0.474***	0.484***	0.498***
	(0.029)	(0.034)	(0.027)	(0.032)	(0.036)	(0.032)	(0.030)	(0.009)
Tax (1,000 2005 euros)	-0.006	-0.002	-0.016*	0.007	-0.014**	-0.02***	-0.007	-0.006***
	(0.006)	(0.011)	(0.009)	(0.007)	(0.006)	(0.005)	(0.006)	(0.001)
Fuel cost (2005 euros/100 km)	-0.086***	-0.096***	-0.087***	-0.089***	-0.134***	-0.08***	-0.083***	-0.086***
	(0.006)	(0.009)	(0.007)	(0.006)	(0.010)	(0.006)	(0.007)	(0.002)
Log horsepower/weight	0.909***	0.915***	0.577***	1.18***	0.914***	0.456***	0.819***	0.909***
	(0.155)	(0.240)	(0.188)	(0.183)	(0.168)	(0.134)	(0.161)	(0.037)
Log weight (tonnes)	2.176***	2.852***	1.505**	3.498***	2.067***	0.812**	1.963***	2.176***
	(0.436)	(0.857)	(0.609)	(0.576)	(0.440)	(0.347)	(0.463)	(0.107)
Log size (m^3)	1.8***	2.003***	1.952***	1.977***	3.409***	2.163***	1.940***	1.8***
	(0.202)	(0.268)	(0.215)	(0.220)	(0.297)	(0.213)	(0.256)	(0.062)
Log number in nest					-0.189***			
					(0.029)			
Within-nest distance across attributes					-0.04***			
					(0.013)			
Luxury						0.558***		
						(0.161)		
Model—body type fixed effect	X		X	X	X	X	X	X
Model—body type—trim fixed effect		X						
Trim fixed effect			X					
Model—year fixed effect				X				
Segment—year fixed effect	X	X	X	X	X	X	X	X
Number of observations	341,659	339,821	341,286	341,378	341,655	356,479	341,659	341,659

Notes: All regressions include country by year fixed effects. Column 1 repeats the specification in column 3 of Table 3.2. Column 2 includes model by body type by trim fixed effects. Column 3 includes model by body type fixed effects and trim fixed effects. Column 4 includes model by body type and model by year fixed effects. Column 5 includes the log number of within-nest vehicles and the distance variable from Houde and Spurlock (2015). Column 6 includes a dummy variable for luxury cars. Column 7 allows the preference parameters to vary across time, and preference parameters shown in column 7 are the averages across time. Columns 2 through 8 are otherwise identical to column 1. Standard errors are in parentheses, clustered by model and trim except for column 8, which reports standard errors that are robust to heteroskedasticity.

Table B.9: Estimated Own-Price Elasticities: Other Demand Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median	-7.51	-9.57	-5.78	-10.28	-4.38	-7.51	-3.28	-7.04
Mean	-7.46	-9.51	-5.75	-10.21	-4.35	-7.46	-3.29	-7.00
Standard deviation	0.88	1.12	0.68	1.20	0.51	0.88	0.43	0.82
5th percentile	-9.02	-11.49	-6.95	-12.34	-5.25	-9.02	-4.13	-8.46
95th percentile	-5.87	-7.48	-4.52	-8.04	-3.43	-5.87	-2.60	-5.51

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table B.8. The calculations are otherwise identical to those in Table 3.3.

Table B.10: Willingness to Pay and Valuation Ratio: Other Demand Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Willingness to pay for 1 percent change (2005 euros)				
Fuel cost decrease	62	53	77	46	90	120	61	62
Horsepower/weight increase	103	79	80	97	96	106	94	103
Weight increase	247	246	209	287	218	189	226	247
Size increase	205	173	271	162	359	503	223	205
				Valuation ratio				
15 years, r = 0.06	0.67	0.57	0.83	0.50	0.96	1.28	0.65	0.67
15 years, r = 0.03	0.56	0.47	0.69	0.42	0.81	1.07	0.55	0.56
10 years, r = 0.06	0.88	0.75	1.09	0.66	1.27	1.69	0.86	0.88

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table B.8. The calculations are otherwise identical to those in Table 3.3.

Table B.11: Demand: Different Fixed Effects

	Dependent variable is log market share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price (1,000 2005 euros)	-0.088***	-0.116***	-0.122***	-0.120***	-0.193***	-0.065***	-0.124***	-0.092***
	(0.015)	(0.031)	(0.032)	(0.032)	(0.033)	(0.025)	(0.019)	(0.028)
Log within segment-origin share	0.774***	0.767***	0.762***	0.766***	0.816***	0.768***	0.774***	0.768***
	(0.018)	(0.024)	(0.024)	(0.025)	(0.024)	(0.020)	(0.019)	(0.021)
Log share of origin within segment	0.498***	0.516***	0.502***	0.500***	0.536***	0.519***	0.491***	0.507***
	(0.029)	(0.034)	(0.035)	(0.038)	(0.038)	(0.029)	(0.032)	(0.031)
Tax (1,000 2005 euros)	-0.006	-0.002	0	0.005	0.022**	-0.018*	0.007	-0.008
	(0.006)	(0.011)	(0.011)	(0.012)	(0.010)	(0.010)	(0.007)	(0.011)
Fuel cost (2005 euros/100 km)	-0.086***	-0.096***	-0.098***	-0.057***	-0.088***	-0.084***	-0.089***	-0.087***
	(0.006)	(0.009)	(0.009)	(0.013)	(0.008)	(0.007)	(0.006)	(0.008)
Log horsepower/weight	0.909***	0.915***	0.956***	0.989***	1.488***	0.488**	1.196***	0.661***
	(0.155)	(0.240)	(0.245)	(0.262)	(0.225)	(0.202)	(0.181)	(0.217)
Log weight (tonnes)	2.176***	2.852***	2.995***	2.517***	1.893***	1.333*	3.599***	2.228***
	(0.436)	(0.857)	(0.875)	(0.657)	(0.262)	(0.689)	(0.581)	(0.811)
Log size (m^3)	1.800***	2.003***	2.025***	2.219***	1.940***	1.852***	1.890***	1.879***
	(0.202)	(0.268)	(0.272)	(0.286)	(0.267)	(0.210)	(0.219)	(0.223)
Fixed Effects:								
Model—body type	X					X	X	X
Segment—year	X	X	X	X	X	X	X	X
Model—body type—trim		X						
Model—body type—trim—segment			X					
Model—body type—trim—segment—fuel type				X				
Vehicle					X			
Model—year								X
Body type—year								X
Trim—year						X		X
Model—body type							X	
Number of observations	341,659	339,821	339,744	338,256	326,775	337,494	341,171	337,221

Notes: All regressions include country by year fixed effects. Column 1 repeats the specification in column 3 of Table 3.2. Column 2 - 6 include different fixed effects. Standard errors are in parentheses, clustered by model and trim.

Table B.12: Estimated Own-price Elasticities: Different Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median	-7.51	-9.57	-9.86	-9.81	-20.08	-5.36	-10.52	-7.63
Mean	-7.46	-9.51	-9.80	-9.75	-19.95	-5.33	-10.45	-7.58
Standard deviation	0.88	1.12	1.15	1.15	2.35	0.63	1.23	0.89
5th percentile	-9.02	-11.49	-11.85	-11.78	-24.12	-6.44	-12.63	-9.16
95th percentile	-5.87	-7.48	-7.71	-7.67	-15.70	-4.19	-8.22	-5.97

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table B.11. The calculations are otherwise identical to those in Table 3.3.

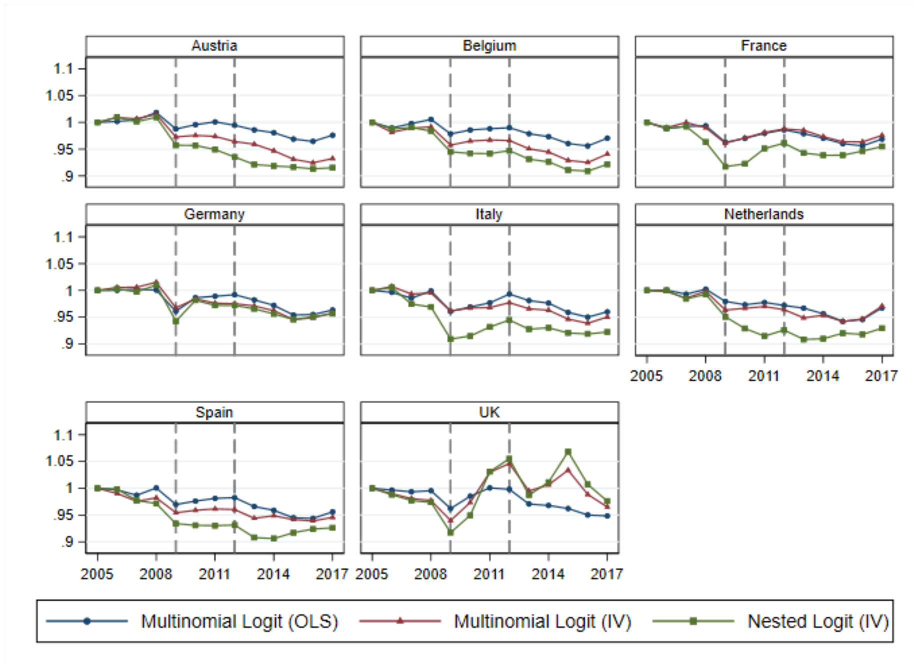
Table B.13: Willingness to Pay and Valuation Ratio: Different Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Willingness to pay for 1 percent change (2005 euros)								
Fuel cost decrease	62	53	51	30	29	82	46	60
Horsepower/weight increase	103	79	78	82	77	75	96	72
Weight increase	247	246	245	210	98	205	290	242
Size increase	205	173	166	185	101	285	152	204
Valuation ratio								
15 years, r = 0.06	0.67	0.57	0.55	0.32	0.31	0.88	0.49	0.65
15 years, r = 0.03	0.56	0.47	0.46	0.27	0.26	0.74	0.41	0.54
10 years, r = 0.06	0.88	0.75	0.73	0.43	0.41	1.17	0.65	0.85

Notes: Each column reports results using preference parameter estimates from the corresponding column in Table B.11. The calculations are otherwise identical to those in Table 3.3.

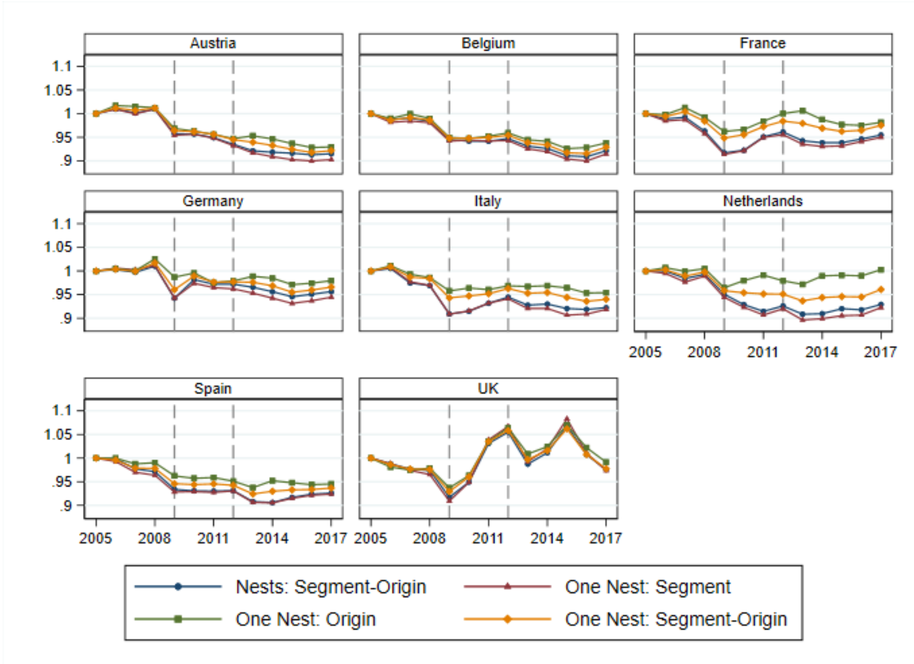
B.9 Trend of quality

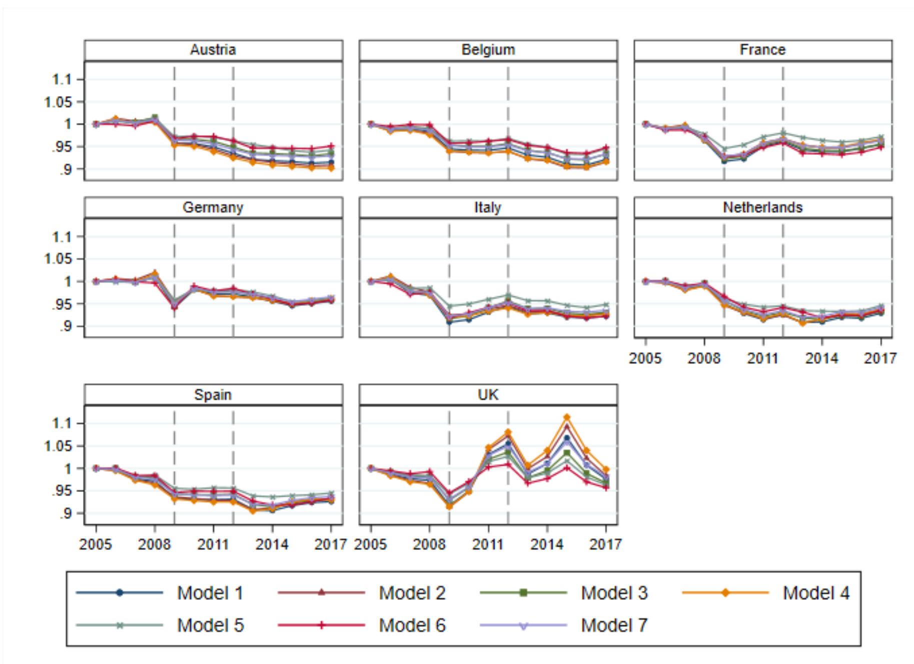
Figure B.4: Mean Quality by Country and Year (2005 = 1)



Notes: The The figure plots the estimated model-weighted quality index by country and year, using estimates from the indicated demand model (see Table 3.2). The country by year fixed effects are added to the quality residuals. The quality is divided by the negative of price coefficient and normalized to equal one in 2005. Vertical dashed lines indicate the cutoffs for the three policy periods.

Figure B.5: Mean Quality by Year (2005 = 1): Alternative Demand Models





Notes: The figure plots the estimated quality index by year, where quality is computed similarly to Figure B.4. The top panel uses estimates from Table B.5, and the lower panel uses estimates from Table B.8.

B.10 Test for Common Pre-Policy Trends

Table B.14: Tests for Common Pre-Policy Trends

	(1)	(2)	(3)	(5)
Dependent Variable	Quality	Log (Horsepower/Weight)	Log Weight	Log Price
Stringency Variable	firm-level	firm-level	firm-level	firm-level
Stringency x Trend	-0.107	0.769***	0.188*	0.016
	(0.679)	(0.174)	(0.109)	(0.018)
Number of Observations	99,993	100,287	100,287	101,947
Adjusted R-square	0.842	0.975	0.986	0.994

Notes: The table use observations from 2005 through 2008. The stringency variable is interacted with a linear time trend, and the regressions are otherwise identical to those in Table 3.4. The number of observations varies across columns because of missing vehicle attributes.

B.11 Quality regressions: Alternative specifications

This section discusses potential bias caused by omitted variables, outliers, and sample construction. The main threat to identification would be an unobserved demand shock correlated with the stringency variable in the cross section and that varies over time. We take several approaches to modify the estimation equation and control for such omitted variables. First, a particular concern is that the 2008 economic recession may bias our results if the recession caused demand shocks correlated with a firm's stringency. If this were the case, we would observe a strong negative correlation between a firm's stringency and the change in a firm's prices and sales over this period. Column 4 of Table 3.4 showed that prices are not correlated with stringency in period 2. Appendix Figure B.6 shows that the percentage change in a firm's 2008-2011 registrations is only weakly correlated with stringency.

Second, column 2 of Appendix Table B.15 shows that stringency is not strongly correlated with registrations in period 2 (column 1 repeats the baseline specification for convenience). These results reduce concerns that demand shocks, related to the recession or otherwise, bias our results. Note that the results in Appendix Table B.25 provide further support that the economic recession does not explain our results. Specifically, much of the reduction in quality occurred between 2010 and 2012, which is well after the recession began.

Third, although various countries introduced vehicle retirement programs (that is, "Cash-for-Clunkers") partly in response to the recession, Appendix Table B.26 shows that controlling for these programs does not affect our results.

Next, we consider demand shocks that may have occurred in the first period and that persisted across periods. To control for such shocks, we compute the changes in quality, horsepower, and fuel consumption rate between 2005 and 2008, and interact the changes with year fixed effects. Adding these interactions to the estimation equation controls for shocks correlated with the corresponding variables that occurred in the first period and persist into the subsequent periods. Columns 3 through 5 of Appendix Table B.15 show that adding these variables does not affect the results.

We allow for demand shocks correlated with stringency that occur during any period. Because stringency depends on the vehicle's fuel consumption rate and weight, such demand shocks could affect the WTP for fuel costs, performance, or weight. The appendix shows that allowing consumer demand for these attributes to vary over time does not affect the results (see column 7 in Appendix Table B.17). Moreover, Appendix Tables B.16 and B.17 show that the results are similar if we compute quality from the range of demand models that were discussed in the previous section. These results support our interpretation that changes in estimated quality reflect supply-side changes in the vehicle.

Finally, we follow a common approach to assessing the magnitude of omitted variables bias, which is to consider whether the key independent variable (i.e., stringency) is correlated with observables, under the presumption that unobserved and omitted variables are likely to be correlated with observables. Appendix Tables B.21 through B.24 show the results if we replace vehicle fixed effects with higher-level fixed effects, such as model-trim fixed effects. Reassuringly, the estimates are similar to the baseline, suggesting that stringency is not strongly correlated with observed vehicle attributes and reducing concerns about omitted variables bias.

We end this appendix section with three additional checks on outliers and sample selection. First, we check that the results are not driven by the presence of outliers. Using a median regression in column 6 of Appendix Table B.15 yields smaller estimates, but they remain statistically significant.

Second, estimated quality is correlated with vehicle price, and some high-end vehicles have particularly high estimated quality. In our baseline regressions, we drop vehicles whose prices are above 99th percentile of the price distribution. Instead of dropping those vehicles, column 7 of Appendix Table B.15 includes them and adds a dummy variable for them in the demand estimation and equation (3.17).

Third, because of the vehicle fixed effects, the stringency coefficients are identified by within-vehicle changes in the dependent variables over time. This specification may omit quality changes caused by entry and exit of individual vehicles due to the standards. We can allow for this possibility by aggregating the data to the model level and reestimating equation (3.17). In this case, the stringency coefficients are identified by within-vehicle quality changes as well as model-level quality changes caused by entry and exit of vehicles belonging to a specific model. This does not include model entry and exit, but the appendix shows that such entry and exit are rare. Column 8 in Appendix Table B.17 shows that aggregating the data to the model-level causes the stringency coefficients to increase, especially for the third period. However, we treat these results with caution because unlike with the disaggregated results, when aggregating to the model level it is not possible to control for potential vehicle-level demand shocks.

Table B.15: Main Robustness Results for Quality

	Dependent variable is quality						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	Baseline	Dependent variable is log vehicle sale registrations	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	-5.512***	-0.262	-5.656***	-5.700***	-6.39***	-3.167***	-10.989***
	(1.782)	(0.523)	(1.760)	(1.820)	(1.766)	(0.003)	(3.564)
Period 3 x Stringency	-2.921	-1.151	-2.879	-3.247	-2.629	-1.191***	-5.126
	(2.363)	(0.757)	(2.406)	(2.511)	(2.309)	(0.011)	(4.714)
Joint F—test	5.562	1.742	6.165	5.728	8.025	439313.080	5.684
P value	0.004	0.175	0.002	0.003	0.000	0.000	0.003
N	339,065	326,775	339,065	339,065	339,065	339,065	353,725

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions use the firm-level stringency, and include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. All regressions are weighted by registrations except for column 2. Column 1 repeats column 1 from Table 3.4. Column 2 uses the log of vehicle registrations as the dependent variable, and is otherwise identical to column 1. Columns 3 through 5 include the change in the variable indicated in the row heading between 2005 and 2008, interacted with year fixed effects. Column 6 reports a median regression. Column 7 includes the dummy variable for luxury cars, which equals one if the car has a price above the 99th percentile. The number of observations varies across columns because of missing vehicle attributes.

Table B.16: Robustness Results for Quality: Alternative Nesting Structures

	Dependent variable is quality			
	(1)	(2)	(3)	(4)
	Nests: Segment-Origin	One Nest: Segment	One Nest: Origin	One Nest: Segment-Origin
Period 2 x Stringency	-5.512***	-4.233***	-5.088***	-4.062***
	(1.782)	(1.543)	(1.549)	(1.534)
Period 3 x Stringency	-2.921	-2.65	-3.259	-1.474
	(2.363)	(2.019)	(2.804)	(2.156)
Joint F—Test	5.562	4.170	7.464	4.251
P Value	0.004	0.015	0.001	0.014
N	339,065	339,065	339,065	339,065

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. Each column uses the quality computed from different nesting structures. Column 1 replicates our baseline results assuming a multi-level nested logit model as in the Column 1 of Table B.5. Column 2-4 assume a one-level nesting structure, and each column assumes the same demand model as in the corresponding column in Table B.5.

Table B.17: Robustness Results for Quality: Alternative Demand Specifications

	Dependent variable is quality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	FE2	FE3	FE4	Congestion effect	Dummy for luxury cars	Time-variant preference parameters	Model—level quality
Period 2 x Stringency	-5.512***	-3.866***	-6.44***	-3.883***	-3.368	-10.989***	-5.341***	-6.938*
	(1.782)	(1.447)	(2.166)	(1.420)	(2.184)	(3.564)	(1.818)	(3.552)
Period 3 x Stringency	-2.921	-2.357	-3.324	-2.387	0.007	-5.126	-3.069	-15.243***
	(2.363)	(1.925)	(2.858)	(1.902)	(3.021)	(4.714)	(2.456)	(3.872)
Joint F—Test	5.562	3.984	5.193	4.145	2.118	5.684	4.778	8.737
P Value	0.004	0.019	0.006	0.016	0.120	0.003	0.008	0.000
N	339,065	337,693	338,769	338,807	339,062	353,725	339,065	16,929

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions except the column 8 include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. Column 1 replicates the baseline results in Table 3.4. Columns 2-7 use the quality computed from different specifications of the demand model as in the corresponding column in Table B.8. All columns assume a multi-level nested logit model for demand. In column 2-4, the demand model includes different fixed effects. Column 5 includes the congestion effect in the demand model. Column 6 uses the full sample instead of dropping cars whose prices are above 99th percentile of the price distribution, and it includes a dummy for those luxury cars. Column 7 allows the preference parameters to vary across time. Column 8 aggregates the data to the model by country by year level, and regresses the model-level quality on the interactions of the firm-level stringency with time periods as well as country by year fixed effects and the model fixed effects.

Table B.18: Robustness Results for Log (Horsepower/Weight): Other Specifications

	Dependent variable is log horsepower to weight					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	1.854***	1.846***	1.484***	1.861***	1.908***	3.811***
	(0.446)	(0.443)	(0.485)	(0.472)	(0.000)	(0.913)
Period 3 x Stringency	0.192	0.234	-0.265	0.55	0.894***	0.453
	(0.705)	(0.700)	(0.749)	(0.795)	(0.000)	(1.437)
Joint F—test	16.932	16.738	11.168	13.867	6.22E+12	16.993
P value	0.000	0.000	0.000	0.000	0.000	0.000
N	345,033	345,033	345,033	345,033	345,033	360,270

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. Each column replicates the same regression as the corresponding column in Table B.15 except the dependent variable is log of the ratio of horsepower and weight.

Table B.19: Robustness Results for Log Weight: Other Specifications

	Dependent variable is log weight					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	-0.085	-0.102	-0.058	0.079	0.096***	-0.168
	(0.289)	(0.287)	(0.308)	(0.304)	(0.000)	(0.589)
Period 3 x Stringency	0.41	0.412	0.567	0.414	0.345***	0.853
	(0.413)	(0.410)	(0.433)	(0.466)	(0.000)	(0.841)
Joint F—test	1.999	2.161	2.949	0.634	8094465.500	2.056
P value	0.136	0.115	0.052	0.531	0.000	0.128
N	345,033	345,033	345,033	345,033	345,033	360,271

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. Each column replicates the same regression as the corresponding column in Table B.15 except the dependent variable is log weight.

Table B.20: Robustness Results for Log Price: Other Specifications

	Dependent variable is log price					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Baseline	Include quality trends	Include horsepower trends	Include fuel consumption trends	Median regression	Include dummy for luxury cars
Period 2 x Stringency	0.087**	0.085**	0.078**	0.101***	0.101***	0.087**
	(0.036)	(0.036)	(0.038)	(0.034)	(0.000)	(0.035)
Period 3 x Stringency	0.025	0.025	0.017	0.065	0.066***	0.025
	(0.051)	(0.051)	(0.055)	(0.052)	(0.000)	(0.050)
Joint F—test	5.439	5.254	4.313	5.309	9653421.700	5.613
P value	0.004	0.005	0.013	0.005	0.000	0.004
N	359,445	359,445	359,445	359,445	359,445	375,528

Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. Each column replicates the same regression as the corresponding column in Table B.15 except the dependent variable is log price.

Table B.21: Robustness Results for Quality: Different Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	-5.861***	-5.652***	-6.083***	-5.987***	-6.171***	-6.292***	-5.905***	-5.56***	-5.512***
	(1.842)	(1.820)	(1.802)	(1.796)	(1.815)	(1.818)	(1.781)	(1.768)	(1.782)
Period 3 x Stringency	-7.63***	-6.638***	-6.205**	-5.868**	-5.542**	-6.266**	-5.182**	-2.912	-2.921
	(2.790)	(2.779)	(2.678)	(2.690)	(2.666)	(2.701)	(2.422)	(2.335)	(2.363)
Stringency	-44.485***	-37.205***	-38.664**	-38.728**	-45.303***	-45.456***	-45.583***	-48.854***	
	(4.554)	(5.314)	(16.498)	(16.437)	(10.383)	(10.497)	(10.460)	(7.687)	
Joint F—Test	5.667	5.057	5.800	5.607	5.784	6.010	5.503	5.418	5.562
P Value	0.003	0.006	0.003	0.004	0.003	0.002	0.004	0.004	0.004
N	336,480	336,295	336,036	335,987	335,384	335,100	334,947	334,657	339,065

Notes: The dependent variable is quality. A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table B.22: Robustness Results for Log (Horsepower/Weight): Different Fixed Effects

	Dependent variable is log (horsepower/weight)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	0.913	0.908	1.51***	1.52***	1.409**	1.385**	1.379**	1.507**	1.854***
	(0.617)	(0.624)	(0.576)	(0.579)	(0.593)	(0.601)	(0.597)	(0.652)	(0.446)
Period 3 x Stringency	-2.013**	-1.832*	-1.392	-1.348	-1.499	-1.399	-1.482	-1.182	0.192
	(0.965)	(0.991)	(0.921)	(0.926)	(0.984)	(0.985)	(0.940)	(1.047)	(0.705)
Stringency	8.596***	8.291***	-6.267***	-6.264***	-3.619***	-3.536***	-3.431***	-3.081**	
	(0.729)	(0.788)	(1.615)	(1.611)	(1.123)	(1.074)	(1.071)	(1.203)	
Joint F—Test	6.592	5.843	8.487	8.367	7.635	7.134	8.594	11.246	16.932
P Value	0.001	0.003	0.000	0.000	0.000	0.001	0.000	0.000	0.000
N	341,748	341,553	341,292	341,233	340,616	340,329	340,175	339,882	345,033

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table B.23: Robustness Results for Log Weight: Different Fixed Effects

	Dependent variable is log weight								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	0.043	0.08	0.147	0.143	0.144	0.126	0.074	0.035	-0.085
	(0.296)	(0.303)	(0.278)	(0.280)	(0.283)	(0.284)	(0.282)	(0.285)	(0.289)
Period 3 x Stringency	1.284***	1.348***	1.281***	1.281***	1.303***	1.216***	0.928**	0.572	0.41
	(0.444)	(0.435)	(0.411)	(0.414)	(0.420)	(0.411)	(0.387)	(0.415)	(0.413)
Stringency	-1.554***	0.853***	-1.124***	-1.124***	-0.886***	-0.921***	-0.921***	-0.991***	
	(0.130)	(0.153)	(0.172)	(0.172)	(0.185)	(0.143)	(0.155)	(0.128)	
Joint F—Test	8.0951	8.8564	8.3022	8.3092	8.6189	8.0720	6.4531	2.3125	1.9987
P Value	0.0003	0.0001	0.0002	0.0002	0.0002	0.0003	0.0016	0.0991	0.1356
N	341,748	341,553	341,292	341,233	340,616	340,329	340,175	339,882	345,033

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table B.24: Robustness Results for Log Price: Different Fixed Effects

	Dependent variable is log price								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects	model-trim	model-trim-body type	model-trim-body type-fuel type	model-trim-body type-fuel type-segment	model-trim-body type-fuel type-segment-transtype	model-trim-bodytype-fuelcat-segment-transmission type-drive type	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors	model-trim-bodytype-fuelcat-segment-transmission type-drive type-number of doors-number of engine cylinders	vehicle
Period 2 x Stringency	0.068**	0.068**	0.075**	0.076**	0.086**	0.079**	0.074**	0.081**	0.087**
	(0.034)	(0.035)	(0.036)	(0.036)	(0.037)	(0.037)	(0.036)	(0.037)	(0.036)
Period 3 x Stringency	-0.024	-0.024	-0.021	-0.019	-0.004	-0.01	-0.023	-0.017	0.025
	(0.049)	(0.049)	(0.049)	(0.049)	(0.051)	(0.051)	(0.054)	(0.056)	(0.051)
Stringency	0.354***	0.389***	0.071	0.071	0.104	0.109	0.108	0.085**	
	(0.031)	(0.034)	(0.114)	(0.114)	(0.075)	(0.076)	(0.077)	(0.043)	
Joint F—Test	5.282	5.388	5.718	5.745	5.896	5.784	6.478	7.080	5.439
P Value	0.005	0.005	0.003	0.003	0.003	0.003	0.002	0.001	0.004
N	354,897	354,699	354,437	354,373	353,740	353,448	353,292	352,976	359,445

Notes: A vehicle is defined as a unique model, submodel, version, trim, market segment, number of doors, body type, fuel type (diesel, gasoline, hybrid, plug-in hybrid, or electric), transmission type, number of engine cylinders, number of gears, and drive type (front-, rear-, or all-wheel). Each column includes the fixed effects indicating in the header, while controlling for all other variables that are used for defining a vehicle. All regressions include the country-year fixed effects, segment-year fixed effects, and use the firm-level stringency.

Table B.25: Robustness Results for Quality: Different Divisions of Time Periods

	Dependent variable is quality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Periods	2005-2008, 2009-2011, 2012-2017	2005-2007, 2008-2017	2005-2008, 2009-2017	2005-2009, 2010-2017	2005-2007, 2008-2011, 2012-2017	2005-2009, 2010-2011, 2012-2017	2005-2008, 2009-2012, 2013-2017	2005-2008, 2009-2013, 2014-2017
Period 2 x Stringency	-5.512***	-3.451**	-5.019***	-3.204*	-3.659**	-4.030**	-5.282***	-5.156***
	(1.782)	(1.523)	(1.788)	(1.809)	(1.506)	(1.821)	(1.813)	(1.803)
Period 3 x Stringency	-2.921				-1.982	-1.33	-3.131	-3.381
	(2.363)				(2.289)	(2.263)	(2.255)	(2.301)
Joint F—Test	5.562	5.136	7.880	3.134	3.380	3.142	4.506	4.260
P Value	0.004	0.023	0.005	0.077	0.034	0.043	0.011	0.014
N	339,065	339,065	339,065	339,065	339,065	339,065	339,065	339,065

Notes: Column 1 repeats the baseline specification from Table 3.4. Column 2-8 try different divisions of time periods.

Table B.26: Robustness Results for Quality: Controlling for Scrappage Schemes

	Dependent variable is quality					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Dummy for all eligible vehicles	Dummy for eligible vehicles (5% window)	Dummy for eligible vehicles (10% window)	Dummy for eligible vehicles (15% window)	Dummy for eligible vehicles (20% window)
Period 2 x Stringency	-5.512***	-5.240***	-5.510***	-5.490***	-5.469***	-5.478***
	(1.782)	(1.794)	(1.788)	(1.780)	(1.774)	(1.778)
Period 3 x Stringency	-2.921	-2.717	-2.916	-2.889	-2.832	-2.795
	(2.363)	(2.369)	(2.376)	(2.356)	(2.348)	(2.349)
Eligibility for Scrappage		2.346***	-0.044	0.293	0.362	0.482*
		(0.310)	(0.528)	(0.285)	(0.267)	(0.255)
Joint F—Test	5.562	4.963	5.551	5.520	5.533	5.551
P Value	0.004	0.007	0.004	0.004	0.004	0.004
N	339,065	339,065	339,065	339,065	339,065	339,065

*Notes:*Column 1 repeats the baseline specification from Table 3.4. Column 2 includes a dummy variable equal to one for all vehicles that are eligible for the scrappage scheme. Column 3 includes a dummy variable equal to one if the vehicle's attribute is within 5 percent of the eligibility cutoff, and columns 4 through 6 are similar except that they use 10, 15, or 20 percent windows. In all columns, the dummy variables equal 1 during years in which the corresponding scrappage programs were running.

Table B.27: Robustness Results for Quality: Different Fixed Effects for Demand

	Dependent variable is quality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period 2 x Stringency	-5.512***	-3.866***	-3.687***	-3.410**	-2.214***	-7.068***	-3.802***	-4.780***
	(1.782)	(1.447)	(1.403)	(1.373)	(0.844)	(2.366)	(1.404)	(1.761)
Period 3 x Stringency	-2.921	-2.357	-2.254	-2.033	-1.146	-3.672	-2.366	-2.783
	(2.363)	(1.925)	(1.873)	(1.838)	(1.182)	(3.128)	(1.881)	(2.330)
Joint F—Test	5.562	3.984	3.846	3.395	4.129	5.241	4.052	4.159
P Value	0.004	0.019	0.021	0.034	0.016	0.005	0.017	0.016
N	339,065	337,693	337,656	336,435	326,775	335,001	338,620	334,748

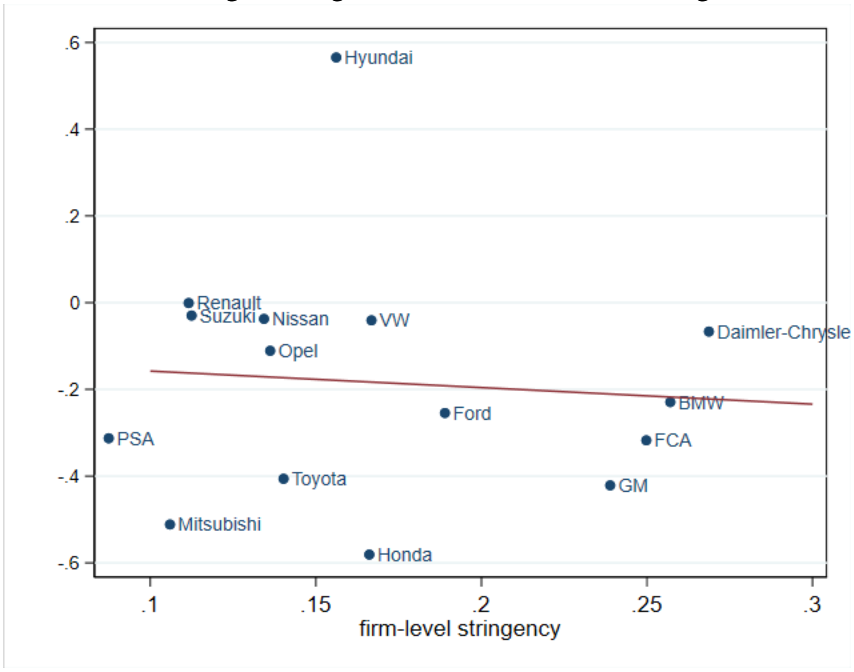
Notes: Standard errors are in parentheses, bootstrapped using 1,000 replications and clustered by model and trim. All regressions include vehicle fixed effects, segment by year fixed effects and country by year fixed effects. Column 1 replicates the baseline results in Table 3.4. Columns 2-8 use the quality computed from different specifications of the demand model as in the corresponding column in Table B.11. All columns assume a multi-level nested logit model for demand.

Table B.28: Robustness Check: Re-design

	(1)	(2)	(3)	(5)
Dependent Variable	Quality	Log (Horsepower/Weight)	Log Weight	Log Price
Stringency Variable	firm-level	firm-level	firm-level	firm-level
Period 2 x Stringency x Re-design	-2.529	-1.786**	0.671**	0.056
	(2.292)	(0.695)	(0.321)	(0.041)
Period 3 x Stringency x Re-design	-3.267*	-1.742***	0.526**	0.029
	(1.967)	(0.523)	(0.244)	(0.035)
Period 2 x Stringency	-5.076**	2.225***	-0.256	0.082**
	(2.013)	(0.448)	(0.313)	(0.034)
Period 3 x Stringency	-2.144	0.516	0.306	0.025
	(2.473)	(0.727)	(0.408)	(0.052)
Period 2 x Re-design	0.538	0.278**	-0.088	-0.017**
	(0.433)	(0.140)	(0.063)	(0.007)
Period 3 x Re-design	0.613*	0.275***	-0.044	-0.008
	(0.353)	(0.100)	(0.049)	(0.006)
Stringency x Re-design	1.895	1.356***	-0.156	-0.058**
	(1.446)	(0.415)	(0.218)	(0.027)
Re-design	-0.331	-0.215***	-0.01	0.012***
	(0.278)	(0.083)	(0.046)	(0.005)
Joint F—test: Period 2, Re-design	6.744	14.316	2.195	3.977
P Value	0.001	0.000	0.111	0.019
Joint F—test: Period 3, Re-design	2.524	5.624	2.648	0.513
P Value	0.080	0.004	0.071	0.599
Number of Observations	339,065	345,033	345,033	359,445
Adjusted R-squared	0.816	0.967	0.986	0.992

Notes: We construct a dummy variable re-design using avarage year-to-year changes in fuel consumption rate, horsepower, size, and weight by modlel. The variable equals one if the absolute percentage change of one of these vehicles is above the 90th percentile of the distribution of model-level changes. The regressions in this table include the re-design variable, the interaction of re-design with stringency, and the triple interaction of re-design, stringency, and period. The F-tests at the bottom of the table report the joint test statistics for the joint F-test that the " Period x Stringency x Re-design" and " Period x Stringency" variables equal zero.

Figure B.6: Percentage Change in a Firm's 2008-2011 Registrations



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