Subsidizing Fuel-Efficient Cars: Evidence from China's Automobile Industry

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Abstract

This paper examines the response of vehicle purchase behavior to China's largest national subsidy program for fuel-efficient vehicles during 2010 and 2011. Using variation from the program's eligibility cutoffs and the rollout of the subsidy program, the program is found to boost sales for subsidized vehicle models, but also to create a substitution effect within highly fuel-efficient vehicles. Estimates imply that ignoring the substitution effect would lead one to conclude that the program is welfare enhancing, whereas in fact the marginal cost of the program exceeds the marginal benefit by as much as 300 percent.

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1 Introduction

Gasoline consumption is a major source of air pollution and carbon dioxide emissions. Various policy tools have been proposed and implemented to reduce gasoline consumption in the United States (Knittel, 2012), and similar efforts have been made in China as well. For example, China's central government launched an energy efficiency program in mid-2010, subsidizing consumer purchases of new fuel-efficient vehicles with an engine size less than or equal to 1.6 liters. The cash subsidy program was very popular—so much so, that it cost 12 billion RMB (1.8 billion USD) by the end of 2011.[1]

Subsidizing energy-efficient products (i.e., energy efficiency programs) may alleviate market failures due to externalities, asymmetric information, credit constraints, and behavioral biases (Allcott and Greenstone, 2012; Gillingham et al., 2009). However, government-provided subsidies may create deadweight loss in the process and place a huge financial burden on the government itself. Evaluating the degree to which energy efficiency programs affect consumption decisions is thus important in designing an effective energy and environmental policy. In this line, several recent studies question the effectiveness of energy efficiency programs. Boomhower and Davis (2014) adopt a regression discontinuity design to study a large-scale energy efficiency program in Mexico and find that a large portion of program participants are free riders. Allcott et al. (2015) show that participants in several U.S. energy efficiency programs are more likely to be wealthy environmentalists who are less subject to asymmetric information, credit constraints, or behavior biases.[2]

In this paper we employ detailed panel data that include vehicle sales at the model-month-province level to study the effectiveness of the fuel efficiency subsidy program in China. Our focus is on how the program affects vehicle purchase behavior for *both* subsidized and unsubsidized products. Exploiting exogenous variation from the cutoff and the

[1] The average exchange rate between 2010 and 2011 was 1 USD = 6.6 RMB.

[2] Borenstein and Davis (2016) also find that energy efficiency tax credits in the U.S. are mostly received by higher-income consumers.

rollout of the subsidy program, we estimate the share of subsidies taken up by marginal consumers and the substitution effect across vehicle types. Such estimates have important policy implications, because if most of the subsidies are taken up by inframarginal consumers or marginal consumers whose original choices were already other fuel-efficient vehicles, then the program is likely to be an expensive way to reduce gasoline consumption and carbon dioxide emissions. We also explore the interactions between the effect of the program and the tendency to purchase relatively fuel-inefficient vehicles in order to learn more about the program's effect on targeting consumers.

Our empirical approach is based on a 'difference-in-differences' set-up. Using vehicle sales data from 2009 to 2011 and exploiting both the eligibility cutoffs and the effective months of the program, we identify the consumption response to the subsidy. Our empirical specification includes vehicle model fixed effects to account for time-invariant, model-specific, unobserved factors. Because this policy program was built up by releasing lists of subsidized models sequentially and unexpectedly, we are less worried about unobserved time-variant factors related to specific subsidized models. Furthermore, we are able to control for time-variant shocks to subsidized vehicles by using unsubsidized vehicles to construct relevant comparison groups.

The validity of our 'difference-in-differences' set-up hinges on having a control group that is insulated from the program's effect (i.e., satisfies the assumption of no interference) and is helpful to mimic sales for vehicles affected by the program in the counterfactual world. An inherent tension in this empirical setting is that the closer the comparison group is in product space to the subsidized vehicles, the better it controls for sectoral changes in supply and demand conditions over time. However, the closer it is, the more likely is that it will also be treated since demand will shift from it, to the subsidized vehicles. We explicitly address these empirical challenges.

We show that vehicles that were 'close substitutes' to those subsidized were not suitable for use as a control group. Instead, we use vehicles in the fourth quartile of fuel inefficiency as our default control group to implement the 'difference-in-differences' strategy. To address the validity of our preferred control group, we construct an alternative control group that only includes a limited number of vehicles that are extremely unlikely to suffer from the program's equilibrium effect. We use this alternative control group to show that our preferred control group does not violate the assumption of no interference. We also examine the results under various comparison groups by adjusting how close they are to the subsidized vehicles in product space. To explore substitution across time and pre-existing trends for different groups of vehicles, we create a pre-event window to implement our 'difference-in-differences' set-up and complement our analysis with an event study analysis to show substitution patterns across different types of vehicles and time periods.

Our results suggest that the program boosted sales for subsidized vehicle models. We find that the share of marginal consumers subsidized by the program is nearly 44%. Thus, about 56% of the program's payments were ineffective and distributional. We also discover that some of the increase in sales of the subsidized models was driven by a substitution effect within vehicle models, and that the substitution effect was not from gas-guzzlers to highly fuel-efficient models, but rather was within highly fuel-efficient models. We do not find evidence supporting an intertemporal substitution pattern. Using our estimates, we conduct a cost-benefit analysis and find that the program was an expensive way to reduce carbon dioxide emissions: the implied cost of a metric ton's reduction in carbon dioxide was more than 80 USD.

Our welfare analysis adopts the framework in Boomhower and Davis (2014), which accounts for the presence of inframarginal consumers, but treats only the cost of raising governmental funds as the cost of the program. We find that the marginal cost of the program exceeds the marginal benefit by almost as much as 300 percent. This is true even when we account for the local pollution benefits from the program. Finally, we show that the program was not well targeted. In fact, the sales response of the program was smaller in areas where consumers were more likely to purchase relatively fuel-inefficient vehicles or with less education.

Our paper builds on the existing literature that evaluates the consumption response to energy efficiency programs (Chandra et al., 2010; Gallagher and Muehlegger, 2011; Davis et al., 2014; Boomhower and Davis, 2014; Ito, 2015; Houde and Aldy, 2017).[3] Several studies point out that most of the consumers who receive subsidies are inframarginal. Mian and Sufi (2012) show that counties in the U.S. that were more exposed to the 2009 "Cash for Clunkers" program faced lower vehicle sales in the 10 months after the program expired, thus offsetting most of the initial sales response. Hoekstra et al. (2017) and West et al. (2017) also examine the effect of the "Cash for Clunkers" program but exploit a discrete threshold in the eligibility for the program to implement a regression discontinuity design. They find that under the eligibility rules of the program, consumers were induced to purchase smaller vehicles with lower cost per mile.

Our paper speaks to the above literature by examining the substitution between subsidized vehicles and consumers' original choices of vehicles. Our paper differs from the previous literature by exploiting the variation in eligibility status created both by the program and by the timing of the government's announcements in order to identify the share of marginal consumers who bought subsidized vehicle models and the extent to which subsidies created substitution among vehicles. To the best of our knowledge, our paper is the first empirical study to evaluate the effect of China's energy efficiency program on vehicle sales. Because China has become the largest global vehicle market and the biggest carbon dioxide emitting country, and as subsidizing fuel-efficient cars has been very popular in China since 2010, it is important to evaluate the effect of the subsidy program at its beginning stage.[4]

[3]For recent studies that evaluate the effect of vehicle taxes on reducing fuel consumption and carbon dioxide emissions, see Xiao and Ju (2014) and Klier and Linn (2015). For recent studies that look at automakers' responses to energy efficiency regulations or subsidies, see Sallee and Slemrod (2012), Ito and Sallee (2018), Reynaert and Sallee (2019), and Reynaert (2020).

[4]The government of China launched another subsidy program for new-energy cars in most of its major cities in 2013.

This paper proceeds as follows. We begin by discussing China's automobile industry, major vehicle regulations, details of the fuel efficiency program, and the data. We then describe the empirical strategy and the corresponding estimation procedures. Finally, we present the empirical results and discuss the implications of the fuel efficiency program.

2 Industry and the Subsidy Program

2.1 Industry Background

Ever since the implementation of the 'reform and open' policies of the 1980s, China's automobile market has grown rapidly. In 1994, the National Development and Reform Commission (a subsidiary of the State Council) gave priority to foreign investors with advanced technologies to create joint ventures with state-owned enterprises (SOEs) and encouraged most global car manufacturers to establish joint ventures in China.[5] Since 2009, China has become the largest global vehicle market, with current annual sales of passenger cars exceeding 20 million.

While celebrating the success of the automotive industry's development, China has experienced the same consequences as other countries experiencing increasing automobile demand: traffic congestion and air pollution.[6] Various policies have been implemented at different government levels to mitigate the negative impacts on the environment from the development of the automobile industry. For instance, the central government applied tax policies (such as a fuel tax and a consumption tax) to control the size of the vehicle fleet (Xiao and Ju, 2014), and subsidy policies (as in our current study) to induce a switch in consumers' choice toward fuel-efficient vehicles. Some local governments employ more stringent policies such as car usage restrictions, e.g. Beijing applied the 'odd-even license plate rule'

[5] Details of the policy can be found at: `http://www.lawinfochina.com/display.aspx?lib=law&id=3556&CGid=`.

[6] For example, according to China's Ministry of Environmental Protection (Ministry of Environmental Protection, 2010), vehicle emissions have become the main source of air pollution in cities of China, large and medium alike. In the World Health Organization's report on road safety (World Health Organization, 2013), China is ranked number one in the reported number of road traffic deaths in the last decade.

(Wang et al., 2009; Viard and Fu, 2015; Chen et al., 2013), or car ownership restrictions, e.g. the vehicle quota systems in Shanghai and Beijing (Xiao et al., 2017; Li, 2017; Hu et al., 2015).[7]

Previous studies have shown that while car restriction policies implemented in Beijing and Shanghai have proved useful in reducing vehicle sales, they have also shifted consumers' purchasing propensity toward low-fuel-efficiency cars (Xiao et al., 2017; Hu et al., 2015). Thus concurrent car ownership restrictions in Beijing and Shanghai will scale down consumers' response to the subsidy program in these two cities. In this paper, we study the implementation of subsidies for fuel-efficient vehicles at the national level. We will look at the program's effect with and without using data in Beijing and Shanghai.

2.2 The Cash Subsidy Program

On June 18, 2010, China's central government launched a national incentive program for fuel-efficient cars (henceforth 'the program') that provided a one-time 3000 RMB (455 USD) cash subsidy to any consumer purchasing a government-certified fuel-efficient vehicle.[8] To qualify for the program, car manufacturers had to submit applications for their vehicles to the government. After receiving an application for a particular vehicle model, the government would verify its attributes and decide whether the vehicle model was eligible.

The program had two distinct features. First, the eligibility status was an explicit function of vehicle attributes. Second, the effective date and the duration of the subsidy for a particular vehicle model were not clear to consumers or even manufacturers. These two features help identification because a vehicle model's subsidy status was not endogenously determined by its manufacturer. We discuss these features in detail below.

[7]The studies listed above have shown that a tax policy and car ownership restrictions can effectively restrain the growth of the vehicle fleet, and that car usage restrictions can markedly reduce pollution during the relevant restriction period.

[8]Car dealers were required to affix an official program sticker to the side window of every program-eligible vehicle. A consumer who purchased such a program-eligible vehicle received a fixed 3000 RMB discount off the agreed-upon transaction price from the dealer. The government then reimbursed car dealers on a monthly basis.

2.3 Program Eligibility

The program only subsidized passenger cars with an engine size (displacement level) less than or equal to 1.6 liters. Any vehicle with an engine size greater than 1.6 liters, regardless of its fuel efficiency status, was excluded from the program. The government explicitly laid out fuel efficiency thresholds used in the program, taking into account a vehicle's weight, transmission (manual or automatic), and seating (two or three rows). Specifically, two-row vehicles equipped with manual transmission were subject to a stricter fuel efficiency standard (cutoff 1) than that faced by the rest of the vehicles (cutoff 2). To show this distinction, we plot eligibility cutoffs in Figure 1, with dashed and solid lines representing eligibility cutoff 1 and cutoff 2, respectively. As shown in the figure, the program cutoffs were step functions of vehicle curb weights, and vehicles that faced cutoff 1 were regulated under higher standards at any given weight.

Figures 2 and 3 show how the above thresholds were applied to vehicle models. We plot fuel inefficiency and curb weights for gasoline vehicle models identified by the data to be eligible (subsidized) and ineligible for the program, respectively.[9] As shown in both figures, eligibility status was 'correct' in most cases: all eligible models (Figure 2) had their fuel inefficiency levels below their associated cutoffs, and most ineligible models (Figure 3) had higher fuel inefficiency than their cutoffs, with few exceptions.[10] In addition, there is a strong positive relationship between a vehicle's weight and its fuel inefficiency, but the variation in fuel inefficiency conditional on vehicle weight remains. To further explore whether eligible

[9]During the time period of this study, almost all vehicles were powered by gasoline (99%), followed by diesel (0.5%), and gasoline/CNG (0.2%). More than 2,000 models were ineligible for the program. To make the graph more presentable and because manufacturers may have been less likely to file applications for models that were going to be discontinued, we exclude vehicles with national sales of less than 500 units in the sample to construct Figure 3.

[10]In both figures, a hollow or a solid circle represents a vehicle with an engine size less than or equal to 1.6 liters and is associated with cutoff 1 or cutoff 2, respectively. In Figure 3, a cross indicates a vehicle with an engine size greater than 1.6 liters which thus could qualify for a subsidy, regardless of its fuel efficiency status. A violation of the eligibility rules occurs when a solid dot is above (below) the solid line, or when a hollow dot is above (below) the hollow line in Figure 2 (3). Violations could happen if a manufacturer did not submit applications for its models.

models had unobserved superior (or inferior) quality, in Appendix A, we show that after controlling for manufacturer fixed effects and observed attributes, a vehicle's eligibility was not associated with its price, suggesting that on average eligible products did not exhibit superior or inferior unobserved product attributes.

2.4 Waves of the Subsidy Program

Another important feature of the subsidy program is that the exact timing for eligible vehicles to enter or exit the program was determined by the central government. This is because the central government only periodically announced a compiled list of eligible vehicle models, and at any given time, little information was known regarding whether the government would continue or terminate the program in the future. During June 18, 2010 to October 17, 2011, the government released seven official lists of eligible models, effectively creating seven waves of subsidies.[11] The initial six waves of subsidies were cumulative, such that the number of subsidized vehicles was increasing as the program expanded over time. However, the seventh list adopted a set of stricter fuel efficiency thresholds that excluded nearly all vehicle models from the previous six lists.[12]

Table 1 provides the release dates of the seven waves of subsidies, along with the number of new vehicle models added to the pool of subsidized models. Because the number of subsidized models was accumulated over the first six waves, there were a total of 423 vehicle models eligible for the subsidy by the end of the program's sixth wave, and 262 of them were identified in the sales data. However, only 19 new vehicle models became eligible after the seventh wave of the program, due to stricter fuel efficiency standards. In addition, only 30

[11] Regarding the sequence of the subsidy, the manufacturers needed to first submit applications to the local government (at the province level). After reviewing these, the local government would send them to the central government, which would review them and compile subsidy lists based on the applications. Because this process took time, older models were more likely to be on earlier lists. In fact, the average launch month of vehicles on lists 1–3 is November 2009 (before the first wave), while the average launch month of vehicles on lists 4–6 is July 2010 (right after the first wave).

[12] The government announced the 8th list of eligible models on July 10, 2012 and finally terminated the program on September 30, 2013. It reopened a new subsidy program with higher fuel efficiency standards on September 3, 2014.

models from all previous lists remained subsidized in the seventh wave, shrinking the total from 423 to 49. Because the lists were mostly released mid-month, we exclude observations from months in which a new wave of subsidies began to take place for our main results. We provide estimation results for the first month when we examine intertemporal substitution patterns with an event study design.

Since the central government never revealed the rules it used to determine the sequence of subsidy waves, an important concern is that the government may have deliberately designed the sequence of subsidy waves to support domestic manufacturers or indigenous brands. We note that this is probably not the case here, because domestic producers' shareholdings in foreign joint ventures are mandated by law to be no less than 50%. As a result, foreign brands are in a sense also produced by 'domestic producers.' Still, to explore the possibility of favoritism, Table 1 tabulates the country of origin of eligible models by list. As shown in the table, even though most eligible cars were China's indigenous products, joint venture manufacturers producing European, Japanese, South Korean, or U.S. models also enrolled some of their models into multiple lists in the program. Moreover, indigenous brands were allocated to multiple lists instead of a particular wave, say, the very first wave.[13]

Another concern about the program's eligibility is whether manufacturers responded to the program in a short time by gaming the test procedures or upsizing, further dampening the effect of the policy (Ito and Sallee, 2018; Reynaert and Sallee, 2019; Reynaert, 2020). First, we note that all information about fuel inefficiency was compiled and verified by the central government and published on the government's official website. We cannot rule out the possibility that manufacturers tuned engines and other components to increase the test fuel economy at the expense of lower on-road fuel economy. However, we have not found any evidence or accusations that this increased during this program. We also note that if manufacturers made efforts to redesign models just to meet the eligibility cutoffs, these

[13] In Appendix B, we provide additional evidence to show that domestic manufacturers mainly producing vehicles with an engine size below 1.6 liters did not receive higher shares of sales from subsidized vehicles compared to their foreign counterparts.

new models may be more likely to appear in the market after they became eligible for the program. However, under our difference-in-differences setting, the effect of the subsidy is identified by existing subsidized models (with sales both before and after being subsidized), and so our empirical results do not directly speak to this issue. Still, model redesign may affect the results of our counterfactual analysis, and we will continue discussion about vehicle redesign in section 6.3.

3 Data

We obtain monthly new passenger vehicle sales data at the province level in China from 2007 to 2011.[14] The sales data include information regarding a vehicle model's identification code, type (indigenous, European, Japanese, South Korean, or U.S.), identity of the manufacturer, vehicle category (small, medium, luxury, etc.), and engine size. Details about the data coverage are further discussed in Online Appendix C. We accompany sales data with vehicle attributes collected from other sources. Information regarding a vehicle's MSRP, power, and physical size is obtained from several leading websites that report new car attributes in China.[15] Vehicle model-level fuel inefficiency, curb weight, and program eligibility are public data from the Ministry of Industry and Information Technology's website. We calculate the quartiles of each vehicle attribute for models sold in a given year.

Using a vehicle's identification code, we match its model attributes and program eligibility to monthly sales in a province. After adjusting the number of days in a month that a vehicle was eligible for a subsidy, we identify 3.62 million vehicles subsidized in the first six waves.[16]

[14] All vehicles are passenger cars purchased by individuals for personal use. Data are obtained through a private arrangement with the IVG Data Center (IVG Data Center, 2011), which provides services in Chinese market research for a variety of industries including the automobile industry.

[15] We look for vehicle attributes on three websites: Sohu.com (`http://auto.sohu.com/`), Yiche.com (`http://beijing.bitauto.com/`), and Autonet (`http://www.wwwauto.com.cn/clgl/index3.htm`).

[16] Because the announcements of each wave of subsidies were made in the middle of a month and our data are at the monthly level, we are not able to calculate the exact number of vehicles subsidized for the first months of each new wave. Still, some vehicles listed on subsidy lists were not identified in our passenger vehicle database. In Online Appendix C, we show that the majority of eligible vehicles not matched in our data were either only launched to the market in later years (in 2012 or 2013), or were classified as commercial vehicles, and so were missing in the passenger vehicle database.

This estimate is consistent with reports by IBTS Investing Consulting Company (2012) that the total amount of vehicles subsidized in the first six waves was 3.57 million vehicles. Among models identified in the sales data, 150 were launched into the market only after they became eligible for the program, leaving a total of 113 models with sales observations both before and after they received their subsidies.

To explore whether the program targeted consumers who were more likely to buy fuel-inefficient models, we use data before the first wave to calculate the share of vehicles sold in a province that were fuel inefficient. We classify a vehicle as fuel inefficient if its fuel inefficiency and weight combination is above the bivariate regression fitted line, i.e., conditional on its weight level, its fuel inefficiency is above the conditional mean. Demographic data at the province level, such as education levels, rural population, and average wage, are obtained from China Population and Employment Statistics Yearbook 2011 (National Bureau of Statistics of China, 2011). Finally, we collect information regarding the maximum retail gasoline prices allowed for Beijing from the National Development and Reform Commission to construct a proxy variable for gasoline expenditure per 100 km for each vehicle model during the time periods studied in this paper.[17]

Because official fuel inefficiency data are only available after 2010, most vehicle models sold before 2009 are missing fuel inefficiency values. As a result, our empirical analysis focuses on vehicle models sold between 2009 to 2011; data before 2009 are only used to identify the month a vehicle was first introduced to the market.[18] The final sample in this paper includes vehicle sales during 36 months and across 31 provinces, for a total of 1115 markets and accounting for approximately 25 million cars sold.[19] As discussed earlier,

[17]The maximum retail gasoline prices in several provinces or major cities were regulated by the central government. During the 3-year period studied in this paper, the central government adjusted the maximum retail gasoline prices allowed for these areas simultaneously 15 times, but the amount of adjustments varied across the country.

[18]For each model sold between 2009 and 2011, we look for the first month of the sample in which a vehicle model appears in the data and accordingly construct its 'age' (the number of months on the market) and indicator variables for its 'birth' quarters. For vehicles that seem to be manufactured in the first month of 2007, we record their product life cycle variables as missing values.

[19]Sales data for Qinghai Province in October 2010 are missing.

Shanghai and Beijing have strict vehicle licensing restrictions, and the consumption response in these two cities is likely to be different from that in other cities. The government also suddenly raised the fuel efficiency standards of the program and stopped subsidizing most of the previously eligible vehicles in the seventh wave, introducing another layer of complexity into the program's effect on vehicle sales. To deal with these complexities, the sample in our main analysis excludes data from these two cities and the seventh wave. We discuss results that include data from Shanghai, Beijing, and the seventh wave in section 5.5.

3.1 Summary Statistics

Panel A of Table 2 provides summary statistics for the main variables at the vehicle level in the final sample. The average monthly sales number for a vehicle model in a province is 36.[20] The average engine size, fuel inefficiency, gasoline expenditure, horsepower, and weight are 1.8 liters, 8 liters per 100 kilometers, 50 RMB per 100 kilometers, 93 kilowatts, and 1345 kg, respectively. Panel B of Table 2 provides summary statistics for variables at the province level. There is large variation across provinces for demographic variables. For example, the share of population with a high school degree ranges from 10.95% (Tibet) to 54.96% (Beijing), and the average wage per year ranges from 27,735 RMB (Heilongjiang) to 66,115 RMB (Shanghai). The average, minimum, and maximum shares of fuel-inefficient vehicles sold were 39%, 35% (Heilongjiang), and 48% (Qinghai), respectively.

3.2 Graphical Evidence

Figure 4 gives national vehicle sales from January 2009 to December 2011 for eligible models that already had sales before being subsidized (the dashed line), as well as sales from ineligible models (solid lines), which are grouped separately by their fuel inefficiency (gasoline/100 km) quartile, i.e., the most fuel-efficient ineligible vehicles belong to the first quartile. As shown in Figure 4, total vehicle sales for different vehicle groups seemed to face similar monthly shocks prior to the program's effective date. December was the highest grossing month,

[20]During the study period, the average number of vehicle models with sales in a given market is 631.

and the month with the Chinese New Year (February or sometimes January) was the lowest selling month. Overall, we find that the sales gap between eligible and the most fuel-efficient models increased dramatically after the program was implemented. Another important point to note is that eligible vehicles seemed to have a higher sales growth rate in the first half of 2009 than ineligible products.

Figure 5 further plots vehicle sales by subsidy wave for eligible models that already had sales before being subsidized. Looking at each individual wave, we find that eligible vehicles' sales seemed to be higher after they became subsidized. Interestingly, the sales pattern in Figure 5 suggests that a large share of subsidized vehicles would have been purchased even without receiving a subsidy.[21]

The above two figures illustrate the main struggle in our empirical setting. Sale trends of subsidized vehicles are difficult to control for, especially when there are few models among them and they are being phased in. Moreover, the closer unsubsidized vehicles lie in product space to the subsidized vehicles, the more likely it is that their sales mimic those from the subsidized vehicles before the program, but the more likely it is that they are subject to the substitution effect or the manufacturers' equilibrium responses.[22] In our empirical analysis, we will include variables to control for a vehicle's type and launched quarter of the sample in order to allow for differential sales trends for different types of vehicles launched in different time periods. More importantly, we rely on our difference-in-differences strategy to quantify the effectiveness of the program.[23] We discuss our identification strategy in detail below.

[21] It is also worth noting that vehicles on the earlier lists tended to include older models, while vehicles on later lists tended to include newer models that only appeared a few months before being subsidized.

[22] We are grateful to an anonymous referee for pointing out the above issues.

[23] We note that even if we do not completely account for the fact that eligible vehicles had higher sales growth rates than our comparison group, we would only overestimate the benefit of the subsidy program, which just strengthens our finding that the program was cost-ineffective.

4 Empirical Strategy

We adopt a 'difference-in-differences' approach to study the extent to which subsidized vehicle models were purchased by marginal consumers. This approach requires a suitable comparison group (control group) consisting of vehicles that were unaffected by the program, but were sold during the same time periods. We face two empirical difficulties in carrying out this approach in the current setting. First, the comparison group needs to be 'clean', i.e., satisfy the assumption of no interference.[24] Second, comparisons need to be made between comparable vehicles. That is, without a policy intervention, vehicles in the control group need to have a sales pattern similar to that of vehicles affected by the program.[25]

Facing these empirical challenges, we explore the choice of the control group in several steps. We start by including all models that were not eligible for subsidies in the control group. As discussed, this is probably a misspecification due to the substitution effect. Next, we consider using only 'poor substitutes' to construct the comparison group. In our preferred setting, we use vehicles in the fourth quartile of fuel inefficiency as our default control group. In Appendix D, we support the validity of our default control group by comparing it to an alternative control group that only included 'extremely poor substitutes,' and so was insulated from the substitution effect. We do not find evidence suggesting that our default control group violates the assumption of no interference. We also provide event study graphs to show pre-event trends for vehicles in our default control group and other vehicles affected by the program. Finally, we show that our main findings are robust under other definitions of the control group. In particular, we examine estimated coefficients under various control

[24] In a differentiated product industry, sales from vehicles never subsidized may decrease due to substitution effects, which may result directly from consumers switching between their original choice of vehicle to a subsidized one, or indirectly from manufacturers revising their pricing or advertising decisions between vehicles. Thus vehicles that were 'close substitutes' to those subsidized or that were produced by manufacturers greatly affected by the subsidy program may not qualify as a clean control group.

[25] To illustrate the empirical challenges we face, suppose that large sport utility vehicles (SUVs) and luxury cars are 'clean' enough for use as a control group because they were poor substitutes for eligible cars. The very reason that these vehicles may be completely insulated by the substitution effect might also make them poor candidates for studying the changes in sales for eligible vehicles, i.e. they had differential pre-event time trends compared to our eligible vehicles.

groups by adjusting how close they are to the subsidized vehicles in attribute space.

In our empirical model, we include vehicle model, province, and month-of-sample fixed effects to account for permanent differences of sales patterns across vehicle models, geographic areas, and time periods in the sample. Furthermore, because vehicles which launched to markets in different time periods or which belong to different categories (such as small or SUV) may share different time trends, in our empirical model, we allow for trends by category and trends by vehicle birth quarter.[26]

To begin with, we fit the data using the following specification:

$$\ln \text{Sales}_{ijt} = \alpha_i + \alpha_j + \alpha_t + \beta 1(\text{Receiving a subsidy})_{jt} + \gamma Gas_{jt} + X_{jt}\delta_1 + Z_{jt}\delta_2 + \epsilon_{ijt}. \tag{1}$$

Here, $\ln \text{Sales}_{ijt}$ is the natural log of monthly sales for model j in province i during month t. In addition, α_i, α_j, and α_t are the province, vehicle model, and month-of-sample fixed effects, respectively. The indicator variable $1(\text{Receiving a subsidy})_{jt}$ takes a value of 1 when a vehicle model j is subsidized during month t and 0 otherwise. The β coefficient provides an estimate of a subsidy on vehicle sales under a 'difference-in-differences' setting with multiple events. The larger the β coefficient is, the stronger is the effect of the program on inducing marginal consumers to buy fuel-efficient models. Gas_{jt} is the gasoline expenditure per 100 kilometers, i.e., the product of gasoline price per liter and fuel inefficiency per 100 kilometers. We also include two sets of control variables, X_{jt} and Z_{jt}, that take a vehicle model's product life cycle and vehicle category time trends into account. The variables in X_{jt} are interaction terms between a vehicle model's age and indicator variables for its birth quarter, as well as interactions between its squared age and indicator variables of birth quarters. The variables in Z_{jt} are time trends and squared time trends specific to vehicle categories.

[26]There are eight vehicle (sub)categories, including (ordered by average weight) micro, small, ordinary, sport, medium, multi-purpose, sport utility vehicle, and luxury, but the number of subsidized (or unsubsidized) vehicles can be extremely small in certain groups. For example, there was no micro vehicle in our default control group. To prevent imbalance in categories across the control and treatment groups, we regroup the first four subcategories into a 'regular' category, and the other four subcategories into another category.

Under the assumption that all increased sales of eligible models were drawn from consumers whose first choice was an outside good (i.e., no substitution effect between new vehicles), the results from equation (1) give the program's true effect on increasing sales of subsidized models. However, if some of the increased sales of eligible models were lost sales diverted from other models in the comparison group, then estimates from equation (1) would overestimate the true effect of the program. Our interpretation is that the results from equation (1) provide an upper bound of the program's effect on boosting sales of subsidized cars.

We deepen our analysis by examining both the substitution patterns across vehicle attributes and over time resulting from the subsidy program. If consumers who purchased program-eligible vehicle models merely substituted between models with similar attributes, then we would expect the β coefficient of equation (1) to be larger than the program's true effect because the control group is contaminated by close substitutes. Similarly, consumers could postpone buying vehicles right before the first wave, because they had heard the news about this new national subsidy program, creating a substitution effect over time. To explore the substitution pattern across vehicle attributes, we locate the attribute quartiles of each vehicle for several attributes, including fuel inefficiency, engine size, and weight. We also construct a three-month pre-event window to detect the effect from delaying purchases.

Our main specification estimates the following equation:

(2)

$$\begin{aligned}
\ln \text{Sales}_{ijt} = {} & \alpha_i + \alpha_j + \alpha_t + \beta 1(\text{Receiving a subsidy})_{jt} \\
& + \beta_1 1(\text{Unlisted})_j \times 1(\text{Post})_t \times 1(\text{Attribute quartile} = 1)_j \\
& + \beta_2 1(\text{Unlisted})_j \times 1(\text{Post})_t \times 1(\text{Attribute quartile} = 2)_j \\
& + \beta_3 1(\text{Unlisted})_j \times 1(\text{Post})_t \times 1(\text{Attribute quartile} = 3)_j \\
& + \gamma_1 1(\text{Post})_t \times 1(\text{Listed but not subsidized yet})_{jt} + \gamma_2 1(\text{Pre})_t \times 1(\text{Close substitutes})_j \\
& + \gamma_3 Gas_{jt} + X_{jt}\delta_1 + Z_{jt}\delta_2 + \epsilon_{ijt}.
\end{aligned}$$

Here, $1(\text{Post})_t$ is an indicator variable for all time periods after the first wave; $1(\text{Attribute quartile} = k)_j$ is an indicator variable for vehicles in the kth attribute quartile; $1(\text{Unlisted})_j$ is an indicator variable for vehicles that were not listed in any of the seven waves of the subsidy; and $1(\text{Listed but not subsidized yet})_{jt}$ is an indicator variable for vehicles that were listed in one of the seven waves and time periods before their wave of subsidy kicked in.

More importantly, $\beta_k, k = 1, 2, 3$, measures whether the program affects sales of unsubsidized vehicles in attribute quartile k. For example, a negative β_1 for fuel inefficiency (with the first quartile encompassing the most fuel-efficient products) would suggest that the program created a substitution effect between highly fuel-efficient models. To detect the delaying purchase effect, we construct an interaction term $1(\text{Pre})_t \times 1(\text{Close substitutes})_j$, where $1(\text{Pre})_t$ and $1(\text{Close substitutes})_j$ are indicator variables for the three-month pre-event window (March 2010 to May 2010) and all vehicles not in the control group, respectively, and so a negative γ_2 would suggest the existence of the delaying purchase effect.

4.1 Event Study Setup

The setting in equation (2) uses the three-month pre-event window to detect an intertemporal substitution effect before the program took place. In fact, we can directly examine the entire intertemporal substitution patterns before, during, and after the program by estimating the following event study specification:

(3)

$$
\begin{aligned}
\ln \text{Sales}_{ijt} &= \alpha_i + \alpha_j + \alpha_t + \sum_{m=-12}^{15} \beta_m 1(\text{Number of months being subsidized} = m)_{jm} \\
&+ \sum_{m=-12}^{15} \beta_{1m} 1(\text{Number of months after 1st wave} = m)_m \times 1(\text{Attribute quartile} = 1)_j \times 1(\text{Unlisted})_j \\
&+ \sum_{m=-12}^{15} \beta_{2m} 1(\text{Number of months after 1st wave} = m)_m \times 1(\text{Attribute quartile} = 2)_j \times 1(\text{Unlisted})_j \\
&+ \sum_{m=-12}^{15} \beta_{3m} 1(\text{Number of months after 1st wave} = m)_m \times 1(\text{Attribute quartile} = 3)_j \times 1(\text{Unlisted})_j \\
&+ \gamma Gas_{jt} + \epsilon_{ijt}.
\end{aligned}
$$

The variables $1(\text{Number of months being subsidized} = m)_{jm}$ are indicator variables for the number of months that had elapsed since a vehicle model acquired its program eligibility status. Similarly, $1(\text{Number of months after 1st wave} = m)_m$ are indicator variables for the number of months that had elapsed since the first wave.[27] In addition, to show sales trends before and after the events, we exclude control variables of category trends. As the program went on, negative values of β_m should provide evidence of intertemporal substitution for subsidized products. We can also explore whether there exist pre-event differential trends by looking at estimated β_m coefficients before the program took place. All standard errors are clustered at the vehicle model level.

[27] A negative value of m indicates the number of months before the event. Because the base month we use is one month before the event, $m = -1$ actually indicates 2 months before the event, and $m = -12$ indicates all months that are 13 months (or more) before the event.

5 Results

5.1 Effect of the Program on Sales of Subsidized Models

Table 3 provides estimation results for the coefficient of 1(Receiving a subsidy)$_{jt}$ using equation (1) and data from the first six waves (January 2009 to September 2011). Column (1) gives the baseline results, while columns (2) and (3) provide further results that include additional control variables. In column (1), the estimated coefficient of 1(Receiving a subsidy)$_{jt}$ is 0.668 and is statistically significant. In columns (2) and (3), we include control variables to absorb variation due to a model's category or launched quarter specific trends. The estimated coefficients are both significant and are 0.702 and 0.683, respectively. The estimated coefficient of gasoline expenditure is positive and statistically significant in column (1), but once we include control variables for category trends, the magnitude of the coefficient becomes much smaller and cannot be estimated with precision. Overall, we find that the program boosted sales for subsidized vehicle models.

5.2 Substitution Across Vehicle Attributes or Time Periods

We examine whether equation (1) is a misspecification due to the fact that part of the increased sales of subsidized models resulted from a substitution effect between models with similar attributes or time periods. Column (1) of Table 4 provides the estimation results of equation (2), with the vehicle attribute used for estimation being fuel inefficiency. Columns (2) to (4) further provide results with additional category trends, trends based on a product's launched quarter, and pre-event/pre-listed control variables, respectively. Once we include control variables for category trends, the coefficient of gasoline expenditure has the correct sign (negative). More importantly, we find that the coefficient associated with the interaction terms of the first fuel inefficiency quartile and the implementation of the program is negative and significant, while the coefficients associated with the second, third, and fourth quartiles are much smaller and insignificant, suggesting a substitution effect between eligible and the most fuel-efficient vehicles. Once we take the substitution effect into account, the estimated coefficients of 1(Receiving a subsidy)$_{jt}$ are between 0.512 and 0.635, lower than those coefficients estimated in Table 3. Taking the results from column (4), the estimated coefficient of 1(Receiving a subsidy)$_{jt}$ implies that subsidizing a vehicle increased the vehicle's sales by 80% ($(\exp(0.586) - 1) \times 100\%$), and so the share of marginal consumers among all subsidy recipients for the first six waves was 44% ($0.8/(1 + 0.8) \times 100\%$).[28]

Column (4) gives the results by including additional pre-event and pre-listed controls. The coefficient of the interaction between the three-month pre-event window and close substitutes (all vehicles in the first three quartiles of fuel inefficiency) is insignificant. In addition, we find that the coefficient of 1(Post)$_t$ $\times$ 1(Listed but not subsidized yet)$_{jt}$ is insignificant. Therefore, even after the first wave, consumers did not postpone buying future would-be-subsidized vehicles, most likely because the continued subsidy of these vehicles was not predictable to consumers.

The above results suggest that once we take the substitution effect into account, the estimated coefficients of 1(Receiving a subsidy)$_{jt}$ are all significant and between 0.512 to 0.635. We will conduct our cost-benefit and welfare analysis using a range of estimates to show robustness. Below we explore the intertemporal substitution patterns and pre-event sales trends using our default control group.

5.3 Intertemporal Substitution

We now present results from an event study setting to show the full path of the program's impact on subsidized and unsubsidized products. The event study setting is particularly useful to detect pre-event differential trends and to show intertemporal substitution patterns. If most of the marginal consumers we identified during our data window were in fact infra-

[28] The above results use vehicles in the fourth quartile of fuel inefficiency as the default control group. In Appendix D, we explore whether vehicles in the fourth quartile also suffered from the substitution effect by comparing their sales pattern to those in our alternative control group. The results are shown in Table D1. We do not find evidence that vehicles in the fourth quartile suffered from the substitution effect.

marginal consumers in a longer time window, then our previous results would overestimate the true effect of the program. In this case, examining consumers' purchasing patterns over time would give us a more complete picture of the program.

Figure 6(a) plots the estimated coefficients corresponding to the subsidized vehicles (β_m), along with their 95% confidence intervals for equation (3), using the data window from January 2009 to September 2011 and vehicle fuel inefficiency to construct attribute quartiles, with vehicles in the fourth quartile as the control group. Notice that in this set-up, we do not include control variables for product life cycles and vehicle category trends in the regression.[29] The base month is the month right before a vehicle model started to receive its subsidy. For coefficients associated after a vehicle received its subsidy, we find that the estimated coefficient is smallest for the month in which a new wave of subsidy took place (month 'zero' in Figure 6(a)), which is most likely due to the fact that none of the release dates were at the beginning of a month. The estimated coefficients for months after the first month are never negative and significant, and so we do not find evidence supporting intertemporal substitution within eligible models as in Mian and Sufi (2012).

Figures 6(b), 6(c), and 6(d) give the estimated coefficients for unsubsidized vehicles from the first (β_{1m}), second (β_{2m}), and third (β_{3m}) attribute quartiles, respectively. Unlike Figure 6(a), in which the event months are time periods when a new wave of subsidy took place, the event month (month 'zero') in these three figures is the beginning of the first wave, i.e. June 2010. Looking at these graphs, we do not find evidence suggesting that there are pre-existing differential time trends across groups. We find that sales of unsubsidized vehicles from different fuel inefficiency quartiles share similar patterns before the program took place in June 2010 and that the sales of unsubsidized vehicles in the lowest quartile began to decrease after the program took place, confirming the substitution effects identified in previous analysis. We find no significant negative impacts on the sales of vehicles in the

[29] We provide event study graphs under alternative specifications in Appendix E. The results are consistent with those from estimating equation (3).

second and third attribute quartiles after the program took place.

5.4 Share of Inefficient Models and Program Participation

One of the main motivations for energy efficiency programs is to address asymmetric information and behavior biases: if some consumers do not have enough information or cannot recognize the benefits of fuel-efficient products in the long run, then subsidizing fuel-efficient products can be welfare improving. This subsection examines whether the fuel efficiency program was effective at targeting those consumers. Specifically, we test whether the effects of the program were stronger in areas where shares of consumers who purchased relatively fuel-inefficient models were higher.[30] We test this hypothesis by interacting (Share of fuel-inefficient models)$_i$ with 1(Receiving a subsidy)$_{jt}$ and 1(Unlisted)$_j$ $\times$ 1(Post)$_t$ $\times$ 1(Attribute quartile $= k)_j$, $k = 1, 2, 3$ in equation (2) and keeping all the control variables. In this specification, a positive and significant coefficient on the interaction term between receiving a subsidy and (Share of fuel-inefficient models)$_i$ provides evidence that the program was effective at targeting marginal consumers who were more likely to purchase fuel-inefficient models. In another specification, we include additional interaction terms constructed from demographic variables, including the share of high school degrees, the share of rural population, and average wage.

Table 5 presents the estimation results. In columns (1) to (3), the estimated coefficients of variables interacting with (Share of fuel-inefficient models)$_i$ tend to have opposite signs compared to their main effect (i.e., without the interaction term) and so offset their main effects. In particular, the estimated effect on subsidized vehicles was lower in areas where the share of consumers buying fuel-inefficient models was higher. Moreover, the results in column (4) show that the increase in sales of subsidized models was higher when the percentage of those with a high school degree was also higher, indicating that the program did not target consumers with lower education levels very well. These results show that the program was not

[30] As discussed in the previous section, we define a vehicle model to be fuel inefficient if its fuel inefficiency is higher than the conditional mean based on its weight.

effective at targeting consumers who were more likely to suffer from asymmetric information or behavior biases and therefore would be more likely to buy fuel-inefficient vehicles.

To sum up, we show that the program created a substitution effect between highly fuel-efficient models, that most of the subsidies went to inframarginal consumers, and that provinces with a higher share of fuel-inefficient vehicles and less-well-educated consumers were less likely to have marginal consumers of the subsidy program.

5.5 Robustness Checks

Our default control group includes unsubsidized vehicles in the fourth quartile of fuel inefficiency. To examine how the selection of the control group would affect our estimates, we calculate the fuel inefficiency percentile of each vehicle and adjust the definition of the control group 'continuously' by estimating a modified version of equation (1) repeatedly:

(4)

$$\begin{aligned}\ln \text{Sales}_{ijt} &= \alpha_i + \alpha_j + \alpha_t + \beta 1(\text{Receiving a subsidy})_{jt} \\ &\quad + \beta_1 1(\text{Unlisted})_j \times 1(\text{Post})_t \times 1(\text{Attribute percentile} < k)_j + \gamma Gas_{jt} + X_{jt}\delta_1 + Z_{jt}\delta_2 + \epsilon_{ijt},\end{aligned}$$

where $1(\text{Attribute percentile} < k)_j$ is an indicator variable for vehicles with fuel inefficiency less than the k percentile of fuel inefficiency from all models. When k is equal to 0, the above equation returns to equation (1), i.e., none of the unsubsidized vehicles are used to estimate the substitution effect (or all of the unsubsidized vehicles are in the control group). Our default control group sets k equal to 75. A larger k indicates that we shift more unsubsidized vehicles from the control group to estimate the substitution effect. We estimate the above equation with k set to 0, 5, 10, ..., 95. If the substitution effect exists within highly fuel-efficient vehicles, we expect to see that the magnitude of the subsidy (β) decreases and the substitution effect increases (β_1) as we increase k from 0, but as k grows, more and more vehicles unaffected by the program would be used to estimate the substitution effect, and so the changes in estimates would eventually diminish.

We plot the corresponding estimated coefficients for β and β_1 in Figures 7(a) and 7(b), respectively. We find that the estimated coefficient for β is highest (0.683) when k is equal to 0, decreases during the first fuel inefficiency quartile ($k \leq 25$), and is stable, taking on values mostly between 0.55 and 0.6 after the first quartile. Estimates around our preferred control group are also quite stable: when k is set at 70, 75, and 80, the estimated coefficients for β are 0.569, 0.574, and 0.595, respectively. Because the estimate of β is biased upward when k is 0, as we conduct our cost-benefit analysis, we will use a high β as a bounding exercise. For the substitution effect, we find that the magnitude of the estimated β_1 gets larger as k moves from 0 to 25, but the pattern reverses after that, supporting our previous findings that the substitution effect is mostly restricted to highly fuel-efficient vehicles.

Our main results exclude samples from the first months in which a new wave of subsidy was launched because policy announcements were often made in the middle of a month. As a robustness check, instead of excluding these months, we adjust the variables $(\text{Receiving a subsidy})_{jt}$, $(\text{Post})_t$, and $(\text{Pre})_t$ in equation (2) to take into account the number of days in a month that a vehicle was eligible for a subsidy for each wave. We present the estimated results in column (1) of Table 6, which show qualitative results similar to those in our main findings.

All estimates reported above are obtained by excluding observations from Shanghai and Beijing in our regressions. This is because the two cities have had strict licensing restrictions on new vehicles since 2000 and 2011, respectively, and so the effect of the subsidy program depends on interactions between these two policies. With the presence of licensing restrictions, marginal consumers of the subsidy program were those who were able to obtain a vehicle license *and* who would switch their choice of vehicles based on a cash subsidy. Therefore, the effects of the subsidy program in Shanghai and Beijing were likely to be dampened. Column (2) of Table 6 reports results that include observations from Beijing and Shanghai. As expected, the estimated coefficient of $1(\text{Receiving a subsidy})_{jt}$ in column (2) is smaller than that excluding Shanghai and Beijing. Our main results use only the variation generated from the first six waves. In the seventh wave, the eligibility threshold was stricter and few vehicles remained on the subsidized list. Column (3) expands the data window to include the variation generated by the seventh wave and tests whether stopping vehicle subsidies had any effect on vehicle sales. As shown in column (3), most of the qualitative results hold when we include data from the seventh wave, but we find that stopping a vehicle subsidy actually increased sales compared to vehicles in the comparison group. One potential explanation is that dealers may have continued to provide discounts or other promotions for these vehicles after their eligibility status was suddenly revoked, and so vehicle sales did not drop immediately after losing eligibility status.

In columns (4) and (5) of Table 6, we provide the results for the first three subsidy waves and the next three waves, respectively. The estimated coefficients of $1(\text{Receiving a subsidy})_{jt}$ in columns (4) and (5) are 0.584 and 0.680, respectively. Even though the effect of the program from later waves seems to be larger, as discussed and shown in Figure 5, sales from later waves account for only a small number of total vehicles subsidized. Column (6) gives the results using a smaller data window (only 2010 and 2011). Finally, in Appendix Table D2, we show that our results are robust to even other definitions of control groups.

6 Cost-Effectiveness and Welfare Analysis

6.1 Implied Price of Gasoline and Carbon Dioxide Saved

We now evaluate the program's cost effectiveness by calculating the implied price of gasoline and carbon dioxide saved from the program. We calculate the counterfactual sales when the subsidy program was not in place and compare them with observed sales after the program became effective. Using our most optimistic estimates of the program from Table 4 (column (4)), we know that the program increased sales of existing subsidized products by 80% and decreased existing unsubsidized products in the first vehicle fuel inefficiency quartile by 31%. We then back out counterfactual sales from observed sales after the program became effective for these groups of vehicles. We make two assumptions for 'new vehicles'. For unsubsidized vehicles that were only available after the program became effective, we assume that the program only lowered their sales by 31% if and only if they were in the first fuel inefficiency quartile; and for subsidized vehicles that were only available after they received their subsidy, we assume that their observed sales were increased by 80% due to the program.

Table 7 summarizes our findings for the program's overall effect on total sales and fleet fuel inefficiency. Column (1) of Table 7 reports average fuel inefficiency by product attributes after the program became effective. Columns (2), (3), and (4) provide monthly observed sales before and after the program, and counterfactual sales after the program, respectively, while column (5) provides the difference between the observed sales and counterfactual sales after the program. Total vehicle sales and average fuel inefficiency across all products are also given in the last two rows of Table 7. We bootstrap across vehicle models to obtain standard errors (given in parentheses) for the program's effect on monthly sales and average fuel inefficiency. Under our assumptions about new vehicles, the program decreased the average fleet fuel inefficiency by 0.150 liters per 100 kilometers (with a p-value of 0.126). The subsidy program also increased national monthly vehicle sales by 77,183, even though this effect on sales could not be estimated precisely. The effect of such additional total vehicle sales had a huge impact on the implied price of gasoline savings, which we will discuss later.

We use estimated changes in average fuel inefficiency and total sales to calculate the implied prices of gasoline and carbon dioxide saved by the program. A vehicle's lifetime mileage is set at 600,000 kilometers.[31] If we fix the total number of vehicles sold during this time at the counterfactual level, then the maximum lifetime savings of total gasoline during this time would be 5.36 billion liters.[32] Given that the actual payment of subsidized vehicles during the same time (excluding the first months of each new wave) was around 7.39 billion RMB, or 1.12 billion USD, we find that for each liter of gasoline saved, the implied price is

[31] The compulsory retirement requirement of vehicles in China was a maximum lifetime of 10 years before May 2013 and is currently a maximum of vehicle mileage traveled of 600,000 kilometers.

[32] Because the current compulsory retirement requirement caps a vehicle's lifetime mileage at 600,000 kilometers, the maximum lifetime savings in gasoline consumption of an average vehicle are capped at $600,000/100 \times 0.150 = 900$ liters.

0.209 USD per liter, or 0.792 USD per gallon. If we assume that each gallon of gasoline emits 8.9 kilograms of carbon dioxide, then the implied price of carbon dioxide of the program is approximately 89 USD per metric ton.[33]

Table 8 summarizes the calculated implied price of gasoline and carbon dioxide saved under different scenarios. We find that under a higher estimate of the program's effect on subsidized vehicles ($\beta = 0.7$), the implied prices of carbon dioxide would be 77 USD per ton when the discount rate is 0% and 90 USD per ton when the discount rate is 3%. Moreover, as shown in columns (7) and (8) of Table 8, if we instead allow the possibility that the program created additional total vehicle sales as implied in Table 7, then the implied price of carbon dioxide saved would be -19 USD per ton and -23 USD per liter under a 0% and 3% discount rate, respectively, suggesting that instead of subsidizing consumers to reduce carbon dioxide emissions, the government would in fact be subsidizing consumers to generate more carbon dioxide under these worst scenarios.

The current carbon price in China is less than 10 USD/metric ton, and most countries in the world have a carbon price or tax less than 20 USD/metric ton.[34] Moreover, the current average social cost of carbon dioxide/metric ton estimated by the U.S. Environmental Protection Agency (EPA) is between 12 and 62 USD.[35] Paying more than 89 USD for a metric ton of carbon dioxide is not a cost effective way to reduce carbon dioxide; if the main policy objective of China's subsidy program on fuel-efficient vehicles was to reduce carbon dioxide emissions, then our results suggest that it was an ineffective way to achieve this goal.

[33]Because we use the compulsory retirement requirement to calculate a vehicle's lifetime mileage with a zero discount rate under the assumption that the program did not generate any additional sales to obtain the above results, the savings in carbon dioxide are also clearly upper bounds, and the implied price should be interpreted as a lower bound.

[34]See Kossoy et al. (2000).

[35]See http://www.epa.gov/climatechange/EPAactivities/economics/scc.html.

6.2 Welfare Analysis

This subsection evaluates the program's effectiveness in a broader context. We consider the program's effect on social benefits and social costs. For the program's impact on increasing social benefits, we consider the case in which a reduction in gasoline consumption is socially beneficial not only by lowering carbon dioxide emissions, but also by lowering local air pollution levels. Using the estimates from Parry et al. (2014), we assume that the marginal benefits from the reduction of air pollution and carbon dioxide in China are 0.05 and 0.08 USD per liter, respectively.

For the program's impact on creating social costs, we consider the efficiency costs from transfers and private costs from driving consumers away from their first choice of vehicles. Following Boomhower and Davis (2014), we use $(\eta-1)$ to denote efficiency loss from transfers and let the benchmark of η be 1.3.[36] A higher η represents a larger efficiency loss from transfers. If η is one, then there is no efficiency loss from transfers. In addition, we assume that the demand for fuel-efficient vehicles is linear, and so the average private cost per induced consumer can be approximated by $3,000/2 = 1,500$.[37] Using the information from Table 4, we calculate that 44% of subsidized consumers are marginal consumers, implying that the marginal social cost per inducement is 3,530 RMB.[38] In addition, based on empirical findings in this paper, marginal consumers who purchased a subsidized vehicle had their original choices of vehicles reside in the lowest fuel inefficiency quartile, and so the average

[36] Consider the following welfare function: $W = U(Q(s)) - C(Q(s)) + \tau Q(s) - (\eta - 1)Q(s)s$, where Q is the number of adopters of fuel-efficient products, and s is the amount of subsidy. $U(Q(s))$ and $C(Q(s))$ are respectively the private benefits and costs from driving fuel-efficient vehicles. τ is the external benefit from driving fuel-efficient vehicles, and η measures the efficiency loss from transfers.

[37] This approximation does not take into account the possibility that vehicles located in the attribute space may not be distributed evenly, and that marginal consumers may value one particular attribute much more than others. To address this concern, in Appendix F, we use structural demand estimates from previous literature on China's automobile industry to explicitly calculate the deadweight loss that takes substitution between attributes into account. We find that our results are robust to the above adjustments.

[38] When the share of marginal consumers is x, the government must subsidize up to $1/x$ consumers to generate one induced purchase. Among those $1/x$ consumers, 1 of them is the marginal consumer, who incurs a 1,500 RMB efficiency loss (due to the deviation from her original optimal choice of vehicle), and all of them incur $(\eta - 1) \times 3,000$ RMB efficiency loss from transfers. As a result, the social cost per induced purchase in this case is $(1.3 - 1) \times 3,000 \times (1/x) + 1,500$ RMB.

fuel inefficiency of their original choice set would be 6.7 liters per 100 kilometers, leading to a saving of 0.201 liters/100 kilometers per induced subsidized vehicle sale.

Table 9 provides the results from our welfare analysis under the assumption that the program created no additional total sales. We place the results from our preferred specification ($\beta = 0.586$) in the first row, and the second row and the third show the results when β is 0.5 and 0.7, respectively. These results suggest that even under the most optimistic scenario (a zero discount rate, and a high β), once we take the substitution effect into account, the social marginal benefit per induced sale is far less than the social marginal costs per induced sale, and under a 3% discount rate, the marginal cost of the program exceeds the marginal benefit by as much as 300 percent.

The above results are obtained by using $\eta = 1.3$ and letting the marginal social benefit from reducing gasoline consumption by one liter be 0.13. Columns (5) and (8) extend the analysis and calculate the maximum η for the subsidy program to have a net social benefit. In addition, columns (6) and (9) provide the minimum social marginal cost from reducing gasoline consumption by one liter for the program to be socially beneficial when η is fixed at 1.3. We find that when the discount rate is 3%, the implied efficiency loss (0.909) needs to be much lower than the benchmark (1.3) for the program to be socially beneficial, and the minimum marginal tax on gasoline needs to be 0.519 (USD/liter) in order for the program to have a net social benefit (when η is fixed at 1.3).

The fourth row of Table 9 reports results from welfare analysis when policymakers ignore the substitution effect within highly fuel-efficient vehicles. In this naive case, the government assumes that a typical marginal consumer's original choice of vehicle was an 'average' unsubsidized car, so that for each induced purchase, a typical marginal consumer's original choice of vehicle would be one with a higher fuel inefficiency level (8.09 liters per 100 kilometers in this case). Thus, the average savings per inducement in this case would be higher than that when the marginal consumer's original choice was also highly fuel efficient. Column (7) shows that when the discount rate is 3% and the gasoline savings are calculated from the national fleet average (all unsubsidized vehicles), the marginal social benefit per inducement is 6,963 RMB, which is much larger than the marginal social cost per inducement. The program would seem even more beneficial if policy makers employ a higher share of marginal consumers than that found in this paper and a zero discount rate.

Overall, our analysis shows that once we take the pervasiveness of inframarginal consumers and the substitution pattern into account, the program was not cost effective in reducing carbon dioxide emissions and was hardly welfare enhancing. An interesting question is the extent to which the program could gain from screening infra-marginal consumers. In the last scenario, we consider the case in which the government applied a hypothetical perfect screening device to the subsidy program, so that none of the program's budget is spent on infra-marginal consumers. The device could be based on observables, such as income (Allcott et al., 2015), or unobservables such as waiting period (Globus-Harris, 2018). The results are shown in the last row of Table 9. Compared to the results under the baseline, we find that by shutting down the 'free-riding' effect, marginal cost per inducement is reduced from 3,530 RMB to 2,400 RMB ($\eta \times 3000 + 1500$), while the marginal benefit per inducemnt remains at 884 RMB (under the 3% discount rate). In this case, a perfect screening device could close the gap of welfare loss from the program by about 43%.

6.3 Implications of Vehicle Redesign in Response of the Program

The above analysis assumes that observed vehicles would carry the same attributes with or without the subsidy program. In particular, fuel inefficiency of new products was taken as given (rows (6) and (7) of Table 7). Because some vehicles were launched after they became eligible for a subsidy, one may worry that they may be redesigned to meet the eligibility cutoffs. In this section, we explore how relaxing the above assumption would affect our estimates of the program's savings in terms of average fuel inefficiency and social welfare.

We consider two alternative cases. In the first case, we assume that in the counterfactual world, new models were drawn from the empirical distribution of existing models. The second case follows the first case, but further assumes that new subsidized vehicles, when in the counterfactual world, were models drawn from the first quartile of fuel inefficiency that missed the eligibility cutoffs. Thus, we assume that new subsidized vehicles were redesigned to meet the eligibility cutoffs. Under this extreme scenario, we endowed new subsidized products with savings in fuel efficiency.

Table 10 shows the results under different cases. Column (1) of Table 10 reproduces the observed average fuel inefficiency by vehicle group used in Table 7 (the preferred setting). Columns (2) and (3) provide average fuel inefficiency by vehicle group under the first case and the second case, respectively. Note that across rows (1)–(7), the differences between cases are only in new products, i.e., rows (6) and (7). For new unsubsidized products (row 6), we do not find much difference between the observed average fuel inefficiency and that constructed from existing products (8.098 L/100 km compared to 8.087 L/100 km). For new subsidized products, we find that the observed average fuel inefficiency is higher than that constructed from existing products in the first case (6.553 L/100 km compared to 6.472 L/100 km). One potential explanation is that manufacturers upsized vehicles to meet the eligibility cutoffs.[39] Therefore, under the first case, the savings in average fuel inefficiency are even smaller than in our preferred setting.

By contrast, under the second case, because we assume that all new subsidized products were ineligible models redesigned to meet the cutoffs, the savings in average fuel inefficiency are slightly higher than in our preferred setting (0.162 L/100 km compared to 0.150 L/100 km). In this extreme case, a marginal consumer could save 0.232 liters of gasoline per 100 km (6.704 L/100 km minus 6.472 L/100 km). We do not find that relaxing the assumption about vehicle redesign would strongly affect our main results from welfare analysis: under a

[39] In Appendix G, we estimate the counterfactual distribution of vehicle weight to test excess bunching at eligibility cutoffs. We find evidence of excess bunching at eligibility cutoffs for vehicles launched after the program, but not for those launched before the program. In addition, our analysis suggests that the majority of excess bunching at eligibility cutoffs is from new eligible models (launched only after receiving a subsidy).

3% discount rate, the marginal benefit per inducement is then 1,019 RMB and the marginal cost per inducement is 3,530 RMB. Thus even if manufacturers could adopt costless gasoline-saving technologies in a short time for ineligible vehicles that were close to the cutoffs to become eligible, the estimated substitution pattern in our paper suggests that the program would be still far from welfare enhancing.

7 Conclusion

In this paper we examine the consumption response to China's subsidy program of fuel-efficient cars within the first six waves of implementation. We show that around 56% of consumers who purchased eligible models were inframarginal and received additional cash simply by buying their original choice of vehicles, and that marginal consumers' original choice of vehicles was not gas-guzzlers. The presence of a large share of inframarginal consumers and the observed substitution patterns bring into question the cost effectiveness of the program for reducing carbon emissions. We also find that the effect of the program was smaller in provinces where consumers were more likely to purchase fuel-inefficient models, indicating that the program was not well targeted. Our estimates imply that ignoring the substitution effect would lead one to conclude that the program is welfare enhancing, whereas in fact the marginal cost of the program far exceeds the marginal benefit.

It is important to note that our study focuses only on the consumption response at the beginning of the program. Subsidizing fuel-efficient cars remains a popular policy tool in China. The subsidy program studied in this paper was shut down in September 2013, but was resumed in September 2014. Moreover, in 2013, the government in China launched another subsidy program for new-energy vehicles (mostly electric cars) in several major cities. The amount of the subsidy is large (it can be up to 120,000 RMB per vehicle), and incidents of fraud from electric car manufacturers have been reported, prompting the government to investigate this issue. Further research is needed to examine manufacturers' responses to fuel efficiency programs in the long run. Finally, we find that the subsidy was slightly less likely to be taken up by marginal consumers in Beijing and Shanghai, where new car licenses were strictly regulated. The interaction of environmental policies remains an important issue to be explored.

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Table 1: Seven Waves of the Cash Subsidy Program

Wave	Release date	Number of new (total) models subsidized	Country					Number (%) of models identified in the data	Number (%) of models launched after receiving a subsidy
			cn	eu	jp	kr	us		
1	June 18, 2010	68 (68)	30	7	5	12	14	56 (82.4%)	20 (35.7%)
2	August 11, 2010	61 (129)	27	10	9	4	11	47 (77.0%)	21 (44.7%)
3	September 25, 2010	74 (203)	51	4	13	3	3	52 (70.3%)	43 (82.7%)
4	November 23, 2010	66 (269)	42	12	2	10	0	45 (68.2%)	35 (77.8%)
5	February 11, 2011	69 (338)	47	2	17	2	1	28 (40.6%)	10 (35.7%)
6	May 11, 2011	85 (423)	60	8	17	0	0	34 (40.0%)	21 (61.8%)
7	October 17, 2011	19 (49)	15	0	0	0	4	1 (5.3%)	0 (0%)
Total		442	272	43	63	31	33	263 (59.5%)	150 (57.0%)

Notes: 'cn': indigenous brands, 'eu': European brands, 'jp': Japanese brands, 'kr': South Korean brands, 'us': U.S. brands.

Table 2: Summary Statistics

	N	mean	s.d	min	max
Panel A: Variables at the vehicle level					
Monthly sales in a province (*Sales*)	703559	36	92.9	1	5066
Eligibility	703559	0.14	0.35	0	1
Engine size (liters)	703559	1.79	0.48	0	5.7
Fuel inefficiency (liters/100 km)	640781	7.98	1.4	2.7	14.7
Gasoline expenditure (*Gas*, RMB/100 km)	640781	49.6	9.8	16.2	104.2
Horsepower (kw)	559716	92.5	28	26.5	252
Weight (kg)	640781	1344.7	273.6	645	2690
Panel B: Variables at the province level					
High school degree (%)	31	25.25	8.49	10.95	54.96
Rural population (%)	31	48.57	14.56	10.69	76.31
Average wage (RMB)	31	36,103	9,652	27,735	66,115
Share of fuel-inefficient models before the 1st wave (%)	31	39	3.2	35.2	47.8

Notes: Demographic variables at the province level are obtained from China Statistical Yearbook 2011. 'Share of fuel-inefficient models before the 1st wave' is the average share of vehicles sold within a province before the 1st wave that have fuel inefficiency and curb weight combinations above the bivariate regression fitted line.

Table 3: Effect of the Subsidy on Vehicle Sales

	(1)	(2)	(3)
Receiving a subsidy	0.668	0.702	0.683
	(0.152)	(0.152)	(0.153)
Gasoline expenditure	0.090	0.009	0.020
	(0.016)	(0.019)	(0.023)
Observations	429381	429381	384438
Category × trend controls	No	Yes	Yes
Birth quarter controls	No	No	Yes
Keep first months of each wave	No	No	No
Keep Beijing and Shanghai?	No	No	No

Notes: This table reports estimates of equation (1) using variation from the first six waves. The dependent variable is the natural log of monthly vehicle model sales in a province. Column (3) presents the results from our preferred specification. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level.

Table 4: Substitution Effect of the Subsidy

	(1)	(2)	(3)	(4)
Receiving a subsidy	0.512	0.635	0.580	0.586
	(0.142)	(0.140)	(0.139)	(0.181)
Unlisted×Post×Attribute quartile 1	-0.463	-0.317	-0.352	-0.365
	(0.112)	(0.117)	(0.125)	(0.140)
Unlisted×Post×Attribute quartile 2	-0.169	-0.010	-0.051	-0.063
	(0.095)	(0.096)	(0.104)	(0.120)
Unlisted×Post×Attribute quartile 3	-0.018	0.037	-0.039	-0.050
	(0.094)	(0.090)	(0.098)	(0.110)
Gasoline expenditure	0.051	-0.008	-0.001	-0.002
	(0.015)	(0.017)	(0.020)	(0.020)
Post×Listed but not subsidized yet				0.084
				(0.143)
Pre-event window×Close substitutes				-0.073
				(0.060)
Observations	429381	429381	384438	384438
Category × trend controls	No	Yes	Yes	Yes
Birth quarter controls	No	No	Yes	Yes
Keep first months of each wave	No	No	No	No
Keep Beijing and Shanghai?	No	No	No	No

Notes: This table reports estimates of equation (2) using variation from the first six waves, with vehicles from the fourth quartile of fuel inefficiency being the control group. The dependent variable is the natural log of monthly vehicle model sales in a province. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level.

Table 5: Share of Fuel-Inefficient Models and Program Participation

	(1)	(2)	(3)	(4)
Receiving a subsidy	1.594	1.601	1.517	0.876
	(0.269)	(0.293)	(0.300)	(0.340)
Receiving a subsidy×Share of fuel-inefficient models	-0.026	-0.026	-0.024	-0.028
	(0.005)	(0.005)	(0.006)	(0.006)
Unlisted×Post×Attribute quartile 1	-0.353	-0.365	-1.123	-1.123
	(0.125)	(0.140)	(0.309)	(0.309)
Unlisted×Post×Attribute quartile 2	-0.051	-0.063	-0.339	-0.338
	(0.104)	(0.119)	(0.268)	(0.268)
Unlisted×Post×Attribute quartile 3	-0.039	-0.050	-0.029	-0.029
	(0.097)	(0.110)	(0.248)	(0.248)
Gasoline expenditure	-0.001	-0.002	-0.002	-0.002
	(0.020)	(0.020)	(0.020)	(0.020)
Post×Listed but not subsidized		0.086	0.086	0.086
		(0.143)	(0.143)	(0.143)
Pre-event window×Close substitutes		-0.073	-0.073	-0.073
		(0.060)	(0.060)	(0.060)
Receiving a subsidy×High school degree				0.021
				(0.004)
Receiving a subsidy×Rural population				0.007
				(0.002)
Receiving a subsidy×Average wage				-0.001
				(0.004)
Unlisted×Post×Attribute quartile 1×Share of fuel-inefficient models			0.020	0.020
			(0.007)	(0.007)
Unlisted×Post×Attribute quartile 2×Share of fuel-inefficient models			0.007	0.007
			(0.006)	(0.006)
Unlisted×Post×Attribute quartile 3×Share of fuel-inefficient models			-0.001	-0.001
			(0.005)	(0.005)
Observations	384438	384438	384438	384438
Category × trend controls	Yes	Yes	Yes	Yes
Birth quarter controls	Yes	Yes	Yes	Yes
Keep first months of each wave	No	No	No	No
Keep Beijing and Shanghai?	No	No	No	No

Notes: The dependent variable is the natural log of monthly vehicle model sales in a province. Vehicles in the fourth quartile of fuel inefficiency are used to construct the control group. Months in which a new wave of subsidy began to take place were excluded. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level.

Table 6: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Include first months	Include Beijing and Shanghai	Include the seventh wave	Waves 1–3	Waves 4–6	Exclude 2009
Receiving a subsidy	0.588	0.565	0.603	0.584	0.680	0.636
	(0.128)	(0.131)	(0.147)	(0.184)	(0.211)	(0.122)
Unlisted×Post× Attribute quartile 1	-0.306	-0.342	-0.364	-0.327	-0.294	-0.267
	(0.114)	(0.121)	(0.133)	(0.127)	(0.128)	(0.120)
Unlisted×Post× Attribute quartile 2	-0.071	-0.037	-0.024	-0.027	-0.003	0.064
	(0.099)	(0.100)	(0.110)	(0.105)	(0.105)	(0.094)
Unlisted×Post×Attribute quartile 3	-0.064	-0.032	-0.026	-0.025	-0.006	0.022
	(0.093)	(0.094)	(0.104)	(0.099)	(0.099)	(0.090)
Gasoline expenditure	-0.011	-0.002	0.001	0.003	0.015	0.058
	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.025)
Stopping a subsidy			0.695			
			(0.165)			
Observations	488774	408762	443916	368527	343933	247543
Category × trend controls	Yes	Yes	Yes	Yes	Yes	Yes
Birth quarter × age controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural log of monthly vehicle model sales in a province. The attribute quartile used is fuel inefficiency, with vehicles in the fourth quartile being the default control group. In column (1), months in which a new wave of subsidy began to take place are included. We adjust the variables "Receiving a subsidy", "Post", and "Pre-event window" to reflect the number of days a vehicle was being subsidized in a given month. In column (2), observations in Beijing and Shanghai are included. In column (3), observations after the 7th wave are included. Columns (4) and (5) provide results using subsidy waves 1–3 and 4–6, respectively. Column (6) provides estimates excluding samples from 2009. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level.

Table 7: Monthly Observed and Counterfactual Sales

	(1) Avg. Fuel Inefficiency	(2) Observed Sales (Before)	(3) Observed Sales (After)	(4) Counterfactual Sales (After)	(5) Difference (3)-(4)
Subsidized	6.472	59,716	161,296	95,809	65,487
Not subsidized (fuel ineff. quartile=1)	6.704	79,985	59,888	86,292	-26,404
Not subsidized (fuel ineff. quartile=2)	7.515	115,695	116,367	116,367	0
Not subsidized (fuel ineff. quartile=3)	8.435	109,366	100,718	100,718	0
Not subsidized (fuel ineff. quartile=4)	9.711	56,402	70,347	70,347	0
New products (not subsidized)	8.098	–	65,773	71,415	-5,642
New products (subsidized)	6.553	–	98,653	54,910	43,743
Total sales		421,163	673,041	595,858	77,183 (65,882)
Average fuel inefficiency (liters/100 km)		7.703	7.476	7.626	-0.150 (0.098)

Notes: We calculate monthly national sales for vehicle groups given in the column and row headings. Column (1) reports the average fuel inefficiency across groups after the program started but before the 7th wave. Column (2) reports observed sales from January 2009 to May 2010. Column (3) reports observed sales from July 2010 to September 2011 (before the 7th wave). Months in which a new wave of subsidy began to take place were excluded. Column (4) reports counterfactual sales based on the estimated coefficients (those with at least 5% statistical significance) from the fourth column of Table 4. We bootstrap across vehicle models to obtain standard errors (given in parentheses) for the program's effect on monthly sales and average fuel inefficiency.

Table 8: Implied Price for Gasoline and Carbon Dioxide Saved

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implied price of gasoline (USD/liter)	0.209	0.245	0.180	0.211	0.241	0.283	-0.045	-0.053
Implied price of CO2 (USD/ton)	89	104	77	90	103	120	-19	-23
β for 1(Receiving a subsidy)	0.586	0.586	0.7	0.7	0.5	0.5	0.586	0.586
Discount rate	0%	3%	0%	3%	0%	3%	0%	3%
Take changes in sales into account?	No	No	No	No	No	No	Yes	Yes

Notes: We calculate total gasoline and carbon dioxide saved by the subsidy program from July 2010 to September 2011 and the total amount paid by the program during this time (excluding Beijing and Shanghai). Average gasoline savings per vehicle sold during this time and additional sales generated by the program are from Table 7. We use 600,000 kilometers to calculate a vehicle's lifetime mileage.

Table 9: Welfare Analysis

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Discount rate: 0%			Discount rate: 3%		
Gasoline savings from a marginal consumer	β	Marginal cost per inducement	Marginal benefit per inducement (RMB)	Break-even η	Break-even marginal tax when $\eta = 1.3$ (USD/liter)	Marginal benefit per inducement (RMB)	Break-even η	Break-even marginal tax when $\eta = 1.3$ (USD/liter)
Take the estimated substitution pattern into account								
0.201	0.586	3,530	1,036	0.931	0.443	884	0.909	0.519
0.201	0.5	3,787	1,036	0.939	0.475	884	0.919	0.557
0.201	0.7	3,289	1,036	0.922	0.413	884	0.897	0.484
Assume substitutes were drawn equally from all ineligible vehicles								
1.586	0.586	3,530	8,163	1.985	0.056	6,963	1.807	0.066
With a costless and perfect screening device								
0.201	0.586	2,400	1,036	0.845	0.301	884	0.795	0.353

Notes: The amount of subsidy received by each eligible vehicle was 3000 RMB. Columns (4) and (7) adopt estimates from Parry et al. (2014), assuming that marginal benefits from the reduction of air pollution and carbon dioxide in China are 0.05 and 0.08 USD/liter, respectively. Columns (5) and (8) report the implied efficiency cost parameter (η) in which the social benefit and the social cost are equal. Columns (6) and (9) assume that the efficiency cost parameter is fixed at 1.3 and report the underlying marginal tax (USD/liter) in which the social benefit and the social cost are equal.

Table 10: Average Fuel Inefficiency under Alternative Cases

	(1) Avg. Fuel Inefficiency (preferred)	(2) Avg. Fuel Inefficiency (alternative 1)	(3) Avg. Fuel Inefficiency (alternative 2)
(1) Subsidized	6.472	6.472	6.472
(2) Not subsidized (fuel ineff. quartile=1)	6.704	6.704	6.704
(3) Not subsidized (fuel ineff. quartile=2)	7.515	7.515	7.515
(4) Not subsidized (fuel ineff. quartile=3)	8.435	8.435	8.435
(5) Not subsidized (fuel ineff. quartile=4)	9.711	9.711	9.711
(6) New products (not subsidized)	8.098	8.087	8.087
(7) New products (subsidized)	6.553	6.472	6.704
Avg fuel inefficiency	7.626	7.617	7.638
Change in avg. fuel inefficiency	-0.150	-0.141	-0.162

Notes: This table reports the average fuel inefficiency (liters/100 km) across groups under various cases. Column (1) reports the observed average fuel inefficiency after the program started but before the 7th wave. Column (2) reports the average fuel inefficiency in the counterfactual world where observed new products would be drawn from the empirical distribution of existing models. Column (3) reports the average fuel inefficiency in the counterfactual world where observed new subsidized vehicles were models from the first quartile of fuel inefficiency and redesigned to meet the eligibility cutoffs after the program was launched.

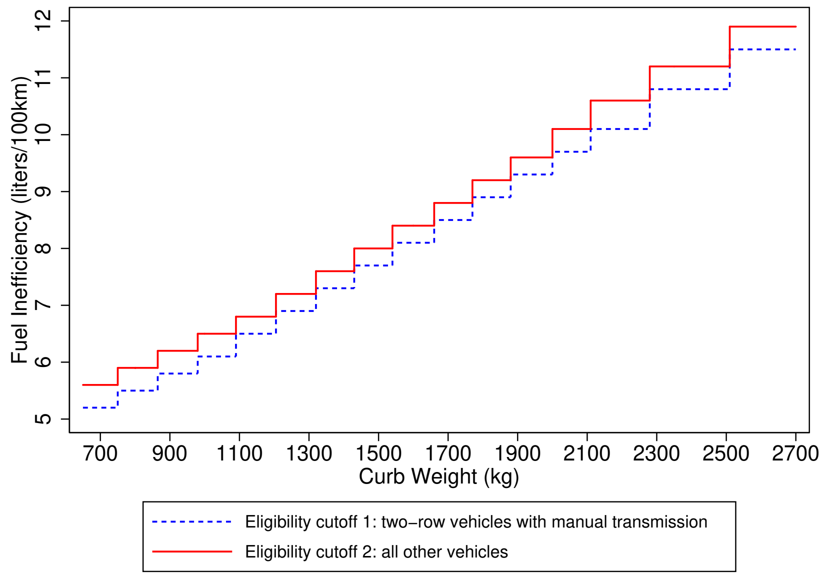


Figure 1: Subsidy Cutoffs for Different Types of Vehicles

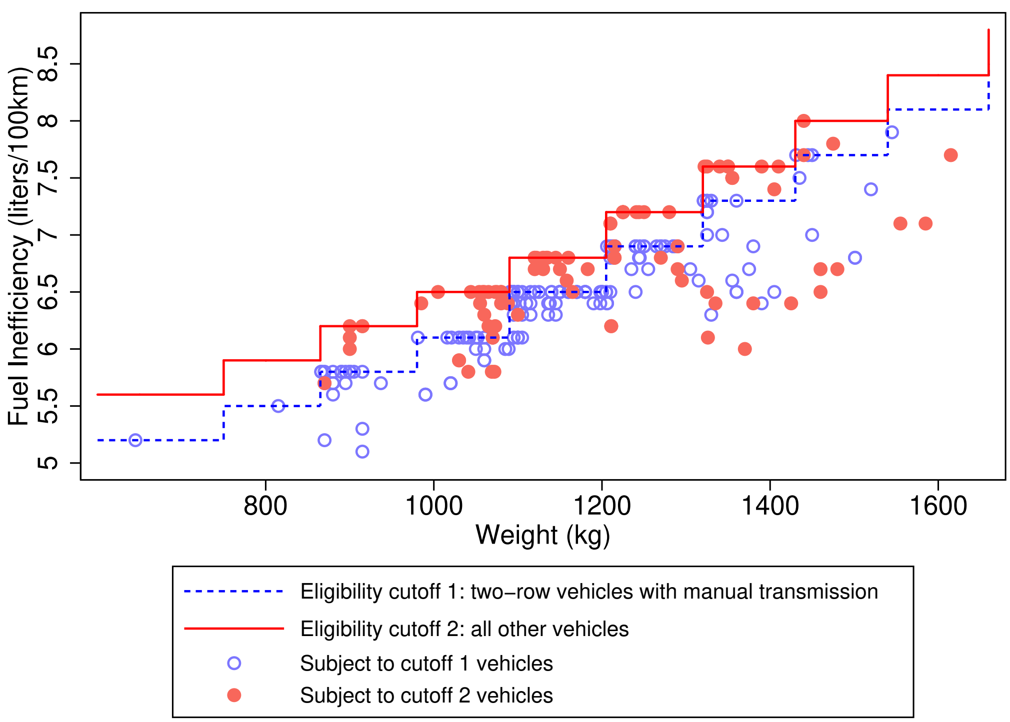


Figure 2: Fuel Inefficiency and Curb Weights: Subsidized Models

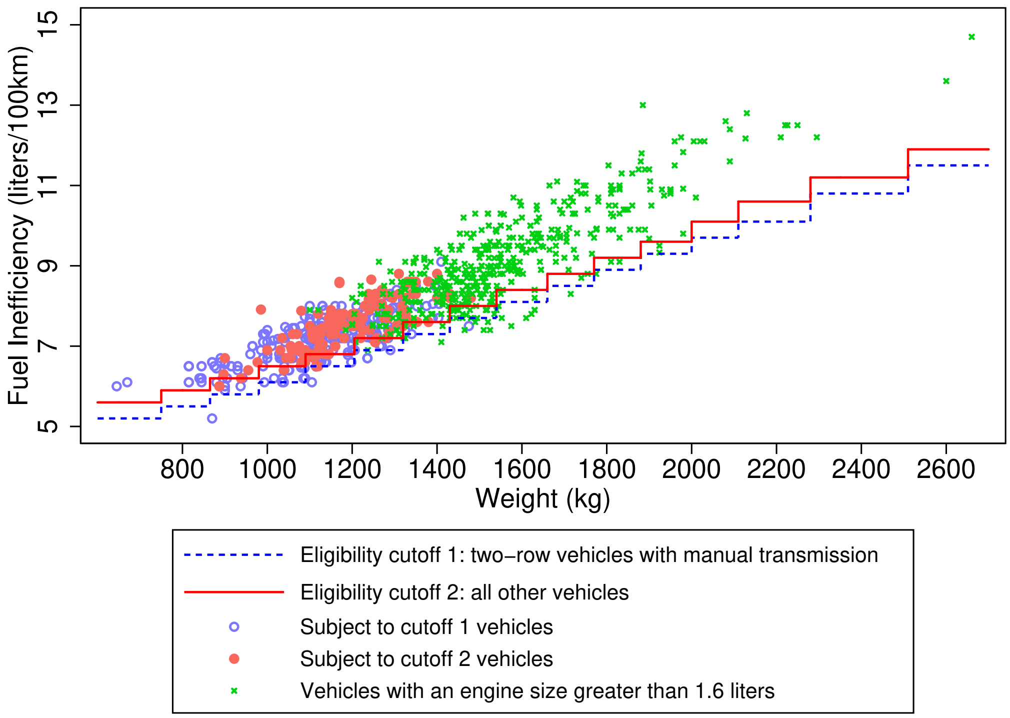


Figure 3: Fuel Inefficiency and Curb Weights: Unsubsidized Models

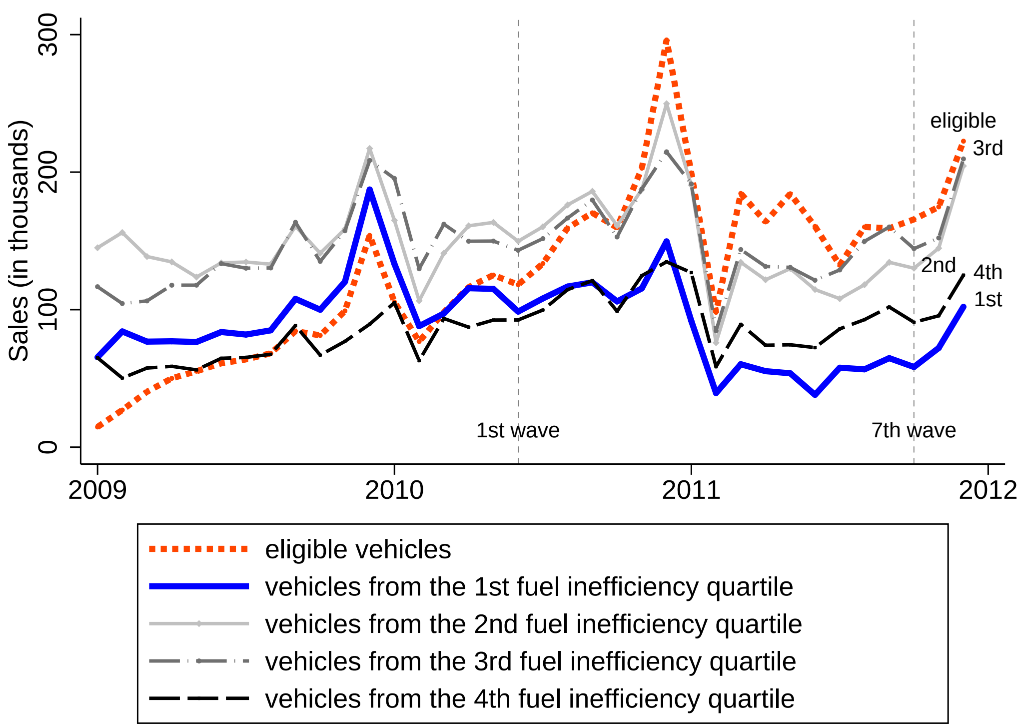
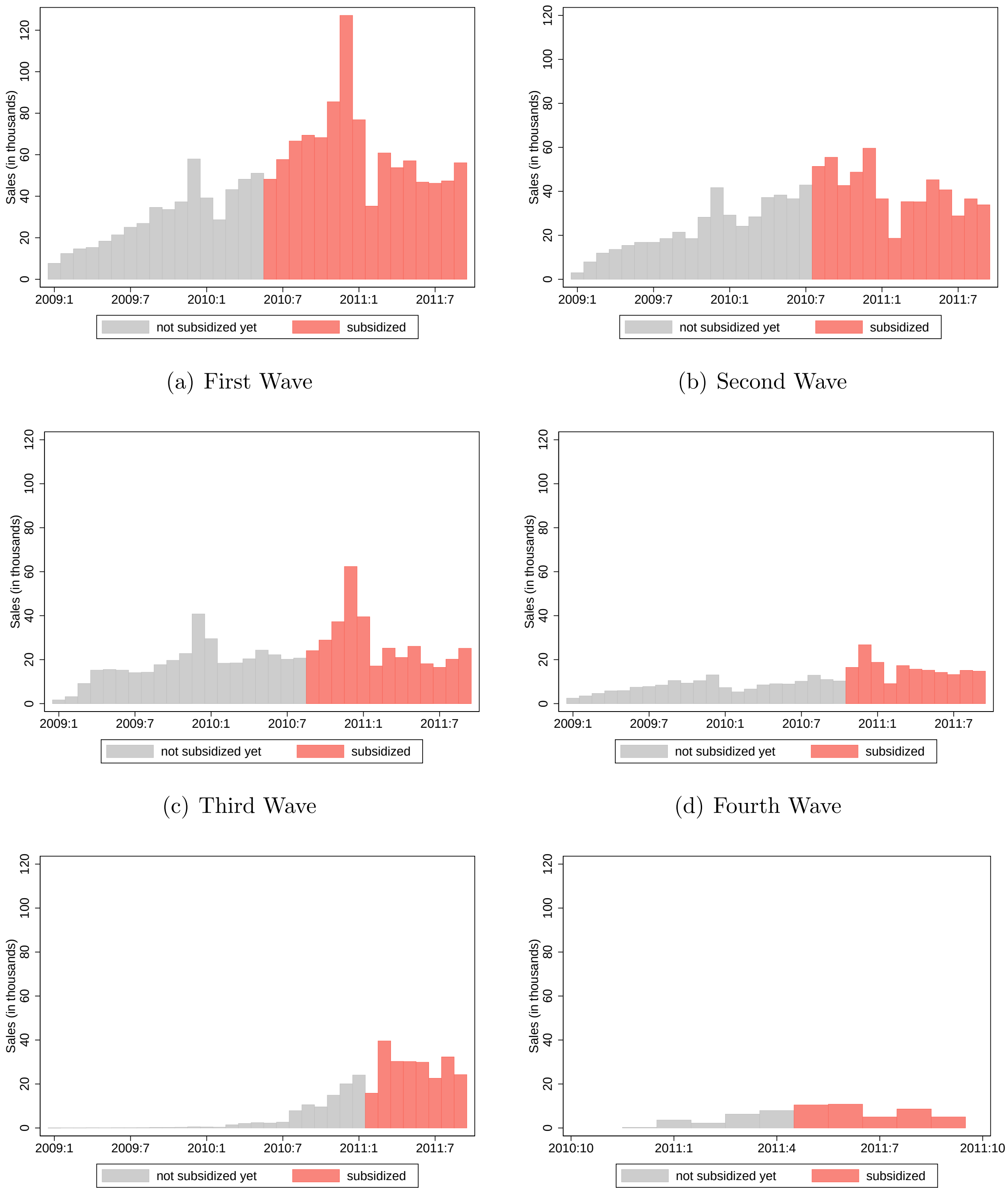


Figure 4: Total Sales by Eligibility and Fuel Inefficiency



(a) First Wave

(b) Second Wave

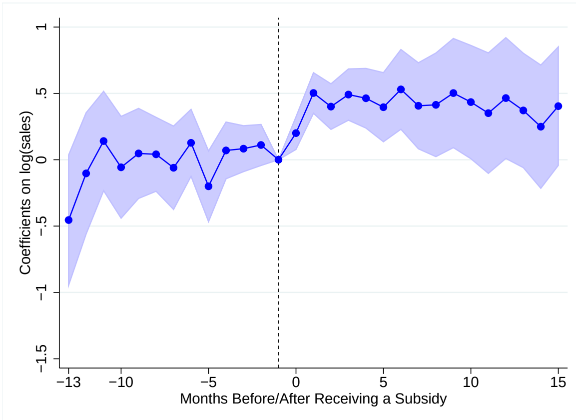
(c) Third Wave

(d) Fourth Wave

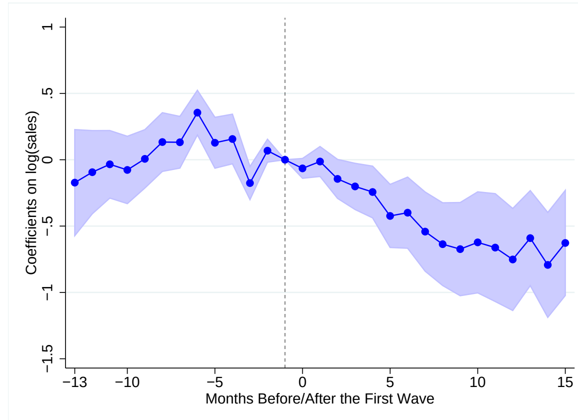
(e) Fifth Wave

(f) Sixth Wave

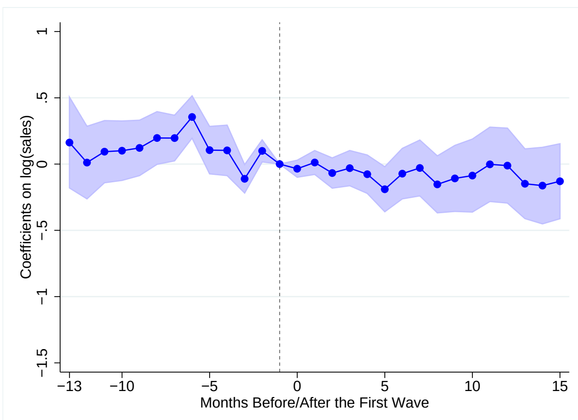
Figure 5: Vehicle Sales by Month Across Six Waves



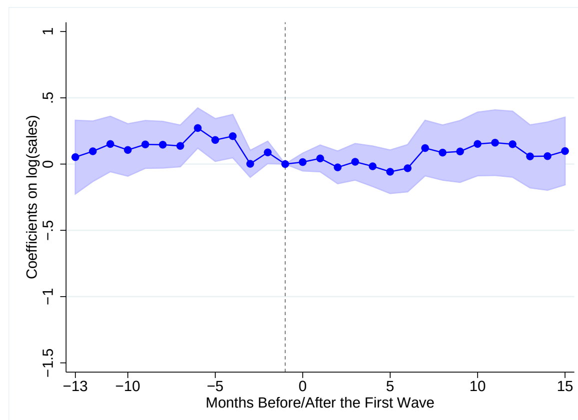
(a) Subsidized Products



(b) Unsubsidized Products in Fuel Inefficiency Quartile 1

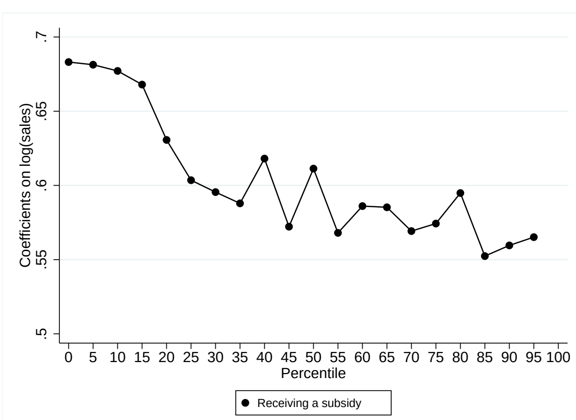


(c) Unsubsidized Products in Fuel Inefficiency Quartile 2

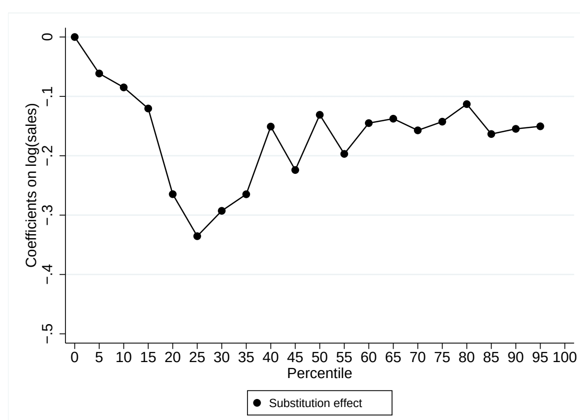


(d) Unsubsidized Products in Fuel Inefficiency Quartile 3

Figure 6: Common Trends and Intertemporal Substitution



(a) Receiving a subsidy



(b) Substitution effect

Figure 7: Continuous Control Group

Appendices

A Eligibility and Vehicle Attributes

In this section, we examine whether eligible vehicles had unobserved product attributes superior to those of other vehicles and whether the program favored indigenous vehicles. Columns (1) and (2) of Table A1 list means of sales and various attributes for eligible and ineligible models, respectively, with differences shown in column (3). All models in the table have an engine size less than or equal to 1.6 liters and were already on the market before the first wave of the program. On average, eligible vehicles had higher average province-model sales, were priced at 14,937 RMB higher, had larger values in horsepower, size, and weight, and were less likely to be indigenous brands than their peers, suggesting that the program was not designed to favor indigenous brands per se. We examine the relationship between vehicle price and eligibility by regressing vehicle price on eligibility status and other attributes. Columns (4) and (5) of Table A1 give results from price regressions that include country fixed effects and manufacturer fixed effects, respectively. After controlling for manufacturer fixed effects and other attributes, we find that a vehicle's eligibility was not associated with its price, suggesting that on average eligible products did not exhibit superior or inferior unobserved product attributes.

B Number of Subsidized Models by Manufacturer and Wave

Because the central government never revealed the rules it used to determine the sequence of subsidy waves, an important concern is that the government may have deliberately designed the sequence of subsidy waves to support domestic manufacturers or indigenous brands. To explore this possibility, we show the entire distribution of subsidized models by manufacturer and subsidy wave in Table B1, as well as information about each subsidized manufacturer's type, the share of vehicles produced and subsidized, the share of vehicles produced and

Table A1: Eligibility and Vehicle Attributes

	Eligible	Ineligible	Difference	Price Regression	
	(1)	(2)	(3)	(4)	(5)
Sales	57.248	30.091	27.157		
	(86.814)	(42.037)	(6.941)		
Price (10,000 RMB)	9.181	7.688	1.494		
	(4.171)	(2.452)	(0.374)		
Automatic transmission	0.338	0.291	0.047	0.238	0.043
	(0.477)	(0.455)	(0.061)	(0.133)	(0.128)
Engine size (liters)	1.431	1.463	-0.032	-3.049	-2.147
	(0.157)	(0.179)	(0.023)	(1.023)	(1.136)
Fuel inefficiency (liters/100 km)	6.526	7.269	-0.743	-0.483	-0.215
	(0.500)	(0.605)	(0.078)	(0.214)	(0.228)
Horsepower (kw)	80.103	72.754	7.350	0.074	0.049
	(15.041)	(11.294)	(1.595)	(0.016)	(0.020)
Size (m^3)	10.988	10.591	0.397	0.046	-0.164
	(1.204)	(1.145)	(0.154)	(0.131)	(0.128)
Weight (kg)	1196.809	1141.433	55.376	0.013	0.015
	(164.377)	(123.147)	(17.403)	(0.002)	(0.002)
Chinese	0.324	0.504	-0.181	-2.236	
	(0.471)	(0.501)	(0.066)	(0.193)	
European	0.191	0.163	0.028	1.106	
	(0.396)	(0.370)	(0.050)	(0.234)	
Japanese	0.132	0.166	-0.034	0.765	
	(0.341)	(0.373)	(0.049)	(0.251)	
Korean	0.162	0.065	0.096	-0.627	
	(0.371)	(0.247)	(0.036)	(0.207)	
U.S.	0.191	0.101	0.090		
	(0.396)	(0.302)	(0.042)		
Eligibility				-0.587	0.084
				(0.215)	(0.217)
Constant				-3.898	-4.727
				(0.930)	(1.360)
Observations	68	337	405	405	405
Manufacturer fixed effects				No	Yes

Notes: This table reports average monthly sales in a province and vehicle attributes for eligible and ineligible models sold between January 2010 and May 2010 (before the first wave of subsidies). All vehicles have an engine size less than or equal to 1.6 liters. Columns (4) and (5) report results from price regressions with country fixed effects and manufacturer fixed effects, respectively.

no greater than 1.6 liters, and each manufacturer's market share in all passenger vehicles during the first six waves (June 2010 to September 2011).[40] Several manufacturers are joint ventures of domestic and foreign manufacturers, offering indigenous and foreign brands at the same time. We thus define a manufacturer as "Chinese" if at least 50% of its vehicles belong to indigenous brands. We apply the same definition to define European, Japanese, South Korean, and U.S. manufacturers accordingly.

Table B1 suggests that manufacturers usually had vehicle models subsidized in multiple waves of subsidy. More importantly, if the program favored domestic manufacturers by adding these vehicles only to certain subsidy waves to boost their sales, then we would expect domestic manufacturers to receive higher shares of *sales* from subsidized vehicles compared to their foreign counterparts producing similar vehicles. For example, a domestic firm producing few vehicles below 1.6 liters may receive a lot of subsidized sales compared to foreign manufacturers also producing few such vehicles as a result of favoritism. Figure B1 visualizes the data in Table B1 by plotting the relationship between a manufacturer's share of models subsidized to all models produced, and its share of models no greater than 1.6 liters to all models produced, using the manufacturer's market share as weights (the size of the circle). As shown in Figure B1, at the manufacturer level, there is a strong positive relationship between the share of subsidized products and the share of vehicles produced no greater than 1.6 liters for both domestic and foreign manufacturers, which is not surprising because all subsidized vehicles must be no greater than 1.6 liters. The slopes of the fitted lines for domestic and foreign manufacturers are almost identical. Moreover, it seems that foreign manufacturers were more likely to produce fuel-efficient vehicles and be subsidized. Overall, we do not find evidence supporting the government favoring domestic manufacturers.

[40] There are 41 firms in the official 7 subsidy lists released by the government. Three different joint ventures owned by SAIC-GM (SAIC-GM, Shanghai GM DongYue Motors, and SAIC GM (ShenYang) NorSom Motors) are named as a single manufacturer (SAIC-GM) in the sales data. Similarly, two different manufacturers owned by Haima Automobile Group are named as a single manufacurer in the sales data. We thus identified 38 of them in the sales data and calculated market shares at the level of these 38 manufacturers.

Table B1: Share of Subsidized Vehicles by Manufacturer

firm ID	firm type	1	2	3	4	5	6	7	total	share subsidized	share no greater than 1.6 liters	market share
1	cn	6	2	2	8	0	23	2	43	0.436	1.000	0.020
2	cn	3	17	9	0	0	0	2	31	0.609	0.958	0.046
3	us	12	5	3	0	0	0	7	27	0.335	0.676	0.103
4	eu	7	0	4	4	2	8	0	25	0.156	0.556	0.094
5	cn	0	0	0	0	10	8	4	22	0.146	0.722	0.009
6	cn	0	0	3	3	13	1	0	20	0.176	1.000	0.003
7	cn	2	0	13	4	0	0	0	19	0.518	0.667	0.027
8	kr	6	4	3	6	0	0	0	19	0.531	0.717	0.066
9	cn	2	0	8	0	0	5	3	18	0.773	0.901	0.043
10	us	0	8	8	0	0	0	0	16	0.283	0.373	0.039
11	jp	0	6	0	0	6	4	0	16	0.188	0.607	0.066
12	cn	0	2	0	7	4	0	1	14	0.359	0.810	0.013
13	jp	0	4	7	0	3	0	0	14	0.467	1.000	0.007
14	cn	0	0	0	8	1	4	0	13	0.255	1.000	0.023
15	jp	2	0	0	0	1	10	0	13	0.393	0.985	0.019
16	kr	6	0	0	4	2	0	0	12	0.348	0.726	0.034
17	cn	8	0	0	0	1	3	0	12	0.353	0.509	0.014
18	us	6	0	0	0	5	0	0	11	0.526	1.000	0.007
19	cn	4	0	2	4	0	1	0	11	0.701	0.904	0.008
20	eu	0	9	0	1	0	0	0	10	0.248	0.655	0.080
21	jp	0	1	2	0	7	0	0	10	0.287	0.491	0.045
22	cn	0	0	0	0	2	5	0	7	0.054	1.000	0.005
23	eu	0	0	0	7	0	0	0	7	0.250	0.759	0.035
24	cn	0	0	0	3	4	0	0	7	0.236	0.997	0.004
25	jp	3	0	0	0	0	3	0	6	0.372	0.443	0.032
26	cn	0	0	0	0	3	2	0	5	NA	NA	NA
27	cn	1	0	0	1	0	2	0	4	0.087	0.965	0.016
28	jp	0	0	0	2	2	0	0	4	0.313	0.771	0.004
29	cn	0	0	2	0	2	0	0	4	0.027	0.445	0.014
30	cn	0	0	0	1	0	3	0	4	NA	NA	NA
31	cn	0	0	1	0	0	2	0	3	0.005	0.955	0.007
32	cn	0	0	3	0	0	0	0	3	0.013	0.560	0.013
33	cn	0	0	0	3	0	0	0	3	NA	NA	NA
34	cn	0	0	2	0	0	0	0	2	NA	NA	NA
35	cn	0	2	0	0	0	0	0	2	0.024	0.398	0.001
36	cn	0	0	2	0	0	0	0	2	NA	NA	NA
37	cn	0	0	0	0	1	1	0	2	0.393	0.668	0.005
38	eu	0	1	0	0	0	0	0	1	0.212	0.223	0.005
Total		68	61	74	66	69	85	19	442			

Notes: This table shows the number of subsidized vehicles by manufacturer and subsidy wave. Each manufacturer listed here has at least one vehicle listed in the subsidy program. 'cn': indigenous manufacturers, 'eu': European manufacturers, 'jp': Japanese manufacturers, 'kr': South Korean manufacturers, 'us': U.S. manufacturers. All shares are calculated using sales data from the first six subsidy waves (June 2010 to September 2011). NA: manufacturers cannot be identified in the sales data.

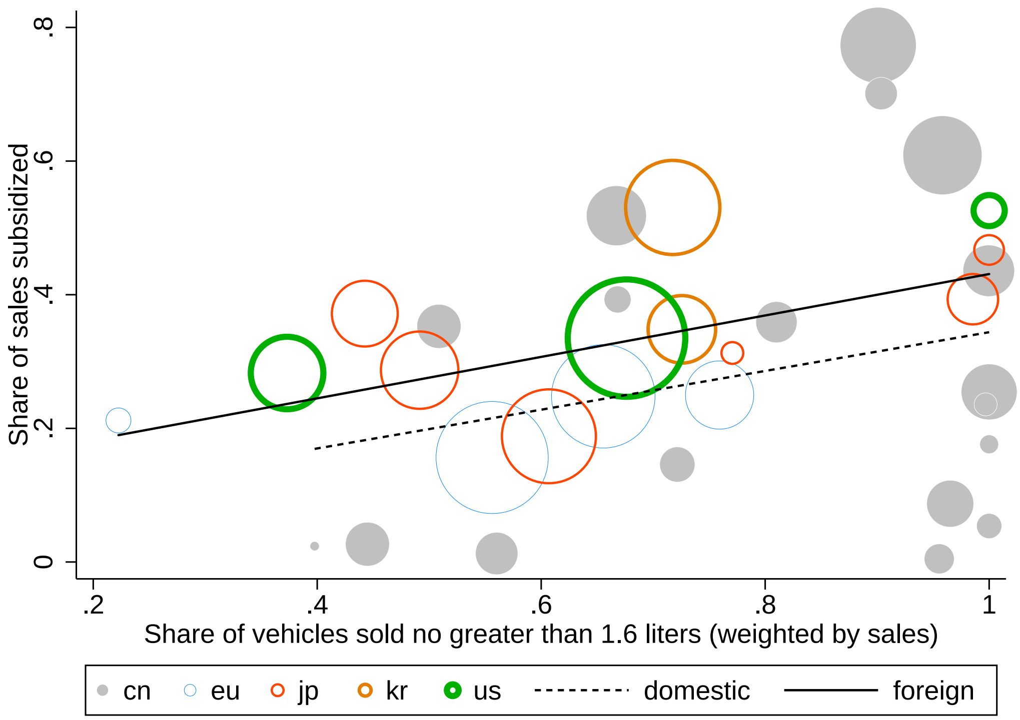


Figure B1: Share Subsidized and Share below 1.6 Liters

C Data Coverage

Our results are based on sales data from all passenger vehicles. There are two measures of vehicle sales in China. The first one is registrations of purchases of new vehicles, including passenger vehicles and commercial vehicles. The second one is sales shipped to dealers (reported by manufacturers), including vehicles purchased by consumers as well as inventories. Our data are registrations of purchases of new passenger vehicles, and so belong to the first type, while the China Association of Automobile Manufacturers (CAAM) publishes annual vehicle sales shipped to dealers (henceforth CAAM sales), and so this belongs to the second type.[41] Table C1 compares annual sales reported by CAAM and data used herein. Given that our data do not include commercial vehicles and inventories, total vehicle sales in the data accounted for 66.17%, 67.32%, and 61.94% of the CAAM sales in 2009, 2010, and 2011, respectively. For the purpose of this study, registered sales are more suitable for studying the effect of a subsidy on sales. Regarding new passenger vehicles, we believe that our data provide great coverage: there is almost no difference in total registered sales reported by biauto.com (a website specializing in publishing news on China's automotive industry) and ours.[42]

Of the subsidized passenger vehicles in the first six waves, only a total of 262 out of 423 can be matched in our data (based on vehicle model identification code). Of the 161 models that are not found in our data, we break them down by subsidy wave and present the cause of such missing data in Table C2 below. Among all missing models, 51 were passenger vehicles that were only available for sale in 2012 or 2013, and so they do not appear in our data (from 2007 to 2011). In addition, we find that there are 42 subsidized vehicles actually categorized as commercial vehicles and thus missing in the passenger vehicle database. Still, there are 68 subsidized vehicles that could not be identified in any sales data from our best

[41] The official website of China Association of Automobile Manufacturers can be found at: http://www.caam.org.cn.

[42] Registered sales reported by biauto.com can be found at http://news.bitauto.com/gdspl/20100223/1105104118.html.

knowledge. Given that there are already nearly 2,500 vehicle models in our 2010 and 2011 sales data, even including more than 500 vehicle models that did not have annual sales of more than five units, we believe that these 68 missing models were never launched to the market. Finally, considering that we have matched 3.62 million subsidized vehicles for the first six waves from 2010 to 2011, which already exceed the sales estimate disclosed by IBTS Investing Consulting Company during this period (3.57 million, see IBTS Investing Consulting Company (2012)), we believe that our sample is a good representation of the passenger vehicle population studied herein.

Table C1: Data Coverage: Sales from CAAM and Registrations

	(1) Sales reported by CAAM	(2) Total registrations	(3) Registration without commercial vehicles	(4) (3)/(1)×100%
2009	10,331,315	7,692,421	6,836,710	66.17%
2010	13,757,794	10,000,659	9,262,051	67.32%
2011	14,472,416	9,539,235	8,963,912	61.94%
Total	38,561,525	27,232,315	25,062,673	

Notes: CAAM: China Association of Automobile Manufacturers.

Table C2: Breakdown of Missing Models

Wave	Number of new (total) models subsidized	Missing	Passenger vehicles	Commercial vehicles		Other
			After 2012	Before 2012	After 2012	
1	68(68)	12	3	5	-	4
2	61(129)	14	4	-	-	10
3	74(203)	22	6	5	1	10
4	66(269)	21	5	5	3	8
5	69(338)	41	16	7	9	9
6	85(423)	51	17	4	3	27
Total	423	161	51	26	16	68

Notes: This table breaks down missing models by vehicle type and model year. 'Missing': models cannot be identified in the passenger vehicles sales data from 2007 to 2011. 'After/Before 2012': models launched after/before 2012.

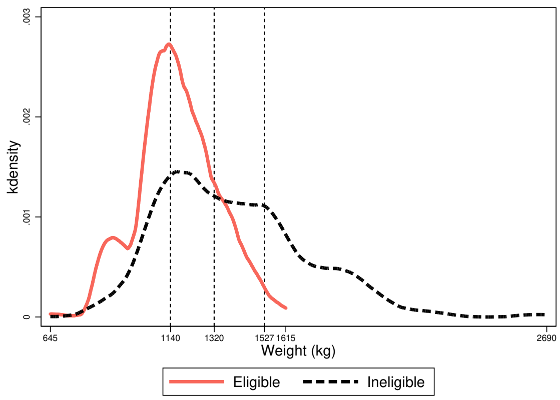
D Construction of the Alternative Control Group

Our identification strategy hinges on using vehicles that were not affected by the program to serve as the control group. We use vehicles in the fourth quartile of fuel inefficiency as our default control group. The subsidy program affected sales of unsubsidized vehicles through mainly two channels: (1) consumers' substitution effect between subsidized and unsubsidized vehicles (2) manufacturers' equilibrium response to the program. To explore the validity of our default control group, we construct an alternative control group. We address the above concerns by removing vehicles susceptible to these concerns from the alternative control group. In this section, we discuss the construction of this control group in detail.

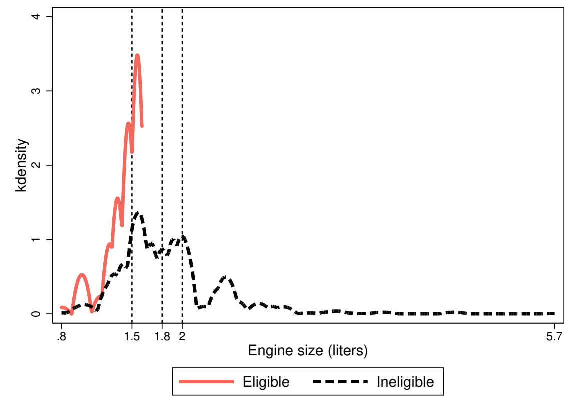
D.1 Substitution Effects

To construct the alternative control group, we first look for vehicles that are 'far enough in the product space' from the subsidized vehicles, and so are extremely unlikely to suffer from the substitution effect. First, we remove vehicles with product attributes that 'overlap' with those from the subsidized products. Figure D1 shows how attributes of subsidized and unsubsidized vehicles overlap with each other in weight, engine size, horsepower and fuel inefficiency. Based on Figure D1, we remove vehicles from the alternative control group that meet any of the following criteria: (1) weight is less than or equal to 1650 kg (2) engine size is less than or equal to 1.6 liters (3) horsepower is less than or equal to 140 kw. We do not place any restrictions on fuel inefficiency because that is the policy effect that we would like to explore. But after applying these three restrictions, the minimum of fuel inefficiency of vehicles left in the control group is larger than that of the maximum of all subsidized vehicles.

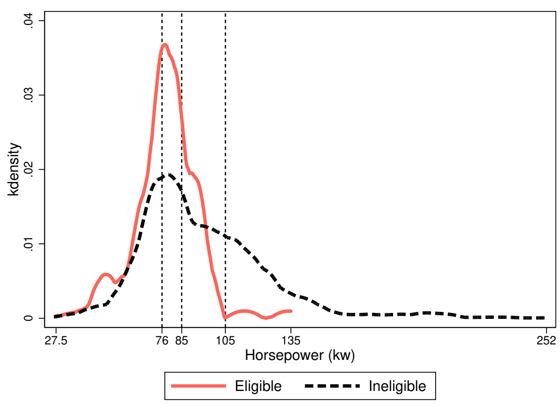
To show that vehicles in the control group would not suffer from the substitution effect of the subsidy program, we calculate the minimum marginal rate of substitution (MRS) of horsepower and weight for a 1% price discount in order for a consumer whose original choice was a control group vehicle to switch to a subsidized vehicle. To this end, we calculate the percentage of the price discount received by each subsidized vehicle and the difference between the vehicle's horsepower and weight to the control group's threshold, i.e., 140 kw and 1650 kg, respectively. Then, for each vehicle, we calculate the minimum MRS of horsepower and weight for a 1% price discount required for a substitution effect between this vehicle and any vehicle in the control group to take place. Figure D2 shows the results from our calculations. In the figure, each solid dot represents a subsidized vehicle. Consider vehicle A on the sixth list, which received a 4.56% price discount after the subsidy became effective. Vehicle A's manufacturer's suggested retail price, horsepower and weight are 65,800 RMB, 83kw, and 1435kg, respectively. If a consumer's original choice was a vehicle in the alternative control group, then she must give up at least 57 kw in horsepower and 215 kg in weight to buy vehicle A. The resulting minimum MRS of horsepower and weight for a 1% decrease in price for this substitution to happen would thus be 12.5 kw and 47 kg for this consumer, which are the coordinates of point A in Figure D2. Previous demand estimates of China's automobile industry (Hu et al., 2014) put such estimates around 1.1 kw and 18.44 kg (point B). As shown in Figure D2, it is extremely unlikely for any alternative control group vehicle to suffer directly from the demand substitution effect due to the program's subsidy. Because we only use thresholds of the control group to calculate these minimum marginal rates of substitution, the actual 'distances' between vehicles in the control group and subsidized vehicles would only be larger than those shown in Figure D2, and so our alternative control group is unlikely to suffer from the demand substitution effect from the subsidy program.



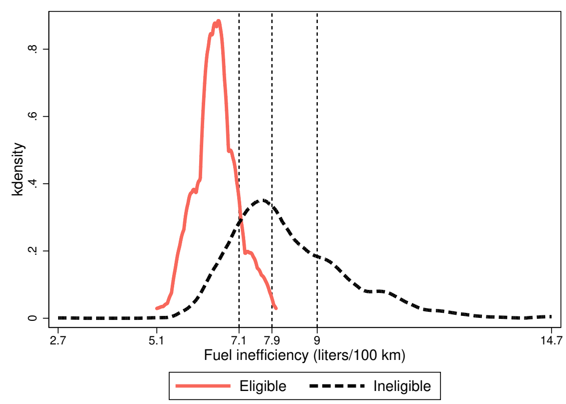
(a) Weight



(b) Engine Size



(c) Horsepower



(d) Fuel inefficiency

Figure D1: Overlapping of Vehicle Attributes

D.2 Manufacturers' Equilibrium Response

Manufacturers may respond to the subsidy program by adjusting their pricing and advertising decisions, especially for those heavily affected by the program. To make our alternative control group more robust to this concern, we remove vehicles produced by manufacturers that may have strong incentives to adjust their pricing and advertising decisions in response to the subsidy program from our alternative control group.

By construction of the subsidy program, manufacturers focusing on producing large-engine (larger than 1.6 liters) vehicles were less likely to be subsidized. Figure D3 gives the distribution of all manufacturers' share of vehicles that were no greater than 1.6 liters in our

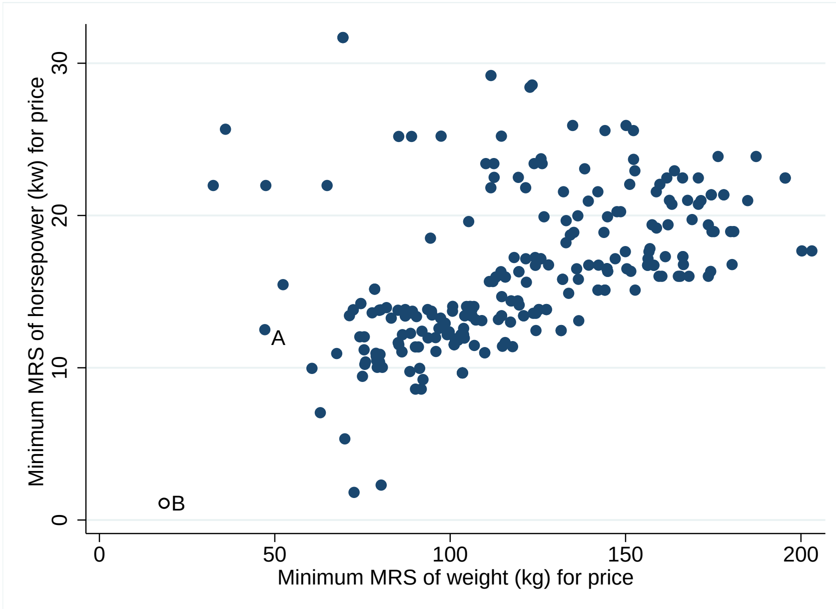


Figure D2: Minimum Marginal Rate of Substitution for a 1% Price Discount

data. As shown in Figure D3, almost all the vehicles produced by some manufacturers were less than 1.6 liters, and so their pricing and advertising decisions may be more likely to be affected by the subsidy program. To account for this concern, we remove vehicles produced by manufacturers whose share of sales from vehicles below 1.6 liters was greater than or equal to 50% from the control group. The final alternative control group thus consists of vehicles that satisfy all of the following restrictions: (1) weight is larger than 1650 kg (2) engine size is larger than 1.6 liters (3) horsepower is larger than 140 kw, and (4) manufacturer's share of sales from vehicles below 1.6 liters is less than 50%.

With this alternative control group, we add $\beta_4 1(\text{Unlisted})_j \times 1(\text{Post})_t \times 1(\text{Attribute quartile} = 4)_j$ to equation (2) and estimate the model using only unsubsidized vehicles to test if β_4 is significant. A significant β_4 would suggest that our default control group used in estimating equation (2) suffers from a substitution effect. As shown in Table D1, none of the estimated coefficients of $1(\text{Unlisted})_j \times 1(\text{Post})_t \times 1(\text{Attribute quartile} = 4)_j$ are significant: the p-values for the coefficients in columns (1) to (3) are 0.83, 0.75, and 0.87, respectively. Therefore, we do not find evidence that our default control group also suffered from the substitution effect.

Table D2 examines the robustness of our estimates for the program's effect on subsidized

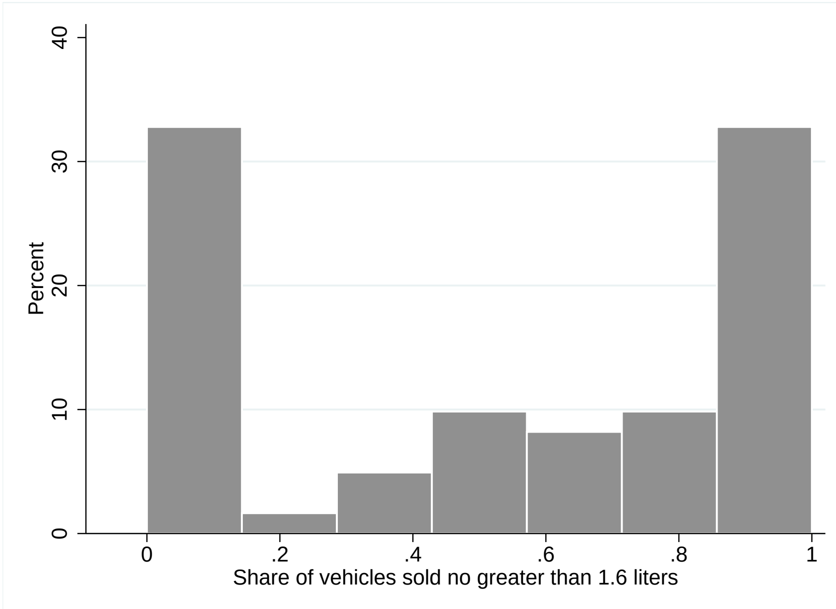


Figure D3: Share of vehicles sold no greater than 1.6 liters

products by exploring different definitions of the control group. Column (1) of Table D2 provides estimation results using an alternative control group. The estimated coefficient for $1(\text{Receiving a subsidy})_{jt}$ is 0.515. Column (2) of Table D2 uses vehicles in the fourth quartile of fuel inefficiency as the control group (default control group), while columns (3) and (4) keep on expanding the control group used in column (2) by adding vehicles in the third and the second quartile of fuel inefficiency to the control group. The estimated coefficients for receiving a subsidy in columns (2) to (4) are between 0.580 to 0.613 and statistically significant, and the coefficients for $1(\text{Post})_t \times 1(\text{Attribute quartile} = 1)_j$ are all negative and significant. Finally, columns (5) and (6) provide estimates using attribute quartiles based on engine size and weight. The specifications in these two columns used the same control group as that used in column (1), i.e., the alternative control group. The estimated coefficients of $1(\text{Receiving a subsidy})_{jt}$ in these two columns are 0.469 and 0.493, similar to that shown in column (1). The results also suggest that the program decreased sales for vehicles with a smaller engine size or a lower weight, without creating a substitution effect in vehicles larger in engine size or heavier.

Table D1: Testing the Assumption of Interference

	(1)	(2)	(3)
Unlisted×Post×Attribute quartile 1	-0.364	-0.283	-0.276
	(0.196)	(0.198)	(0.181)
Unlisted×Post×Attribute quartile 2	-0.083	0.010	0.011
	(0.185)	(0.187)	(0.164)
Unlisted×Post×Attribute quartile 3	0.049	0.034	-0.004
	(0.187)	(0.188)	(0.162)
Unlisted×Post×Attribute quartile 4	0.038	-0.057	-0.025
	(0.175)	(0.180)	(0.157)
Gasoline expenditure	0.076	0.017	0.022
	(0.015)	(0.017)	(0.020)
Observations	370884	370884	328024
Category × trend controls	No	Yes	Yes
Birth quarter controls	No	No	Yes
Keep first months of each wave	No	No	No
Keep Beijing and Shanghai?	No	No	No

Notes: This table reports estimates of equation (2) using only unsubsidized products with an alternative control group. The dependent variable is the natural log of monthly vehicle model sales in a province. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level.

Table D2: Different Control Groups and Attributes

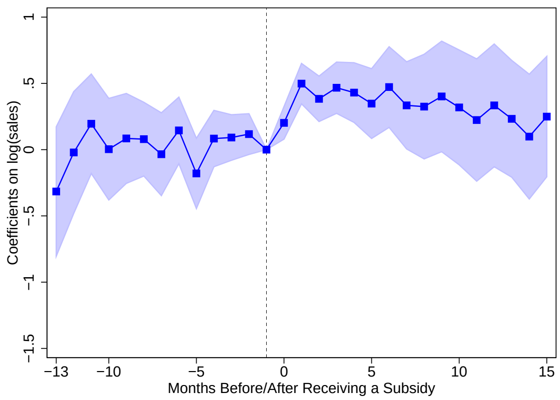
	(1) Fuel Inefficiency	(2) Fuel Inefficiency	(3) Fuel Inefficiency	(4) Fuel Inefficiency	(5) Engine Size	(6) Weight
Receiving a subsidy	0.515	0.580	0.602	0.613	0.469	0.493
	(0.116)	(0.139)	(0.147)	(0.152)	(0.117)	(0.117)
Unlisted×Post×Attribute quartile 1	-0.434	-0.352	-0.326	-0.313	-0.468	-0.359
	(0.144)	(0.125)	(0.128)	(0.121)	(0.154)	(0.140)
Unlisted×Post×Attribute quartile 2	-0.133	-0.051	-0.026		-0.388	-0.354
	(0.131)	(0.104)	(0.105)		(0.125)	(0.131)
Unlisted×Post×Attribute quartile 3	-0.124	-0.039			-0.021	-0.005
	(0.124)	(0.098)			(0.160)	(0.138)
Unlisted×Post×Attribute quartile 4	-0.104				0.066	-0.012
	(0.114)				(0.105)	(0.113)
Gasoline expenditure	-0.001	-0.001	0.001	0.002	0.002	0.007
	(0.020)	(0.020)	(0.020)	(0.021)	(0.022)	(0.022)
Observations	384438	384438	384438	384438	384438	384438
Category × trend controls	Yes	Yes	Yes	Yes	Yes	Yes
Birth quarter controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of equation (2) using variation from the first six waves, exploring different definitions of comparison groups. Columns (5) and (6) reports the results using engine size and weight to construct attribute quartiles, respectively. The dependent variable is the natural log of monthly vehicle model sales in a province. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level.

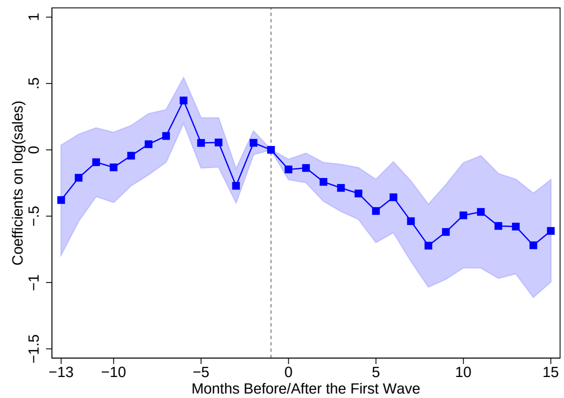
E Additional Event Study Graphs

In the main text, we provide event study graphs with coefficients from estimating equation (2). In this section, we explore the robustness of the parallel trend assumption by providing event study graphs under other specifications. The first specification is still based on equation (2), but instead of estimating the model jointly, we estimate the model separately, each time only including vehicles from a selected treatment group and the control group. The second specification allows for two types of event time for subsidized vehicles: the month when a vehicle became eligible for the subsidy, which is wave specific, and the month when the subsidy program began, i.e., June 2010. Note that vehicles listed in the first wave can only have one event time, which was set at the month they became eligible for the program. The third specification provides estimation results using only vehicles that were on the market before 2009 and still available after the sixth wave, and so estimated coefficients were less affected by vehicle entries or exits.

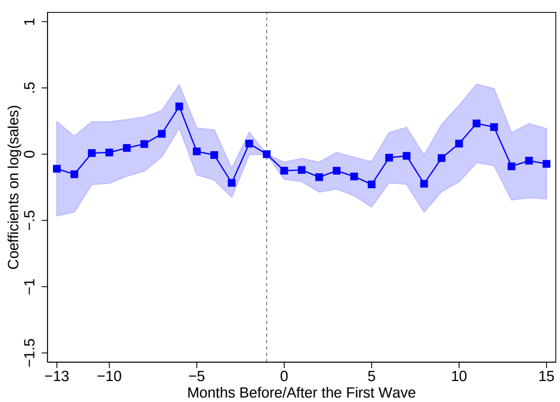
Figure E1 provides estimated coefficients for the first specification. The results are consistent with those shown in the main text. Figure E2 provides results following the same specification but with variables controlling for the category trend. The results are extremely close to those in Figure E2. Figure E3 provides estimated coefficients from the second specification. The main difference between Figure E3 and Figure 6 in the main text is that Figure E3 allows subsidized vehicles not listed in the first wave to have different monthly fixed effects (shown in Figure E3(b)) compared to those in the first wave and the control group. We also provide the results from the second specification with a category trend in Figure E4. Finally, Figures E5 and Figure E6 give the results from the third specification, excluding and including a category trend, respectively. We note that in this specification, by focusing on models that were available throughout the study period, we lose the majority (80%) of vehicle models in our sample and are left with only 12 subsidized products. The patterns from these graphs are in general consistent with those in the main text, but the coefficients in general cannot be estimated precisely.



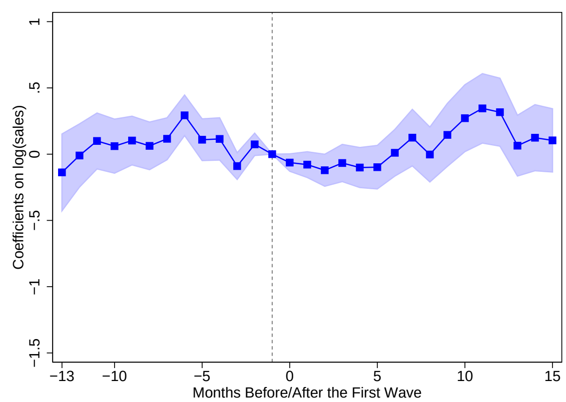
(a) Subsidized Products



(b) Unsubsidized Products in Fuel Inefficiency Quartile 1

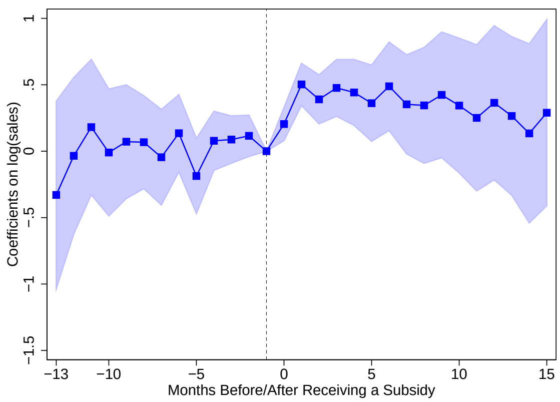


(c) Unsubsidized Products in Fuel Inefficiency Quartile 2

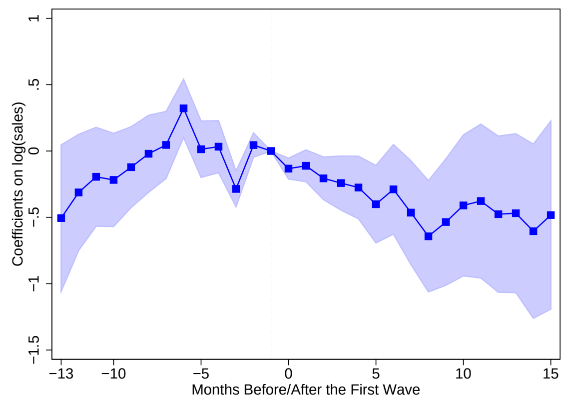


(d) Unsubsidized Products in Fuel Inefficiency Quartile 3

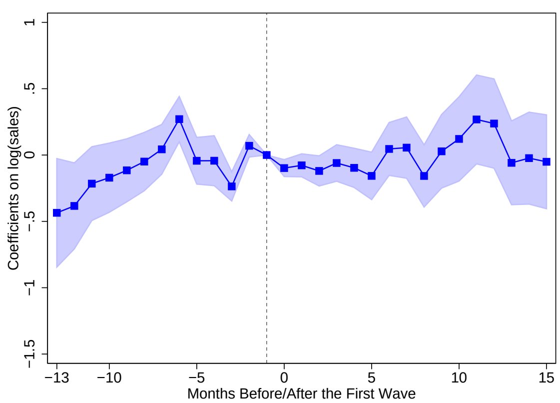
Figure E1: Single Treatment Group Estimation



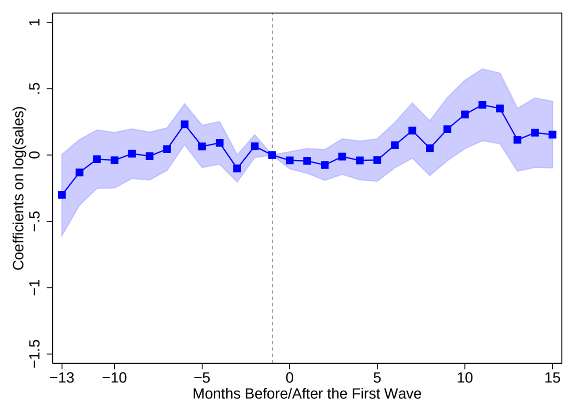
(a) Subsidized Products



(b) Unsubsidized Products in Fuel Inefficiency Quartile 1

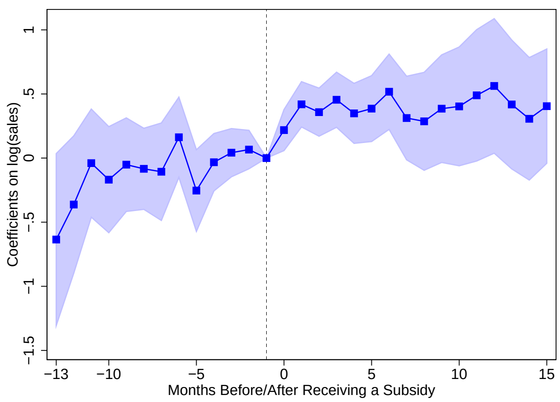


(c) Unsubsidized Products in Fuel Inefficiency Quartile 2

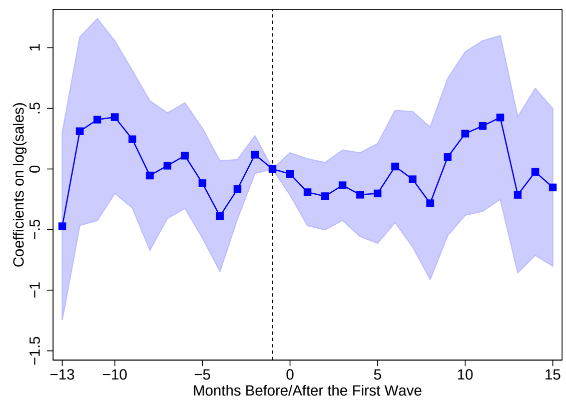


(d) Unsubsidized Products in Fuel Inefficiency Quartile 3

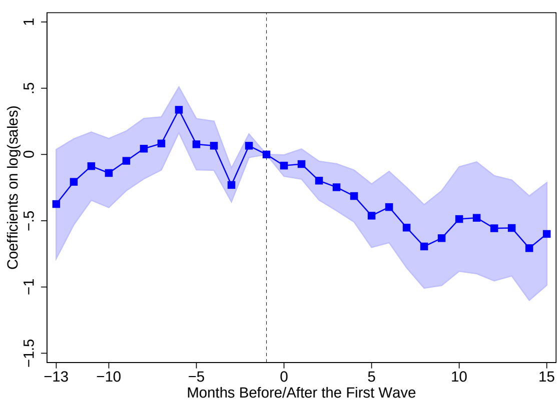
Figure E2: Single Treatment Group Estimation (with Category Trend)



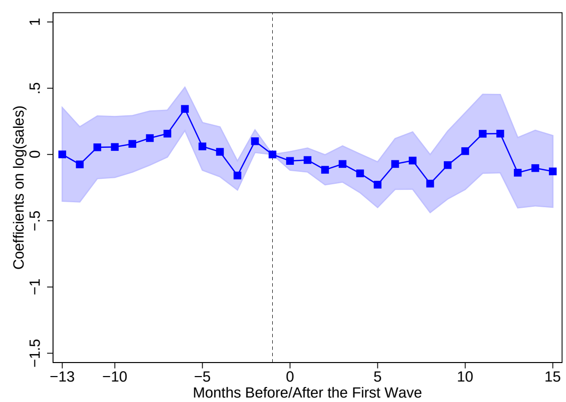
(a) Subsidized Products



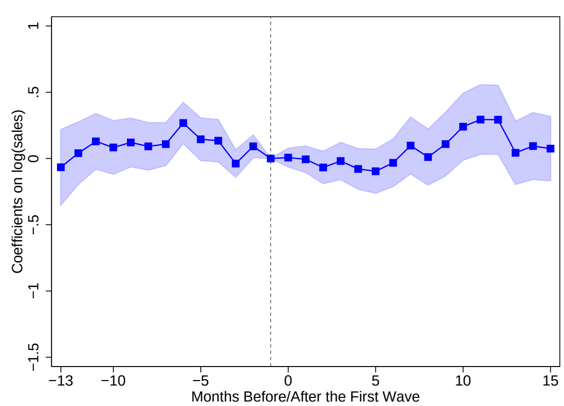
(b) Subsidized Products



(c) Unsubsidized Products in Fuel Inefficiency Quartile 1

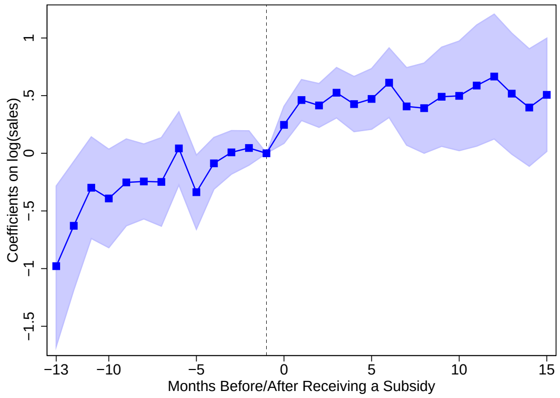


(d) Unsubsidized Products in Fuel Inefficiency Quartile 2

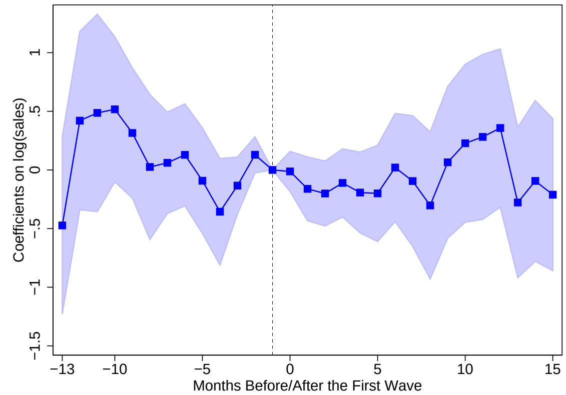


(e) Unsubsidized Products in Fuel Inefficiency Quartile 3

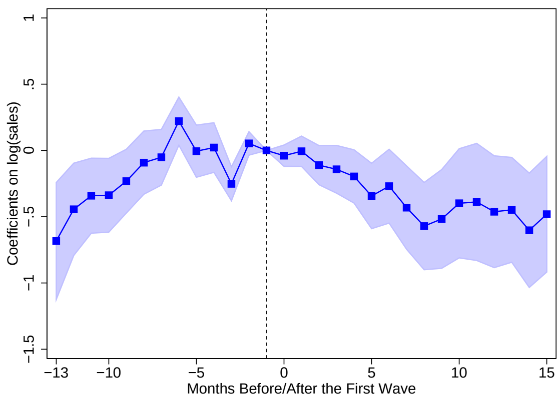
Figure E3: Allowing for Two Types of Event Time for Subsidized Vehicles



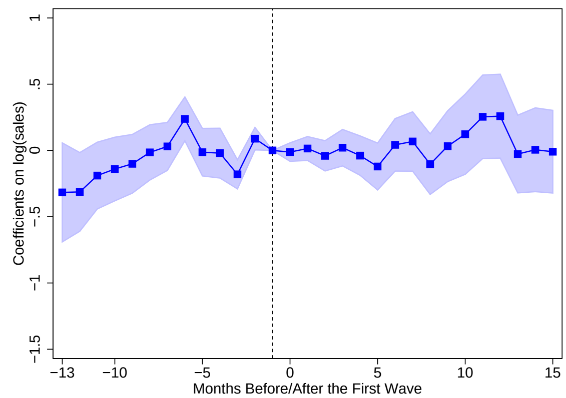
(a) Subsidized Products



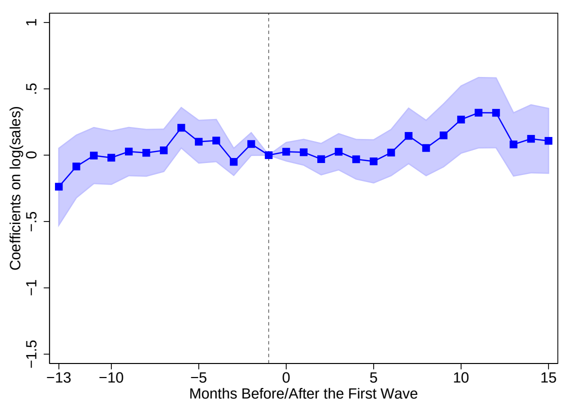
(b) Subsidized Products



(c) Unsubsidized Products in Fuel Inefficiency Quartile 1

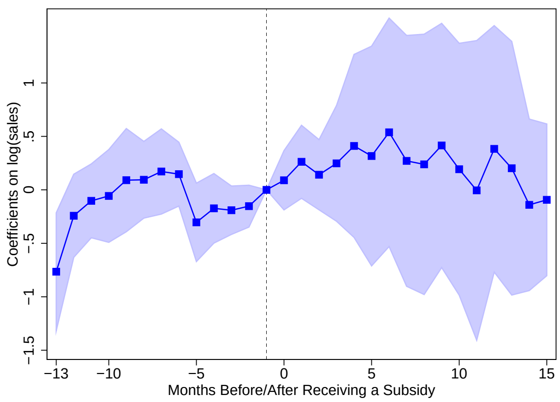


(d) Unsubsidized Products in Fuel Inefficiency Quartile 2

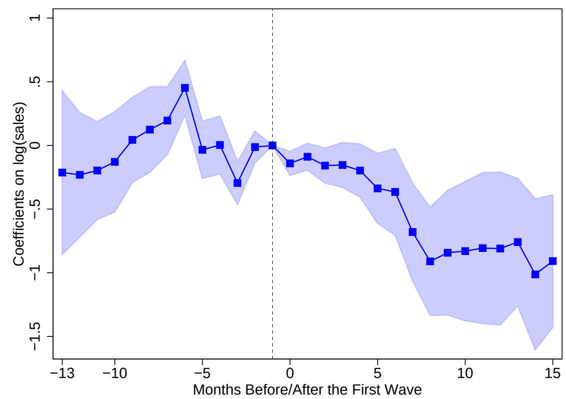


(e) Unsubsidized Products in Fuel Inefficiency Quartile 3

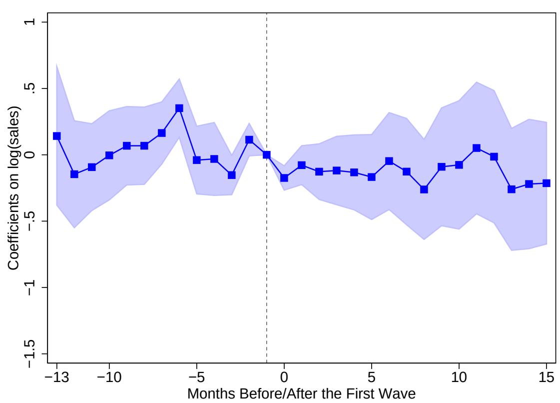
Figure E4: Allowing for Two Types of Event Time for Subsidized Vehicles (with Category Trend)



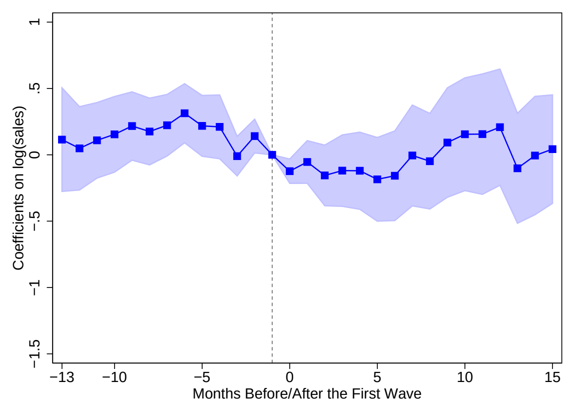
(a) Subsidized Products



(b) Unsubsidized Products in Fuel Inefficiency Quartile 1

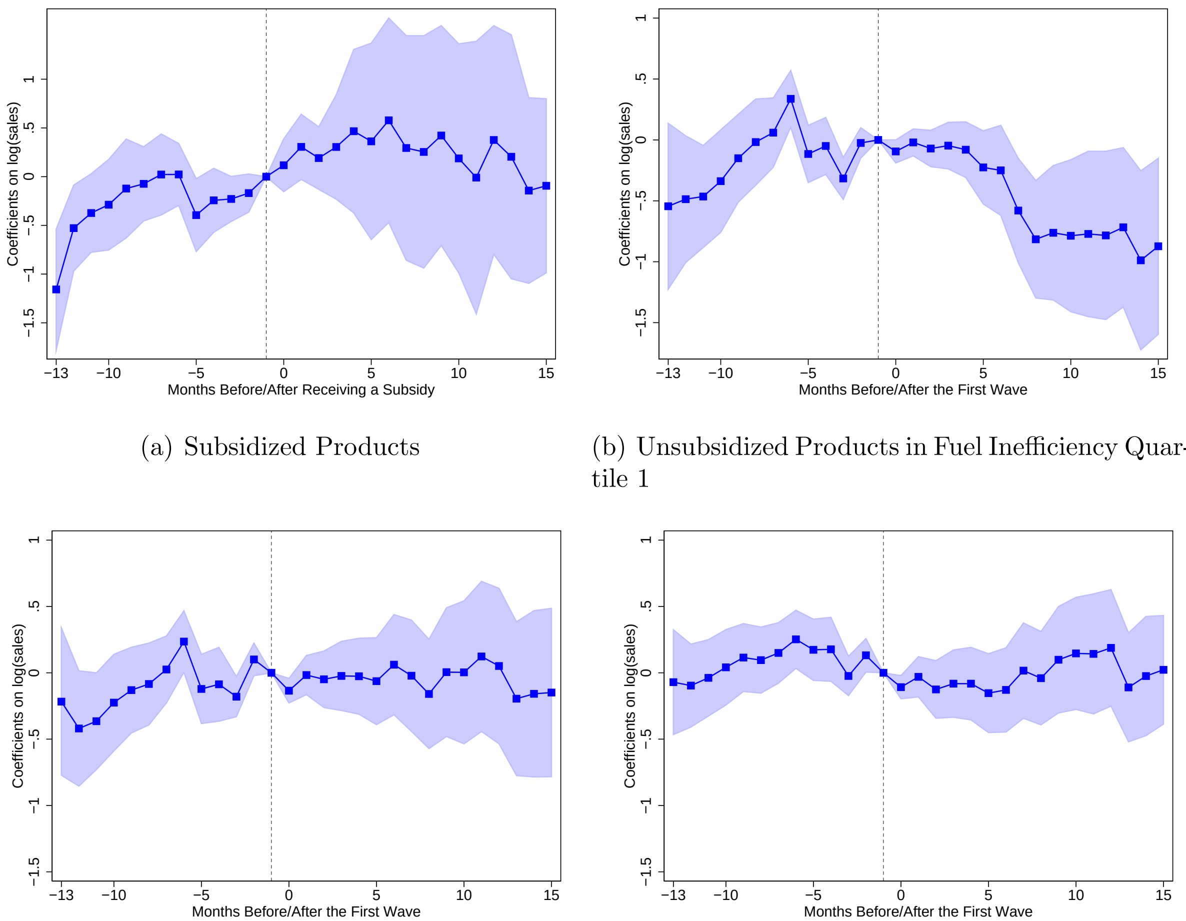


(c) Unsubsidized Products in Fuel Inefficiency Quartile 2



(d) Unsubsidized Products in Fuel Inefficiency Quartile 3

Figure E5: Balanced Panel without Category Trend



(a) Subsidized Products

(b) Unsubsidized Products in Fuel Inefficiency Quartile 1

(c) Unsubsidized Products in Fuel Inefficiency Quartile 2

(d) Unsubsidized Products in Fuel Inefficiency Quartile 3

Figure E6: Balanced Panel with Category Trend

F Welfare Calculations with Attribute Adjustments

In the main text, our estimates of welfare loss for consumers switching between their original choice of vehicles and subsidized vehicles do not take attribute adjustments into account. When there were many close subsidized substitutes around each consumer's original choice of vehicle, the welfare loss for consumers to make a substitution may be less than that estimated under a simple linear demand assumption. In this section, we discuss how to use existing estimates from Hu et al. (2014) to calculate deadweight loss from the subsidy program that takes attribute adjustments into account. We find that our results in the main text are robust to the above attribute adjustments.

Consider a subsidized vehicle B. Let the marginal consumer's original choice be A. After vehicle B was subsidized, the marginal consumer decided to purchase B instead of A. The utilities from consumer products A and B for the marginal consumer are as follows:

$$u(x_A, p_A) = \beta' x_A + \alpha \ln(p_A)$$
$$u(x_B, p_B) = \beta' x_B + \alpha \ln(p_B),$$

where $x = (\text{horsepower}, \text{weight}, \text{fuel inefficiency})'$. Because the consumer's original choice was vehicle A, it must be the case that $u(x_A, p_A) - u(x_B, p_B) > 0$. Thus

$$\Delta \equiv \beta' (x_A - x_B) + \alpha \big[\ln(p_A) - \ln(p_B)\big] > 0.$$

In addition, because the consumer would choose to purchase vehicle B once B was subsidized, it must be that $u(x_A, p_A) - u(x_B, p_B - 3000) < 0$. Thus

$$\beta' (x_A - x_B) + \alpha \big[\ln(p_A) - \ln(p_B - 3000)\big] < 0.$$

Rewriting the above equation using Δ,

$$\Delta + \alpha\big[\ln(p_B) - \ln(p_B - 3000)\big] < 0 \Rightarrow \Delta < -\alpha\big[\ln(p_B) - \ln(p_B - 3000)\big].$$

Therefore, it must be that $0 < \Delta < -\alpha\big[\ln(p_B) - \ln(p_B - 3000)\big]$. Once we know the range of Δ, we can turn Δ, which is the difference in utility, into a monetary measure, to find the equivalent loss of income for the consumer without any change in vehicle attribute. We find that the deadweight loss is $-p_A + \exp\big[\ln(p_A) - \Delta/\alpha\big]$.[43]

To find the deadweight loss, we follow three steps. First, for each subsidized vehicle in the first fuel inefficiency quartile, we find all unsubsidized vehicles with attributes satisfying $0 < \Delta < -\alpha\big[\ln(p_B) - \ln(p_B - 3000)\big]$. Second, for unsubsidized vehicles with Δ satisfying step one, we calculate the average deadweight loss $-p_A + \exp\big[\ln(p_A) - \Delta/\alpha\big]$ for these subsidized vehicles, using sales before the program as weights. Third, we weight the deadweight loss associated with each subsidized vehicle using their sales after the subsidy program.

We use demand estimates from Hu et al. (2014) (both nested-logit OLS and nested-logit with IV) for (α, β) and calculate the corresponding Δ and deadweight loss for each subsidized vehicle. The results suggest that the deadweight loss from the marginal consumers is around 1320 RMB, which is close to our simple back-of-envelope estimate of 1500 RMB used in the paper, and our welfare calculations are robust after we take attribute adjustments into account.

[43] We look for x such that $u(x_A, p_A) - u(x_A, p_A + x) = \Delta$. Thus

$$\Delta = \alpha\big[\ln(p_A) - \ln(p_A + x)\big] \Rightarrow x = -p_A + \exp\big[\ln(p_A) - \Delta/\alpha\big].$$

G Bunching Analysis

In the subsidy program, heavier vehicles face less stringent standards of fuel economy, and so manufacturers may change vehicle weight to meet the eligibility cutoffs. If so, the program could have unintended consequences by affecting the distribution of attributes other than fuel inefficiency. To illustrate, suppose that the fuel inefficiency cutoffs for vehicles with weight w (kg) in the range of $1205 < w \leq 1320$, and $1320 < w \leq 1430$ are 6.9 L/100 km and 7.3 L/100 km, respectively. A manufacturer producing an ineligible vehicle weighing 1300 kg and 7.2 L/100 km fuel inefficiency and seeking to benefit from the program could either adopt gasoline-saving technologies to meet the fuel inefficiency cutoff (making it be at most 6.9 L/100 km), or increase vehicle weight to meet the weight cutoff (making it heavier than 1320 kg). The manufacturer's final decision would depend on the cost structure of vehicle attributes and the demand response from product repositioning. If the manufacturer chose to meet the weight cutoff, and increasing vehicle weight had an additional cost, we would expect to see an excess bunch in the distribution of vehicle weight at the 1320 kg cutoff.

Ito and Sallee (2018) study Japan's fuel efficiency program and find excess bunching in the distribution of vehicle weight at eligibility cutoffs, suggesting that manufacturers manipulated vehicle weights to meet the government's fuel-economy regulations. Following their methods, we estimate the counterfactual distribution of vehicle weight to test excess bunching at eligibility cutoffs (or notches). The idea is straightforward: use the data *not* at the notch to fit a flexible model, take the model to estimate the density of vehicle weight at the notch, and compare the observed density to the estimated density at the notch. However, the actual implementation requires additional distributional assumptions to meet the integration constraint. In particular, one has to make assumptions about where excess bunches at the notch come from. Excess bunches at the notch are assumed to be drawn from vehicles weighing between the notch and the notch right before it, but they could be drawn uniformly (the 'uniform' assumption) or in a particular way that led to discrepancies in the observed and the predicted distribution (the 'empirical' assumption). We refer interested readers to Ito and Sallee (2018) for more details.

In our estimation, each bin has a width of 5 kg.[44] For example, the 1320 kg bin includes all vehicles with $1320 < w \leq 1325$. Columns (1) and (2) of Table G1 report notches associated with vehicles with engine size less than 1.6 liters and the number of vehicles at each notch. For notches with a positive number of vehicles in the corresponding 5 kg bin, columns (3) and (4) report the estimated excess bunching at the notch, under the uniform and the empirical assumption, respectively. Panel A provides results using vehicles launched before the program. We do not find evidence of excess bunching under either the uniform or the empirical assumption. Panel B shows results using vehicles launched after the program. Here, we find excess bunching at notches 1090 kg, 1205 kg, and 1320 kg: the estimated numbers of excess vehicles at each notch are 12.04, 9.06, and 11.63, respectively, suggesting that after the program was launched, manufacturers adjusted vehicle weights to meet the eligibility cutoffs of the program. Finally, we note that the above analysis does not use any information from each vehicle's actual eligibility status, yet we find that the numbers of eligible vehicles launched after receiving a subsidy at the above three notches are 12, 8, and 6, respectively (shown in Figure G1), suggesting that the majority of excess bunching at notches may come from new eligible models. Such distortion of attributes other than fuel inefficiency was not the goal of the subsidy program and may even increase the overall fuel inefficiency. Even though a comprehensive welfare analysis taking vehicle redesign into account is beyond the scope of this paper, we do note that because changes in vehicle weights would affect vehicle safety or driving behaviors, it is important to examine the long-term effect of fuel efficiency programs that takes vehicle redesign into account (Jacobsen, 2013; Anderson and Auffhammer, 2013).

[44] All notches are multiples of 5 kg.

Table G1: Excess Bunching

(1) Notches	(2) Number of Cars	(3) Uniform assumption	(4) Empirical assumption
Panel A: Vehicles launched before the program			
750	0	-	-
		-	-
865	5	2.78	2.81
		(4.83)	(5.06)
980	1	-5.06	-5.05
		(4.54)	(4.54)
1090	4	-5.29	-5.30
		(4.65)	(4.71)
1205	15	5.75	5.74
		(4.66)	(4.78)
1320	10	5.19	5.19
		(4.85)	(5.08)
1430	0	-	-
		-	-
1540	1	-1.95	-1.96
		(5.52)	(5.34)
Panel B: Vehicles launched after the program			
750	0	-	-
		-	-
865	4	2.48	2.60
		(2.37)	(2.31)
980	4	0.42	0.47
		(2.39)	(1.92)
1090	17	12.04	12.05
		(2.28)	(2.25)
1205	14	9.06	9.06
		(2.23)	(2.16)
1320	15	11.63	11.64
		(2.30)	(1.95)
1430	2	0.69	0.69
		(2.47)	(2.11)
1540	0	-	-
		-	-

Notes: Standard errors are defined as the standard deviations of corresponding estimates from 1000 bootstrap samples (with random resampling of residuals).

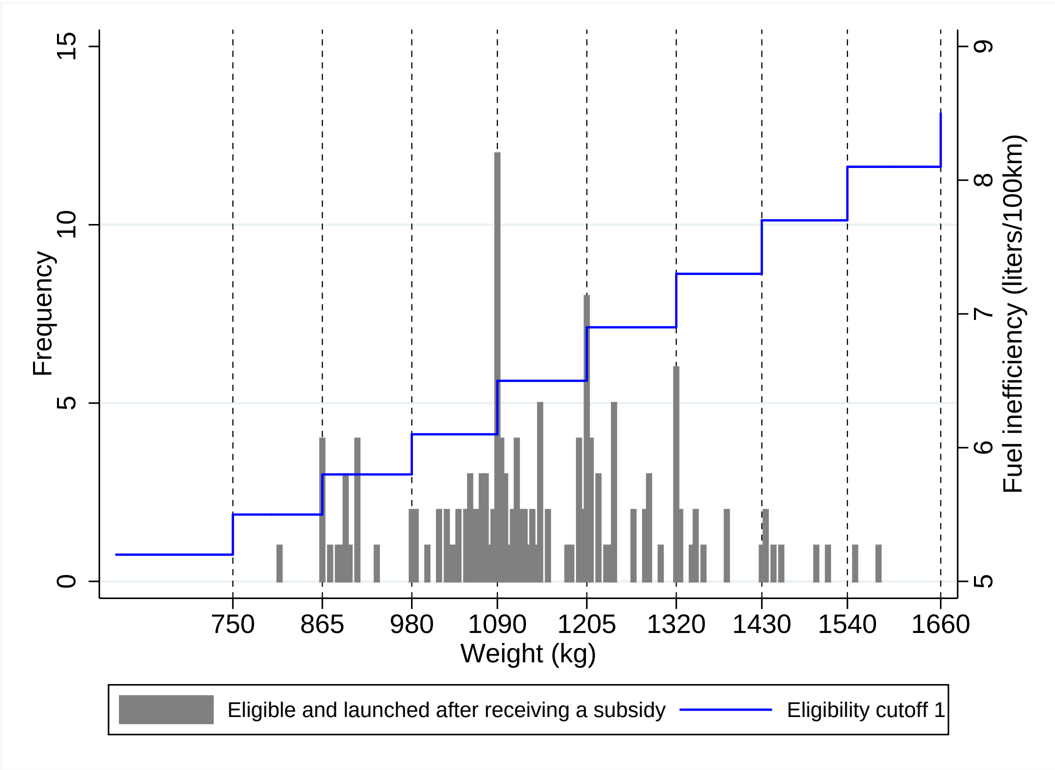


Figure G1: Number of New Eligible Vehicles at Each Notch