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

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Abstract

We examine the consumption response to China's national subsidy program for fuel efficient vehicles during 2010 and 2011. Using the variation from the program's eligibility cutoffs and effective months, we find that the program boosted sales for subsidized vehicle models. However, we show that the program also created a substitution effect within highly fuel efficient vehicles and that most of the subsidies went to inframarginal consumers. We also present that the program was not well-targeted: the effect of the subsidy on sales of fuel-efficient vehicles was smaller in areas where consumers were more likely to purchase fuel-inefficient models or were lower educated. Overall, our results suggest that the program was an expensive way to reduce carbon dioxide emissions.

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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 in China, similar efforts have been made. For example, China's central government launched an energy efficient program in mid 2010, subsidizing consumers who purchase 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.

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

In this paper we employ detailed panel dataset that includes vehicle sales at the model-month-province level to study the effectiveness of the fuel efficient subsidy program in China. Our focus is the consumption response to the program. We estimate the share of subsidies taken up by marginal consumers and the extent to which the substitution effect across vehicle types. Such estimates have important policy implications, because if most of the subsidies were taken up by inframarginal consumers or marginal consumers whose original choices were other fuel efficient vehicles, then the program can be deemed ineffective in reducing gasoline consumption and carbon dioxide emissions. We also explore the interactions between the effect of the program and the tendency to purchase a relatively fuel inefficient vehicles to learn more about the program's effect on targeting consumers.

Our empirical approach is based on a 'difference-in-differences' set-up. We use both the eligibility cutoffs and the effective months of the program to identify the consumption response to the subsidy. Thus, vehicles that were not subsidized are taken as a comparison group. Our empirical specification includes vehicle model fixed effects to account for time invariant, model specific, unobserved factors. Because this policy program builds up by releasing lists of subsidized models sequentially and unexpectedly (to consumers), 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 using vehicles that are not subsidized to construct relevant comparison groups.

Our 'difference-in-differences' may over-estimate the true effect of the program if vehicles in the comparison group had lower sales, because their potential consumers chose to buy subsidized vehicles instead. We thus look at the sale pattern of vehicles that were not subsidized to find out which types of vehicles were more likely to suffer from the substitution effect and to remove them from our comparison group. To this end, we adopt an instrumental variables approach. For each new wave of a subsidy, we calculate the share of vehicles sold in a province that were subsidized (the intensity of the program in a province) and how many eligible vehicle models were available in each province right before the wave of a subsidy took place (availability in a province). Using vehicle availability (interacting with vehicle attributes) as instruments, we estimate how program intensity (interacting with vehicle attributes) affected the sales pattern of ineligible vehicles.

Our results suggest that the program boosted sales significantly for subsidized vehicle models. Under the assumption that none of the increased sales of subsidized vehicles crowded out sales of ineligible models, we find that the share of marginal consumers subsidized by the program is around 35%. We then show that such an assumption is likely to be invalid. We discover that some of the increase in sales of the subsidized models was driven by a substitution effect, and that the substitution effect was not mainly from gas-guzzlers to highly fuel efficient models, but rather was within relatively highly fuel efficient models. Once we take the substitution effect into account, our estimates suggest that the share of marginal consumers is around 30%. Thus, nearly 70% of the program's payments were ineffective and distributional. We then take our estimates to conduct a cost-benefit analysis and find that the program was expensive in reducing carbon dioxide emissions: the implied cost of a metric ton's reduction in carbon dioxide was 146 USD. 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 inefficiency vehicles or were lower educated.

Our paper builds on the existing literature that evaluates the consumption response to energy efficient programs. Several studies point out that most of the consumers who receive subsidies are inframarginal (Boomhower and Davis, 2014; Chandra, Gulati, and Kandlikar, 2010; Houde and Aldy, 2014). 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. Chandra, Gulati, and Kandlikar (2010) note that sales of high performance cars are crowded out as a result of subsidizing hybrid cars.

This paper differentiate from the previous literature by exploiting the variation in eligibility status created by the government's announcements in order to identify the share of marginal consumers who bought subsidized vehicle models. The subsidy program is also interesting in itself by subsidizing efficient vehicles with a small engine size in a developing country. A high take-up rate of the program shifts the average vehicle fleet toward a smaller one and may have other safety implications. In this regard, evaluating the cost-benefit of the program on achieving its intended policy goals (i.e., reducing gasoline consumption and carbon dioxide emissions) is extremely important.

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

2 Industry and the Subsidy Program

2.1 Industry Background

Since the implementation of "reform and open" policies of the 1980s, China's automobile market has grown rapidly. In order to satisfy domestic demand for quantity, product quality, and variety and to accelerate industry upgrading and to bolster economic growth, in 1994 the State Council chose the automotive industry as one of the pillars of the economy and aimed to strengthen investment directed into it. At the same time, the National Development and Reform Commission (a subsidiary of the State Council) issued the Policy on Development of Automotive Industry[1] (PDAI) giving priority to foreign investors with advanced technologies to create joint ventures with SOEs (state-owned enterprises). Attracted by these policies, most global car manufacturers began to establish joint ventures in China, and after China's entrance into the World Trade Organization (WTO) the number of them surged further. With the boost in joint ventures, vehicle sales stepped up from 1.34 million in 1994 to 19.31 million in 2012. Since 2009, China has become the largest global vehicle market with annual sales of passenger cars exceeding 10 million.

While celebrating the success of the automotive industry's development, China has experienced the same consequence as countries experiencing increasing automobile demand:

[1] http://www.lawinfochina.com/display.aspx?lib=law&id=3556&CGid=

traffic congestion and air pollution. For example, according to the China Vehicle Emission Control Annual Report 2010[2] published by the Ministry of Environmental Protection, vehicle emissions have become the main source of air pollution in cities of China, large and medium alike. In WTO's Global Status Report on Road Safety 2013,[3] China is ranked number one in the reported number of road traffic deaths in the last decade.

To mitigate the negative impact on the environment resulting from the development of automobile industry, various policies have been implemented at different government levels. A few studies have evaluated their effectiveness. For instance, the central government applied tax policies (such as a fuel tax and a consumption tax (Xiao and Ju, 2014) to control the size of the vehicle fleet 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" (Wang et al., 2009; Viard and Fu, 2015; Chen et al., 2013), or car ownership restriction, e.g. the vehicle quota system (VQS) in Shanghai (Xiao et al., 2015; Li, 2015) and Beijing (Li, 2015; Hu et al., 2015).

The studies listed above have shown that, aside from the consideration of industry development, a tax policy and car ownership restriction can effectively restrain the growth of the vehicle fleet, and car usage restriction can markedly reduce pollution, at least during the relevant restriction period. However, it should be noted that the car restriction policy implemented in Shanghai and Beijing, although it has proved useful in reducing vehicle sales, shifts consumers' purchasing propensity toward high quality/high price and thus low fuel efficient cars (Hu et al., 2014; Xiao et al., 2015; Hu et al., 2015). In this paper we study the implementation of subsidies for fuel efficient vehicles, but note that concurrent car ownership restrictions in Beijing and Shanghai will scale down consumers' response to the subsidy in these two cities. Therefore, the issue of concurrent policies needs to be addressed

[2] http://www.vecc-mep.org.cn/news/e_home_reports/2010engreport.pdf

[3] http://www.who.int/violence_injury_prevention/road_safety_status/2013/en/

and carefully handled in our estimation.

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 who purchases a government certified fuel efficient vehicle.[4] The program was very popular. It had subsidized more than 4 millions of cars and paid out more than 12 billion RMB by the end of 2011.

There are several distinct features of this program. First, the program only subsidizes 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, is excluded from the program. The government explicitly lays out fuel efficiency thresholds used in the program, which take into account a vehicle's weight, transmission method (manual or automatic), and seating (two rows or three rows). To qualify for the program, car manufacturers must submit applications for their vehicles. After receiving a application for a particular vehicle model, the government verify its attributes and decide whether the vehicle model is eligible.

The second distinct feature of the program is that even for a vehicle model that qualifies for the program at the beginning, the effective date and the duration for the subsidy are not clear to manufacturers (and especially to consumers). The reason is that the government only announces a complied list of eligible vehicle models (a wave of subsidies) from time to time, and at any given time, little is known regarding whether the government will continue or terminate the program in the future. During June 18, 2010 to October 17, 2011, the government released 7 official lists of eligible models, thus creating 7 waves of subsidies.

[4] Car dealers must affix an official program sticker to the side window of every program eligible vehicle. A consumer who purchases such an program eligible vehicle receives a fixed 3000 RMB discount off the agreed-upon transaction price from the dealer. The government then reimburses car dealers on a monthly basis.

The initial six waves of subsidies were cumulative in their nature, so that the number of subsidized vehicles was increasing as the program expanded during this time. However, when the government released the 7th list, it announced that it had adopted a set of stricter fuel efficiency thresholds, and so it stopped subsidizing vehicle models from the previous six lists (unless the model was listed again on the 7th list).

The government announced the final list (the 8th list) of eligible models on July 10, 2012 and terminated the program on September 30, 2013. It reopened a new subsidy program (subject to vehicles that meet higher fuel efficiency standards) on September 3, 2014.

3 Data

We obtain monthly sales data at the province level for new vehicle models produced and sold in China during 2007 to 2011.[5] For our empirical analysis, we focus on vehicle models sold between 2009 to 2011 and only use data before 2009 to identify the month a vehicle was first introduced to the market.[6] The final sample in this paper thus includes vehicle sales during 36 months and across 31 provinces, for a total of 1115 markets.[7] The data include information regarding a vehicle model's identification code, type (indigenous, European, Japanese, Korean, or U.S.), the identity of the manufacturer and engine size.

We accompany sales data with vehicle attributes collected from other sources. Information regarding a vehicle's price, power, and physical size is obtained from the Pacific Online Auto, one of the leading websites that reports new car attributes in China. Vehicle model level fuel inefficiency, curb weight, and program eligibility are public data from the Ministry of Industry and Information Technology's website. Using a vehicle's identification code, we

[5]All vehicles are passenger cars purchased by individuals for personal use. Data are obtained through private arrangement. To protect the proprietary information of the data provider, we cannot release the data source.

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

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

match its model attributes and its program eligibility to its monthly sales in a province. For each year, we calculate the quartiles of each vehicle attribute for models sold in the same year. Demographic data at the province level, such as education levels, rural population, and average wage, are obtained from China Statistical Yearbook 2011.

3.1 Program Eligibility

Figure 1 provides a scatter plot of fuel inefficiency and curb weights for all gasoline vehicle models (eligible or not eligible for the program) with at least 100 units of sales during 2010.[8] As shown in the figure, there is a strong positive linear relationship between a vehicle's weight and its fuel inefficiency. Figure 1 also suggests that, even though a vehicle's program eligibility depended on many factors, eligible vehicles did on average have a lower level of fuel inefficiency than ineligible vehicles with similar weights. Moreover, vehicles with weights above the average were less likely to be eligible, because the subsidy program was only available for those with an engine size less than or equal to 1.6 liters, and vehicles with a higher weight tend to have a larger engine size.

We now turn to program eligibility across time. Table 1 provides the released dates of the 7 waves of subsidies, along with the number of new vehicle models added to the pool of subsidized models. Because the pool of subsidized models was cumulative in the first 6 waves, by the end of the program's 6th wave, there was a total of 391 vehicle models eligible for the subsidy and 280 of them were identified in the sales data. However, due to a set of stricter fuel efficiency thresholds imposed after the 7th wave of the program, only 19 new vehicle models were eligible for the 7th wave. In addition, because only 29 models from all previous lists were listed again in the 7th list, the total number of eligible models after the 7th wave were 48, which was a significant drop from 391. Because the release dates were mostly in the middle of a month, we exclude observations from months in which a new wave

[8] During the time period of this study, almost all vehicles are powered by gasoline (99%), followed by diesel (0.5%), and gasoline/CNG (0.2%). Manufacturers may be less likely to file applications for models that were going to be discontinued. Therefore, we exclude vehicles with national sales less than 100 units in 2010 to construct Figure 1.

of subsidies began to take place for our main results. We provide estimation results for the first month when we examine intertemporal substitution patterns.

Table 1 also tabulates the country of origin of eligible models for each list. As shown in the table, most eligible cars are China's indigenous products. Nevertheless, joint venture manufacturers producing European, Japanese, Korean, or U.S. models also enrolled some of their models into the program. Out of the total 410 models that ever became eligible for subsidies during 2010 and 2011, we are able to match 298 models with the sales data. We find that 189 models of these models were launched into the market only after they became eligible for the program, leaving us with 109 models with sales observations both before and after they received their subsidies.

Table 1 also provide suggestive evidence that manufacturers may strategically alter vehicle attributes to make them eligible. For the first 4 waves and the 7th wave, at least 75% of eligible models were launched into the market (either had positive sales in our dataset or were listed in Pacific Online Auto). The above shares dropped to 59% and 58% for models of the 5th and 6th lists, respectively, in which manufacturers would later find out that these models were no longer eligible and might not be worthwhile to be launched into the market.

3.2 Summary Statistics

Panel A of Table 2 provides summary statistics for all vehicles in the final sample. The average monthly sales number for a vehicle model in a province is 36. The average engine size, weight, fuel inefficiency, power, price, and size are 1.8 liters, 1345 kg, 8 liters per 100 km, 92 kilowatts, 13.24 RMB (in 10,000 thousands), and 12 m^3, respectively. Nearly 38% of vehicles sold in China are indigenous brands. Joint venture brands from Japan, Europe, the U.S., and South Korea account for 25%, 20%, 10%, and 8% of total vehicles sold, respectively. Panel B of Table 2 provides the same summary statistics for program eligible vehicle models that had already seen sales before being subsidized. As shown in the table, these models on average have higher sales, smaller engine size, and lower weight, and are more fuel efficient. Only 31% of these vehicles are indigenous brands, suggesting that the program was not designed to favor indigenous brands per se. By contrast, Panel C of Table 2 provides summary statistics for program eligible vehicle models that were only launched after being subsidized. For these vehicles, 40% of them are indigenous brands, which is an amount closer to the national average percentage sold by indigenous brands in the full sample.

To study the program's effect across provinces, we construct three variables. To measure the intensity of the program, we calculate the share of vehicles sold in a market (province-month) that were eligible for a subsidy. We also calculate the number of vehicle models sold in a market that will remain or become eligible for the next wave of the subsidy, which is later used to construct instrumental variables for the program's intensity. Finally, 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/weight combination is above the regression fitted line, i.e., conditional on its weight level its fuel inefficiency is above the conditional mean. We use this variable to examine whether the program's effect on increasing the sales of fuel efficient vehicles was stronger in provinces where consumers were more likely to purchase fuel inefficient vehicles, i.e., whether the program was well-targeted.

Table 3 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). For the share of vehicles sold that are fuel inefficient, its average, minimum, and maximum numbers are 39%, 35% (Heilongjiang), and 48% (Qinghai), respectively. The number of eligible models in a province *before* the first wave varies from 16 models to 34 models, and the province/month share of subsidized models ranges from 0 (before the first wave) to 35%.

4 Empirical Strategy

We adopt a 'difference-in-differences' approach to study the extent to which subsidized vehicle models were purchased by marginal consumers. Our empirical investigation compares sales of subsidized models before and after receiving subsidies to sales of models that were never subsidized but were sold during the same periods of time. In other words, models that were not eligible for subsidies are used to construct comparison groups. Note that newer models that were launched only after receiving subsidies did not have sales before receiving subsidies and thus are not included in the following analysis. We fit the data using the following specification:

$$\ln \text{Sales}_{ijt} = \mu + \alpha_i + \alpha_j + \alpha_t + \beta 1(\text{Receiving a subsidy})_{jt} + \gamma X_{jt} + \epsilon_{ijt}. \quad (1)$$

Here, $\ln \text{Sales}_{ijt}$ is the natural log of monthly sales for model j in province i during month t. In addition, μ is a constant, and 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 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, the stronger is the effect of the program on inducing marginal consumers to buy fuel efficient models. We also include control variables X_{jt} that take a vehicle model's product life cycle 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.[9]

Under the assumption that all increased sales of eligible models were drawn from consumers whose first choice was outside goods (i.e., no substitution effect between new vehicles)

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

and that vehicles in the comparison group had similar trends to those in the treatment (subsidized) group, the results from equation (1) give the program's true effect on increasing sales of subsidized models. In contrast, 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.

We deepen our analysis by examining both the substitution pattern across vehicle attributes and over time resulting from the subsidy program. If comparison groups we use in estimating equation (1) suffer from a substitution effect and had lower sales due to the program, then the estimates from equation (1) would be biased upward. To explore the substitution pattern across vehicle attributes, we examine to which extent the intensity of the subsidy program affected sales for models that were never subsidized. We use the share of total eligible vehicles sold in a province to total vehicles sold in a province to measure the intensity of the program. Therefore, we estimate the following equation:

(2)

$$\ln \text{Sales}_{ijt} = \mu+\alpha_i+\alpha_j+\alpha_t+\sum_{k=1}^{4}\beta_k(\text{Program intensity})_{it}\times 1(\text{Attribute quartile})_k+\gamma X_{jt}+\epsilon_{ijt}.$$

Here, $\ln \text{Sales}_{ijt}$ is the log of sales of vehicles that were never subsidized. The coefficient of interest is β_k, which measures whether a higher intensity of the program affects sales of vehicles with their attributes lying in attribute quartile k. For example, a negative β_1 for fuel inefficiency (with the first quartile being the most fuel efficient products) would suggest that the program created a substitution effect between highly fuel efficient models.

Because the intensity variable is constructed at the market (province-month) level, the estimated coefficient may be biased if there are unobserved shocks that affect sales both for eligible models and ineligible ones at the market level.[10] To account for this problem, we

[10]For example, suppose that there was a boom in market it, and so all consumers had some extra money on hand. Some consumers who were suddenly able to afford a vehicle responded to this shock by purchasing a low-end subsidized car, while others who were already shopping for cars responded to this shock by upgrading

estimate equation (2) using the instrumental variable method. We construct instrumental variables for a subsidy wave's intensity in market *it* using the number of all eligible models already available for that subsidy wave *before* the wave began. The idea is that if many eligible models already had distribution channels in a province before a subsidy wave, then the intensity of the subsidy wave would be stronger in that province than those without proper distribution channels.[11]

We complement the above analysis of the substitution effect by providing estimation results of equation (1) using different comparison groups, which are constructed based on a vehicle's attributes. If consumers who purchase program eligible vehicle models merely substitute between models with similar attributes, then we would expect the β coefficient of equation (1) to be larger when the comparison group include models that are closer to those subsidized in product attributes space.

We finally examine the intertemporal substitution pattern of the program by estimating the following event study specification:

(3)

$$\ln \text{Sales}_{ijt} = \mu + \alpha_i + \alpha_j + \alpha_t + \sum_{m=-12}^{15} \beta_m \times 1(\text{Number of months being subsidized} = m)_{jm} + \gamma X_{jt} + \epsilon_{ijt}.$$

Here, 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. As the program went on, negative values of β_m would provide evidence of intertemporal substitution. All standard errors are clustered at the vehicle model level.

their vehicle options. In this case, a higher intensity of the program may be associated with lower sales of other low-end vehicles, and yet, the original choice of the consumers who purchased a subsidized car was an outside good (would not purchase), and so there was in fact no substitution effect between low-end vehicles models.

[11]The exclusion restriction requires that the availability of eligible models in a province *before* a wave of the subsidy and the unobserved shocks followed after the wave of the subsidy at the market level were uncorrelated, which is more likely to be the case when the availability of eligible models was predetermined by consumers' preferences and manufacturers' distribution decisions in a province.

5 Results

5.1 Effect of the Program on Sales of Subsidized Models

Table 4 provides estimation results for the coefficient of 1(Receiving a subsidy)$_{jt}$ using equation 1. Column (1) of Table 4 gives the baseline results, while columns (2) and (3) provide results that control for a vehicle model's age and squared age (interacting with a set of birth quarter indicator variables). Our first set of the estimation results uses data from the first six waves (January 2009 to September 2011). In the baseline setting, the estimated coefficient of 1(Receiving a subsidy)$_{jt}$ is 0.55 and is statistically significant, indicating that, providing a 3000 RMB cash subsidy to a fuel efficient model on average increases its sales by 55%. In columns (2) and (3), we include additional control variables to absorb the potential variation due to a vehicle model's product life cycle. The estimated coefficients are significant and are 0.559 and 0.539, respectively.

The rest of Table 4 provides estimation results by narrowing the data window. If there were other unobserved major shocks that affected sales of fuel efficient vehicles during the first six waves, then our baseline results might pick up some of the effects from these unobserved shocks. To address this concern, we provide estimation results using 24-, 18-, and 12-month data windows, respectively. Overall, all estimated coefficients for 1(Receive a subsidy)$_{jt}$ in column (3) are statistically significant and lie between 0.346 to 0.539.

The pattern emerging in Table 4 suggests that the program boosted sales for subsidized vehicle models. The estimated coefficient of receiving a subsidy on a vehicle model's (log of) sales is 0.54 (column (3)), implying that the share of marginal consumers among all subsidy recipients for the first six wave was 35% ($0.54/(1 + 0.54) \times 100\%$). These results, as discussed earlier, are interpreted as the upper bounds of the true effect of the program under the assumption that none of the increased sales were lost sales diverted from other new vehicle models.

5.2 Substitution Across Vehicle Attributes

This subsection examines whether part of the increased sales of subsidized models resulted from a substitution effect between models with similar attributes. Columns (1) to (3) of Table 5 provide the estimation results of equation (2) for the substitution effect across fuel inefficiency, engine size, and weight, respectively. We find that the coefficients associated with the interaction terms of the attribute quartile and program intensity are negative and significant for vehicles with their attributes in the first quartile. The interaction terms for vehicles with their weights or engine sizes in the second quartile and program intensity are also negative, but are only statistically significant at the 10% level.

The results in Table 5 suggest that the subsidy program created a substitution effect between vehicles that were already fuel efficient in absolute terms, with an smaller engine size, or had a lower weight. If some consumers who purchased subsidized vehicle models merely substituted from vehicles with similar attributes, then our results in Table 4 would overestimate the true effect of the program. Therefore, we construct different comparison groups based on vehicles' attributes and re-estimate equation (1).

Table 6 provide estimated results based on different comparison groups. We split vehicle models that were not subsidized in the first six waves into 4 groups based on their attributes. Columns (1) to (4) provide estimated results using comparison groups with attributes from the 1st attribute quartile to the 4th attribute quartile, respectively, while column (5) gives results using attributes from attribute quarters 2 to 4 so as to construct the comparison group. Our first set of results employ fuel inefficiency to construct comparison groups. Unsurprisingly, the estimated coefficient is the largest when the comparison group is the most fuel efficient. Similarly, we find that the estimated coefficients are largest if the comparison group used in estimation encompasses the lightest vehicles or those with the smallest engine size.

The revealed substitution patterns suggest that some of marginal consumers' original choices were fuel efficient models that are light weighted with a smaller engine size, and thus our estimates in Table 4 are too optimistic about the program's effect. Given that the results from the instrumental variables approach suggest that the substitution effect was more likely to occur from vehicles with their attributes lying in the lower quartiles of fuel inefficiency, engine size and weight, we reestimate equation (1) by excluding those vehicles and provide the estimation results in column (4) of Table 4.[12] After taking the substitution effect into account, we find that the estimated coefficient of the program's effect is 0.432, suggesting that 30% of subsidized sales were from marginal consumers, dropping from 35% as implied in Table 4.

5.3 Intertemporal Substitution

Our empirical results suggest that about 30% of consumers who purchased subsidized models are marginal consumers who substituted their original choice for subsidized models. An important aspect for evaluating a subsidy program is whether the program creates intertemporal substitution. If most of the marginal consumers we identified during our data window are in fact inframarginal consumers in a longer time window, then the above results overestimate the true effect of the program. Moreover, because the released dates of all subsidies were in the middle of a month, we obtain our previous results by excluding months in which a new wave of subsidy took place. In this section we examine consumers' purchasing pattern over time to give a more complete picture of the program.

Figure 2 plots the estimated coefficients, along with their 95% confidence intervals for equation (3) using the data window from January 2009 to September 2011 with a full set of control variables. The base month is the month right before a vehicle model started to receive its subsidy, and the comparison group includes vehicles that were never subsidized and were not in either the first quartiles of fuel inefficiency or engine size. We find that sales

[12]Specifically, we exclude vehicles that meet the following three criteria at the same time: with fuel inefficiencies in the first quartile, with weights in the first or the second quartile, and with engine sizes in the first or the second quartile.

before the base month were significantly lower than sales in the base month only for time periods that are 13 months (or more) away from the base month. Other than that, there was no significant difference between a vehicle model's previous sales before it received its subsidy and its sales in the base month.

The above results reassure us that the announcements of eligible vehicles were more likely to be exogenous events. We find that the estimated coefficient is smaller for months in which a new wave of subsidy took place (month "zero" in Figure 2), probably due to the fact that all of the released dates are not at the beginning of a month. In addition, we find that most of the estimated coefficients lie between 0.3 and 0.5 for months after the base month. Even though several coefficients are not precisely estimated, all the estimated coefficients for months after the base month are still positive, and so we do not find evidence supporting intertemporal substitution within eligible models as in Mian and Sufi (2012).

5.4 Share of Inefficient Models and Program Participation

One of the main motivations for energy efficient 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 efficient 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 relative fuel inefficient models were higher.[13] We test this hypothesis by including an interaction term to equation 1:

(4)

$$\begin{aligned}\ln \text{Sales}_{ijt} = \mu + \alpha_i + \alpha_j + \alpha_t + \beta_1 1(\text{Receiving a subsidy})_{jt} + \\ \beta_2 1(\text{Receiving a subsidy})_{jt} \times (\text{Share of fuel inefficient products})_i + \gamma X_{jt} + \epsilon_{jpt}.\end{aligned}$$

[13]Recall that we define a vehicle model to be fuel inefficient if its fuel inefficiency is higher than the conditional mean based on its weight.

Here, the variable (Share of fuel inefficient products)$_i$ measures the share of fuel inefficient models sold in a province, constructed using data before the introduction of the program. In this specification a positive and significant coefficient on the interaction term β_2 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 those with a high school degree, rural population, and average wage.

Table 7 presents the estimation results. In both columns (1) and (2), the estimated coefficients β_2 are negative and statistically significant, suggesting that the increase in sales of subsidized models was smaller when the share of consumers buying fuel inefficient models were higher. Moreover, the results in column (2) 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 low-educated consumers very well. The above results therefore do not support that the program was effective at targeting consumers who were more likely to suffer from asymmetric information or behavior biases and were more likely to buy fuel inefficient vehicles. We overall 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 low-educated consumers were less likely to have marginal consumers of the subsidy program.

5.5 Robustness Checks

All estimates reported above are obtained by excluding observations from Shanghai and Beijing in our regressions, because the two cities have implemented 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* would switch their choice of vehicles based on a cash subsidy. Therefore, the effects of the subsidy program in Shanghai and Beijing are likely to be dampened.

As a robustness check, Table 8 reports results that include observations from Beijing and Shanghai. As expected, the estimates in Table 8 are indeed smaller than those in Table 8, but the difference is small in magnitude. For example, from the estimation results of the first 6 waves with the specification that takes the substitution effect into account (column (4)), we find that the additional decrease in sales without using observations in Beijing and Shanghai is 2.3%.

Our main results use only the variation generated from the first six waves. In the 7th wave, the eligibility threshold were stricter and few vehicles remained on the subsidized list. The last set of results in Table 4 expands the data window to include the variation generated by the 7th wave. We find that using the variation generated by the 7th wave reduces the effect of the program: the estimated coefficients in column (4) drop from 0.432 to 0.316. One potential explanation for this result is that consumers were less likely to change their purchasing behavior when there were fewer eligible vehicles on the market. Another explanation is that dealers might have provided discounts or other promotions for vehicles with their eligibility status being suddenly revoked, and so their sales did not drop immediately after losing their eligibility status.

6 Cost-Benefit Analysis

We conduct a cost-benefit analysis for the subsidy program in two steps. First, we calculate the reduction in gasoline consumption and carbon dioxide emissions per subsidized vehicle. Next, we find the implied price of carbon dioxide in the subsidy program and discuss whether the subsidy program is an effective way to reduce carbon dioxide emissions.

To find the savings in gasoline consumption due to the program, we need to characterize vehicle choices made by a typical marginal consumer before and after the program. By definition, a marginal consumer's choice of vehicle after the program's effective date must be a subsidized model. In addition, our empirical evidence suggests that the substitution effect occurs for vehicles with their attributes in the lower quartiles. Therefore, we calculate the (sales weighted) average fuel inefficiency for two sets of models, i.e., (1) models that were never subsidized but had an engine size (or weight) in the first or second quartile, or with fuel inefficiency in the first quartile, and (2) models that were subsidized. We arrive at the average fuel inefficiency of 7.295 and 6.562 liters per 100 km for the first and the second sets of models, respectively, and so a typical marginal consumer saves 0.733 liters of gasoline per 100 kilometers by switching to subsidized models.[14]

We also calculate the lifetime reduction in gasoline consumption generated by a marginal consumer. Because the current compulsory retirement requirement caps a vehicle's lifetime mileage at 600,000 kilometers,[15] the maximum lifetime savings in gasoline consumption of any marginal consumer are thus capped at $600,000/100 \times 0.74 = 4,440$ liters, implying maximum lifetime savings in carbon dioxide of 10.32 metric tons per subsidized marginal consumer.[16] However, we have already shown that only 30% of subsidized consumers are marginal consumers, and so the maximum lifetime savings in carbon dioxide for a subsidized vehicle are 3.12 metric tons. Finally, because each subsidized car costs the government 3000 RMB (455 USD), our results suggest that the implied price of carbon dioxide is 146 USD/metric ton.

Table 9 summarizes our cost-benefit analysis using different shares of marginal consumers (30% and 35%). By contrast, we also consider a naive case that assumes a typical marginal consumer's original choice is an "average" car. Because the sales-weighted average fuel inefficiency for all ineligible vehicles is 7.958 liters/100 km, the implied price of carbon dioxide in this case is much lower (77 USD/metric ton) than that from our previous case (when we assume a typical marginal consumer's original choice is a car with similar attributes).

[14]We construct average fuel inefficiency using vehicle models sold in the month right before the first wave of the program (May 2010).

[15]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.

[16]Each liter is around 0.264 gallons. Each gallon of gasoline emits 8,889 grams of carbon dioxide.

Therefore, using a naive way to conduct the cost-benefit analysis greatly underestimate the true cost of the program. Because we use the compulsory retirement requirement to calculate a vehicle's lifetime mileage and use a zero discount rate to obtain the above results, the savings in carbon dioxide are also clearly upper bounds and the implied prices in Table 9 are lower bounds.

The current carbon price in China is less than 10 USD/metric ton and most countries in the world have a carbon price/tax less than 20 USD/metric ton.[17] 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.[18] Therefore, paying 146 USD for a metric ton of carbon dioxide is hardly an efficient way to reduce carbon dioxide. Even if we use 35% as the share of marginal consumers to calculate the implied prices of carbon dioxide, which we have already shown is too optimistic, the implied price is still 126 USD/metric ton. Therefore, 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.

7 Conclusion

In this paper we have shown that China's fuel efficient program boosted sales for eligible models during the first six waves of its implementation, creating a distributional effect: around 70% of consumers who purchased eligible models are inframarginal and received additional cash simply for buying their original choices of vehicles. We show that most of the marginal consumers' original choices of vehicles were not heavy-weighted, fuel consuming vehicles with a large engine size. The presence of a large share of inframarginal consumers and the observed substitution pattern question the cost effectiveness of the program on obtaining its policy goals. We find that the implied cost of the program on reducing carbon

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

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

dioxide emissions is around 146 USD/metric ton, suggesting that the subsidy program was an expensive way to reduce carbon dioxide. Our empirical evidence also shows that the effect of the program was smaller in provinces where consumers were less educated or were more likely to purchase fuel inefficient models, indicating that the program was not well-targeted.

Our analysis suggests that in Beijing and Shanghai, where new car licenses were issued by lotteries or auctions, the subsidy was less likely to be taken up by marginal consumers. Interactions of environmental policies thus remains an important issue to explore. Finally, because the subsidy program was popular, but only encouraged consumers to buy fuel efficient models with a smaller engine size, it effectively changed China's vehicle mix toward smaller vehicles. Future work that evaluates the program's effect on the mix of vehicle fleets and safety issues will be highly valuable.

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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	59 (86.8%)	23 (39.0%)
2	August 11, 2010	61 (129)	27	10	9	4	11	51 (83.6%)	25 (49.0%)
3	September 25, 2010	55 (184)	40	4	5	3	3	40 (72.7%)	31 (77.5%)
4	November 23, 2010	56 (240)	35	11	0	10	0	42 (75.0%)	35 (83.3%)
5	February 11, 2011	66 (306)	45	2	16	2	1	39 (59.1%)	22 (56.4%)
6	May 11, 2011	85 (391)	60	8	17	0	0	49 (57.6%)	36 (73.5%)
7	October 17, 2011	19 (48)	15	0	0	0	4	18 (94.7%)	17 (94.4%)
Total		410	252	42	52	31	33	298 (72.7%)	189 (63.4%)

Table 2: Summary Statistics: Vehicle Sales and Attributes

	Sales	Engine (liters)	Weight (kg)	Fuel (liters/100 km)	Power (kw)	Price (10,000)	Size (m^3)	cn	eu	jp	kr	us
All products												
mean	35.62	1.79	1344.86	7.99	92.46	13.24	12.00	0.38	0.20	0.25	0.08	0.10
s.d.	92.90	0.48	273.67	1.40	28.01	9.98	1.99	0.48	0.40	0.43	0.27	0.30
N	703559	703559	640433	640433	559716	703180	700516	703559	703559	703559	703559	703559
Subsidized: existing products												
mean	72.12	1.45	1201.28	6.60	81.04	9.36	11.08	0.31	0.19	0.20	0.14	0.16
s.d.	156.26	0.17	159.94	0.56	15.09	4.33	1.17	0.46	0.39	0.40	0.35	0.37
N	59640	59640	59292	59292	59292	59640	59640	59640	59640	59640	59640	59640
Subsidized: new products												
mean	47.57	1.44	1151.80	6.53	76.40	7.99	10.83	0.40	0.14	0.18	0.12	0.16
s.d.	106.56	0.18	148.66	0.53	13.83	3.05	1.15	0.49	0.35	0.38	0.33	0.37
N	35247	35247	35247	35247	35247	35247	35247	35247	35247	35247	35247	35247

Table 3: Summary Statistics: Province Level Variables

	N	mean	s.d	min	max
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	38.69	3.2	34.7	47.52
Number of eligible models available before the 1st wave	31	30.13	3.18	16	34
Share of subsidized models (%)	1115	9.98	11.1	0	35.09

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/curb weight combinations above the bivariate regression fitted line. 'Number of eligible models available before the 1st wave' is the aggregate number of eligible vehicle models (in the first wave) sold in a province before the first wave. 'Share of subsidized models' is the share of vehicles sold in a province that are subsidized in a given month.

Table 4: Effect of a Subsidy on Vehicle Sales

	(1)	(2)	(3)	(4)
First 6 waves (2009m1 to 2011m9)	0.550**	0.559**	0.539**	0.432**
	(0.158)	(0.160)	(0.159)	(0.158)
Observations	455878	390481	390481	330964
24-month window (2009m6 to 2011m5)	0.597**	0.516**	0.529**	0.435**
	(0.135)	(0.136)	(0.136)	(0.136)
Observations	302671	263317	263317	222250
18-month window (2009m9 to 2011m2)	0.607**	0.500**	0.516**	0.438**
	(0.108)	(0.109)	(0.111)	(0.112)
Observations	221390	193718	193718	163208
12-month window(2009m12 to 2010m11)	0.441**	0.313**	0.346**	0.310**
	(0.081)	(0.070)	(0.075)	(0.075)
Observations	134154	117609	117609	99169
First 7 waves (2009m1 to 2011m12)	0.423**	0.422**	0.393**	0.316**
	(0.118)	(0.114)	(0.118)	(0.118)
Observations	515134	445460	445460	378107
Birth quarter $\times$ age	No	Yes	Yes	Yes
Birth quarter $\times$ age squared	No	No	Yes	Yes
Take substitution effect into account?	No	No	No	Yes
Drop Beijing and Shanghai?	Yes	Yes	Yes	Yes

Notes: This table reports estimates from 20 separate regressions using equation 1. Data windows used in estimation are given in row headings. Months in which a new wave of subsidy began to take place were excluded. The dependent variable is the natural log of monthly vehicle model sales in a province. The reported coefficients correspond to 1(Receive a subsidy), an indicator variable equal to one after a vehicle model becomes eligible for the program. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level. ** $p < 0.01$

Table 5: Substitution Effect: Instrumental Variables Results

	Inefficiency	Weight	Engine Size
Intensity×1(Attribute Quartile 1)	-0.026**	-0.020*	-0.025*
	(0.011)	(0.010)	(0.011)
Intensity×1(Attribute Quartile 2)	-0.009	-0.020+	-0.022+
	(0.011)	(0.010)	(0.011)
Intensity×1(Attribute Quartile 3)	-0.003	0.002	-0.002
	(0.011)	(0.011)	(0.012)
Intensity×1(Attribute Quartile 4)	0.007	0.007	0.006
	(0.010)	(0.009)	(0.009)
Observations	370923	370923	397024

Notes: 'Intensity' is the share of vehicles sold in a province that are subsidized in a given month. The instrumental variables for a wave of subsidy are the number of all eligible models available for that wave of subsidy before the wave begins, interacted with attribute quartiles. * $p < 0.05$

Table 6: Effect of a Subsidy on Vehicle Sales: By Vehicle Attributes

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4	(5) Quartiles 2-4
Fuel inefficiency	0.951**	0.586**	0.446**	0.322*	0.453**
	(0.172)	(0.163)	(0.164)	(0.155)	(0.158)
Observations	102584	145756	146153	124452	344343
Weight	0.849**	0.747**	0.360*	0.292+	0.451**
	(0.168)	(0.164)	(0.167)	(0.155)	(0.158)
Observations	124135	128699	132838	133273	322792
Engine size	0.881**	0.819**	0.417*	0.287+	0.488**
	(0.170)	(0.164)	(0.172)	(0.156)	(0.158)
Observations	103399	163779	98717	198010	388488

Notes: This table reports estimates from 15 separate regressions using equation (1) with different comparison groups constructed based on vehicle attributes given in column and row headings. Months in which a new wave of subsidy began to take place were excluded. The average fuel inefficiencies of vehicle models in the comparison group in each quartile are 6.61, 7.48, 8.41, and 10.15 liters/100 km, respectively. The average weights of vehicle models in the comparison group in each quartile are 1050, 1224, 1428, and 1730 kg, respectively. The average engine sizes of vehicle models in the comparison group in each quartile are 1.25, 1.57, 1.8, and 2.3 liters, respectively. The dependent variable is the natural log of monthly vehicle model sales in a province. The reported coefficients correspond to 1(Receive a subsidy), an indicator variable equal to one after a vehicle model becomes eligible for the program. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 7: Share of Fuel Inefficient Models and Program Participation

	(1)	(2)
Receiving a subsidy	1.802**	1.170**
	(0.340)	(0.387)
Receiving a subsidy × share of fuel inefficient models	-0.033**	-0.034**
	(0.007)	(0.007)
Receiving a subsidy × high school degree		0.024**
		(0.005)
Receiving a subsidy × rural population		0.006*
		(0.003)
Receiving a subsidy × average wage		-0.005
		(0.004)
Observations	390481	390481

Notes: This table reports estimates using equation (3). Months in which a new wave of subsidy began to take place were excluded. 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. ** $p < 0.01$

Table 8: Effect of a Subsidy on Vehicle Sales using the Full Sample

	(1)	(2)	(3)	(4)
First 6 waves (2009m1 to 2011m9)	0.530**	0.535**	0.514**	0.409**
	(0.147)	(0.150)	(0.149)	(0.148)
Observations	483518	415116	415116	352303
24-month window (2009m6 to 2011m5)	0.578**	0.496**	0.509**	0.417**
	(0.127)	(0.128)	(0.129)	(0.128)
Observations	321470	280270	280270	236855
18-month window (2009m9 to 2011m2)	0.591**	0.486**	0.501**	0.425**
	(0.104)	(0.104)	(0.107)	(0.107)
Observations	235344	206342	206342	174032
12-month window(2009m12 to 2010m11)	0.433**	0.310**	0.341**	0.305**
	(0.081)	(0.070)	(0.075)	(0.075)
Observations	142620	125243	125243	105713
First 7 waves (2009m1 to 2011m12)	0.409**	0.405**	0.377**	0.301**
	(0.110)	(0.108)	(0.111)	(0.111)
Observations	545924	473107	473107	402129
Birth quarter × age	No	Yes	Yes	Yes
Birth quarter × age squared	No	No	Yes	Yes
Take substitution effect into account?	No	No	No	Yes

Notes: This table reports estimates from 20 separate regressions using equation 1 using the full sample (including Beijing and Shanghai). Data windows used in estimation are given in row headings. Months in which a new wave of subsidy began to take place were excluded. The dependent variable is the natural log of monthly vehicle model sales in a province. The reported coefficients correspond to 1(Receive a subsidy), an indicator variable equal to one after a vehicle model becomes eligible for the program. All regressions include vehicle model, province, and month-of-sample fixed effects. Standard errors are clustered at the vehicle model level. ** $p < 0.01$

Table 9: Cost-Benefit Analysis: Implied Price of Carbon Dioxide

Savings: by a marginal consumer		Share of	Savings: by a subsidized consumer		Implied price
Gasoline (liters/100 km)	Lifetime CO_2 (metric ton)	marginal consumers	Gasoline (liters/100 km)	Lifetime CO_2 (metric ton)	of CO_2 (USD/metric ton)
0.73	10.32	0.30	0.22	3.12	145.78
1.39	19.65	0.30	0.42	5.93	76.59
0.73	10.32	0.35	0.26	3.61	125.79
1.39	19.65	0.35	0.49	6.88	66.09

Notes: We use 600,000 kilometers to calculate a vehicle's lifetime mileage. We assume each gallon (liter) of gasoline emits 8,889 (2,348) grams of carbon dioxide.

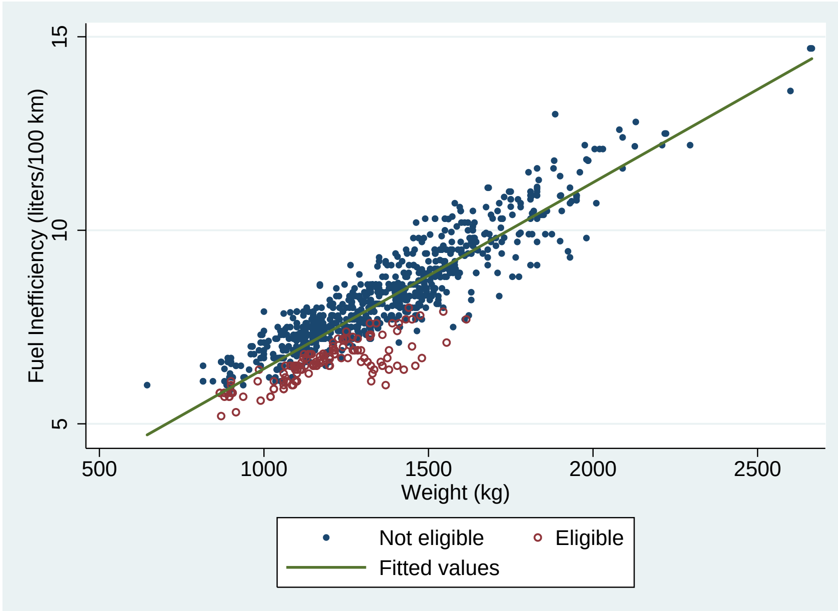

Figure 1: Relationship Between Fuel Inefficiency and Weight for Vehicles (Powered by Gasoline) with at Least 100 Units of Sales During 2010

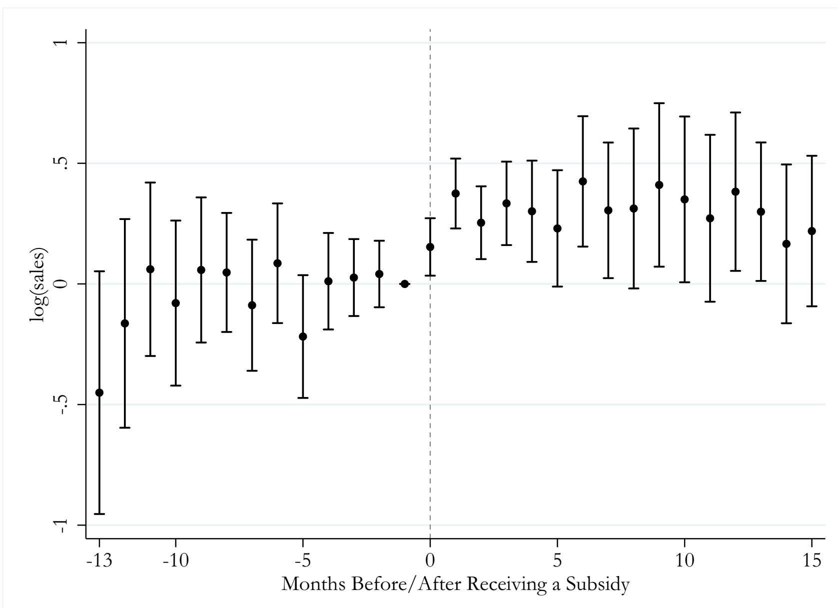

Figure 2: Intertemporal Substitution