Vehicle Scrappage in the Developing World: Evidence from Brazil

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Abstract

The transportation sector contributes to nearly a third of total greenhouse gas emissions, primarily due to the prevalence of older, less fuel-efficient vehicles running on fossil fuels. In this paper, I investigate how sales tax policies and the introduction of bi-fuel technology impacted the scrap sensitivity of gasoline cars in an emerging country. I define scrap rates based on annual changes in the fleet covered by private insurance and estimate an instrumental variable panel to examine the impact of used car prices on scrap rates. Using as an instrument a measure of fuel prices weighted by fuel efficiency, I found Brazil's scrap elasticity to be -0.43, which is consistent with an environment with low average income, credit restrictions, and anti-scrapping incentives. My results indicate that car sales taxes may have induced the scrappage of an additional 185,000 vehicles, helping to offset anti-scrapping incentives. The introduction of flex-fuel technology had a stronger but temporary effect, lasting only while its market share was continuously increasing in the actual fleet. I find that flex-fuel vehicles may have been responsible for another 465,000 vehicles scrapped per year.

Keywords: Vehicle Scrappage, Flex Fuel Vehicles, Tax Reduction Policies, Technology Innovation, Transportation-Driven Air Pollution

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1 Introduction

Current debates on climate change are focusing on the urgency of reducing greenhouse gas (GHG) emissions by substituting all fossil fuel energy for cleaner and renewable sources (York and Bell (2019), Marques, Fuinhas and Pereira (2018), Sovacool (2016)).[1] In 2020, five emerging countries contributed with 55% of all GHG produced, and the transportation sector was responsible for one-third of the emissions (Inger et al. (2022)). In this context, old vehicles are not only less efficient but also the most pollutant and several policies can be used to accelerate the elimination of these outdated vehicles, replacing them with more efficient and sustainable versions (Jacobsen et al. (2023)). However, data limitations, particularly in the developing world, have made it challenging to examine the degree to which vehicle owners respond to incentives encouraging them to dispose of their old vehicles.

To investigate consumers' incentives in replacing old vehicles, I leverage insurance data and define scrap rate as the number of vehicles leaving the insurance database, compared to the previous period. This information allows me to examine the relationship between used car prices and scrap rates (i.e. the scrap elasticity) in Brazil. I address three main questions. First, what is the effective scrap elasticity for automobiles in Brazil. Second, how sales tax reductions on new vehicles have impacted used vehicles' scrap sensitivity. Finally, I analyze the diffusion path of flex-fuel vehicles in the fleet, investigating how the adoption of this new technology induced older vehicle replacement.

I use the information on Brazilian-insured vehicles to construct a novel database with detailed information on vehicle models and insurance characteristics. This database covers the period of 2003 to 2020, with vehicle vintages varying from the 1970s to 2020. This information represents about one-third of the total fleet.[2] While my work is restricted to the

[1]The Paris Agreement (2015) adopted in the 21st Conference of the Parties (COP21) established the goal to limit the temperature increase to below 2.0 degrees Celsius above pre-industrial levels, with emphasis on efforts to limit the temperature increase even further to 1.5 degrees. This commitment was reinforced at COP26 where the parties agreed on strengthening efforts to combat climate change and curb greenhouse gases. At COP27, discussions switched from negotiating policies and actions to implementing those changes.

[2]According to estimates from the Union of Auto Parts (Sindipeças), estimates of the full actual fleet are about three times the amount of privately insured vehicles (38.1 million cars as of 2020). The problem

universe of vehicles with private insurance, I discuss how, after considering characteristics of risk-averse agents and features of the insurance market, my findings can be seen as an upper bound, in absolute terms, for the full fleet scrap elasticity. [3]

My main empirical approach is a panel instrumental variable model, with the first stage exploring the relationship between used vehicle prices and a measure of fuel prices weighted by fuel economy. The identifying assumption is that conditional on vehicle model-by-age and age-by-year fixed effects, shocks in fuel prices affect scrap rates only through their impact on used car prices. Similar to Jacobsen and Van Benthem (2015), these fixed effects isolate the differential impact of gasoline prices on vehicle models of varying fuel efficiency and the impact on specific vintages across different periods of time. My results are robust to different combinations of fixed effects.

I highlight three main findings. First, I estimate the scrap elasticity of the insured fleet in Brazil to be -0.43. This number is significantly smaller than estimates found for the US market using more conventional settings (Jacobsen and Van Benthem (2015)). The smaller estimates are consistent with the environment found in a typical emerging country, such as low average income, worse income distribution, credit restrictions, and anti-scrapping incentives. When investigating heterogeneous effects, I find no significant difference for gender, but results suggest some variability for younger versus older drivers (-0.36×-0.17), and for personal versus firm use, especially for older vehicles (-0.47×-0.62).

Second, my results indicate that tax reductions on new vehicles have an indirect impact on scrappage resulting in the elimination of an extra 185,000 cars per year from the fleet. I interact fuel prices and a dummy for sales tax reduction on new vehicles to investigate any salience effect of tax policies on used car prices. By further decomposing the impact

with using Brazilian official records is that they only accumulate registration over the years, never excluding vehicles that were scrapped or incurred in total loss accidents, resulting in a significant overestimation of the fleet.

[3] Among the assumptions regarding risk-averse agents, I assume they (i) will always buy insurance, (ii) have higher income, on average, (iii) prefer newer vehicles to older versions. In addition, I also assume maintenance and repair costs to be, on average, the same for both risk-averse and non-risk-averse individuals.

into newer and older vehicles,[4] I found evidence of older cars becoming more sensitive to tax reduction, being responsible for 82% of all car replacements, and completely offsetting any anti-scrapping incentives present in Brazil.

Lastly, my results indicate that while the share of the flex-fuel technology increases in the actual fleet, owners of gasoline-driven vehicles have a larger scrap sensitivity to used car prices, resulting in an additional 465,000 gasoline cars scrapped per year. The main mechanism in action is the release of more efficient bi-fuel vehicles and the fast adoption of the new technology by the major manufacturers.

On the introduction of new technologies, I show how, as the share of the flex-fuel vehicles (FFV) in the fleet grows, the overall scrap elasticity substantially increases, and consumers start to replace their older, less efficient gasoline vehicles for the new bi-fuel technology. Once this process is completed and the FFV becomes the new standard in the fleet, the scrap elasticity returns to levels of pre-flex fuel. The fast adoption of flex-fuel in the Brazilian fleet was the result of a combination of factors, such as major manufacturers quickly switching their production lines to flex-fuel vehicles, better fuel economy, and high availability of ethanol at the retailers.

This work contributes to two literatures. First, to the best of my knowledge, this is the first empirical approach to examine the used vehicle price elasticity of scrappage for Brazil and one of the first for a large emerging country.[5] Previous studies on vehicle scrappage or vehicle replacement were carried out for developed economies such as the US (Jacobsen and Van Benthem (2015), Bento, Roth and Zuo (2018)) or the European market (Baltas, Xepapadeas et al. (2001)). Considering the restricted setting I use, my results show a less sensitive effect to used car price changes. This could be a reflection of Brazil's economic

[4] I considered 10 years as the age threshold to split my data into older and newer vehicles.

[5] I am using scrap elasticity as a synonym to used vehicle price elasticity of scrappage. When studying scrappage, some authors focus instead on what Bento, Roth and Zuo (2018) refers to as engineering scrappage, i.e., the natural mechanical failure. Others analyze survival rates of used cars (Hao et al. (2011), Greene and Leard (2023)), which is an indirect way of studying scrap elasticity due to natural deterioration over the years. My estimations focus on what they call cyclical factors, i.e., controlling for age and model characteristics, I study how changes in used car prices induce the scrappage of older vehicles.

conditions, such as lower average income, credit restrictions, and anti-scrapping incentives.

Second, my work contributes to the literature on the impacts of fuel prices on used car valuation (Busse, Knittel and Zettelmeyer (2013), Leard, Linn and McConnell (2017)) and allows me to extend the analysis to study the impact of sales tax incentives and technological changes on scrap rates. The literature on policy-induced scrappage is vast, ranging from impacts of fuel standards (Leard, Linn and McConnell (2017), Davis and Knittel (2019), Bento et al. (2020)), impact of new technologies in the fleet (Heywood (2010)), fuel taxation (Dahl (1979), Grigolon, Reynaert and Verboven (2018)) to externality impacts (Forsythe et al. (2022), Davis and Kilian (2011), Langer, Maheshri and Winston (2017), Axsen, Plötz and Wolinetz (2020)). My work highlights how tax incentives for the purchase of new vehicles have a greater effect on owners of older vehicles (above 10 years), being negligible to owners of newer cars. In particular, these incentives may have the effect of offsetting anti-scrapping incentives such as ownership tax exemption for older vehicles or lack of an official scrapping program.

This paper proceeds as follows. Section 2 highlights the evolution of transportation in Brazil, from the introduction of sugarcane-based ethanol-driven vehicles to the development and adoption of flex-fuel vehicles. Section 3 introduces the main assumptions used in the empirical analysis. Next, I describe my dataset, and in section 5 I present my empirical strategy. Section 6 reports the results, followed by the analysis of heterogeneous effects. In section 7 I show some robustness checks, discuss potential reasons for the success of flex-fuel vehicles and the sales tax reduction policy in section 8 and conclude in section 9.

2 Background

2.1 The Path from Ethanol-driven Cars to Flex Fuel Vehicles

Brazilian automobile and fuel markets have gone through several transformations and interventions. In the 1980s, the government established the addition of anhydrous ethanol to the regular gasoline and the production of hydrated ethanol for use as the main fuel in Otto cycle engines to reduce dependence on imported fossil fuel and diminish environmental impacts (Bajay (2004)). Ethanol-driven vehicle sales had only a temporary success, fading out in the second half of the 1990s. The anhydrous ethanol, however, was widely used, especially after 2000, as a policy instrument to either diminish pollution in major cities or to control gasoline price fluctuations.

The development of the flex-fuel technology was motivated by the crisis of ethanol in the 1990s. After increases in the production of ethanol-driven vehicles in the 1980s, partially promoted by government subsidies and favorable fuel pricing policies, a significant shortage in the supply of sugarcane ethanol occurred around 1990 due to the increase of international sugar prices and the diminishing of governmental subsidies. This scenario led some manufacturers, in association with Bosch and Magneti Marelli, to develop an engine that could run on any mix of gasoline and ethanol.

The first flex-fuel vehicle was released in May 2003 by Volkswagen, followed by Chevrolet in June and Fiat in October of the same year. Ford released its first flex-fuel model in 2004. The participation of these four manufacturers in the registration of new vehicles varied from 83.7% in 2003 to 61.1% in 2020. Each of them chose their most popular model to be the first flex-fuel car and introduced versions with an engine above the popular 1.0 engine as a strategy to show their captive consumers the strength and benefits of a bi-fuel vehicle.[6]

The acceptance of a bi-fuel vehicle was relatively fast. By using their most popular vehicle model as test marketing, the major manufacturers diminished quality uncertainty. By releasing more potent versions first, they guaranteed a minimum satisfactory efficiency, increasing the competitiveness of this new technology. As a result, consumers quickly switched to the new flex-fuel models (figure 11.2).

On the demand side, consumers are usually unaware of all the relevant information before they purchase a new vehicle. For instance, comfortability, effective fuel efficiency,

[6] The first flex-fuel vehicle from each of these manufacturers was, respective: "Volkswagen Gol 1.6 Total Flex", "Corsa Corsa 1.8 FlexPower", "Fiat Palio 1.3" and "Ford Fiesta 1.6".

and driveability are some aspects that vary by individuals' perception and can only be fully assessed after purchasing and experiencing the car. They also tend to be myopic to future fuel costs (Busse, Knittel and Zettelmeyer (2013)). As it occurs with any other experience good, consumers may rely on extra sources of information such as brand reputation, the experience of other consumers (word of mouth and reviews), or even purchase repetition based on previous experience.

Releasing vehicle models based on popular versions was the strategy the manufacturers used to minimize these uncertainties about the new bi-fuel engine technology. Figure 11.1 shows the evolution of gasoline and ethanol consumption. The considerable increase in ethanol volumes indicates that consumers quickly adhered to flex-fuel vehicles.

Regarding the movement on the supply side, the four large manufacturers quickly switched their entire production to FFV and induced other smaller or entrant firms to also adopt the technology.[7] Figure 11.2 reports a strong increase in the registration of new flex-fuel cars after 2005. As a result, estimates from market agencies indicate that, by 2010, 95% of the new car sales were flex-fuel.

Flex-fuel vehicles revolutionized the market in at least two ways. First, they expanded consumers' choice set by allowing them to choose between gasoline or ethanol when pumping at a retailer. This aspect substantially increased consumer's sensitivity to fuel prices.[8] Second, they brought a significant increase in overall fuel efficiency as can be seen in figures 11.4 and 11.3.

[7] According to the Associação Nacional dos Fabricantes de Veículos Automotivos (2023) report, the share of FFV in the registration of new vehicles increased from 3.5% in 2003 to 21.5% in 2004 and 52.6% in 2005. After 2006, the participation of flex-fuel cars among new registrations was above 80%, indicating fast adoption of this technology by other firms and a good acceptance by consumers.

[8] In my working paper entitled "Price Stabilization Policy, Gasoline Consumption, and Health Externality: Evidence from Brazil", I show how gasoline price elasticity changes from inelastic to elastic after FFV becomes the majority of the fleet in 2011.

2.2 Vehicle Registrations in Brazil

Official vehicle registration numbers in Brazil are highly overestimated. This occurs due to the lack of recurrent updates to remove vehicles that were scrapped, involved in total loss accidents, or stolen. To illustrate the magnitude of the overestimation, between 2016 and 2018, the government mandated all truck owners to renew their vehicle registration with the respective local authorities. The result was a sharp fall in numbers from 2.55 million trucks in 2016 to 1.53 million trucks in 2018, which represents an overestimation of at least 67% of the actual truck fleet (see figure B.1).

There are two main sources of insurance in Brazil. First, there is mandated government-issued insurance, which only covers some medical costs in case of accidents, limited to a small amount of expenses. Second, there is private insurance. Only private insurance information is publicly available, in an anonymous manner to protect the identity of each contract owner. Insurance firms report twice a year information regarding contracts issued in the past three semesters.[9]

It is important to emphasize that not all vehicles in Brazil are mandated to have the "traditional" private insurance. The type of insurance that covers repairs, accidents, thefts, and even total loss are all private contracts. While the Union of Auto Parts (Sindipeças) estimates that the actual car fleet numbers are about 38.0 million (or 45.9 million for all vehicles),[10] the total number of insured vehicles with full coverage is about 13.4 million cars in 2020. In general, private insurance covers one-third of the estimated actual fleet.

This discrepancy between full fleet estimates and insured fleets may be reflected in scrap rates. By defining scrap rates as annual changes in the number of vehicles covered by insurance compared to the previous year, the calculated scrap rates tend to be higher either because each change in the numerator (vehicles leaving the database) has a higher weight, or because the denominator tends to be smaller (private insurance doesn't cover all vehicles).

[9] Reports from insurance are usually due in June and December.

[10] Their estimates take into account sales of new vehicles, accidents, and assumptions for a natural scrappage curve. For the number referred to in this paper, I am not accounting for motorcycles.

In section 3 I explore some assumptions under which, given the characteristics of the contracts I observe and assumptions over the type of agents contracting insurance, the insured-based scrap elasticity I estimate in this paper can be seen as an upper bound, in absolute terms, for the full fleet scrap elasticity.

3 Conceptual Framework

Before I delve more into the data aspects and develop the main empirical approach to estimate the scrap elasticity, I need to set all the necessary assumptions and clarify why I use the turnover of the insured fleet as a synonym for scrappage.

The insurance database, as mentioned, corresponds to about one-third of the actual fleet. In principle, the turnover of this particular fleet may not accurately reflect the turnover of the full population of non-insured vehicles. However, under some assumptions described next, it is possible to see the private insured fleet turnover as an upper bound for the full fleet turnover.

First, the insurance database has information on accidents that led to a total loss of the vehicle, which ended up being scrapped.[11] Additionally, if we consider the potential moral hazard due to the insurance contract, these accidents, and therefore the true scrappage in the insurance dataset, are expected to be over-represented compared to the non-insured fleet. This could cause a bias towards higher scrap rates, as mentioned before.

I assume that risk-averse and non-risk-averse individuals behave very differently with respect to purchasing private insurance. I assume the former group will always buy insurance, while the latter will never buy it. I also assume agents don't switch their risk preferences.[12] This basically means the increase of both insured and uninsured fleets over time is due to

[11] In general, an insurance firm decides that it is not worth repairing the vehicle if the estimated total costs are equal to or above 75% of the current vehicle price. In such cases, they declare a total loss, pay the full insured amount, and terminate the contract.

[12] If I allow agents to switch, perhaps based on economic conditions, and given it may be more likely that new agents buy insurance contracts than stop buying them, this could lead the higher scrap rates calculated in the insurance database to fall toward the scrap rates of the non-insured fleet. In this sense, the scrap rates of insured and uninsured fleets tend to converge to a common denominator.

new individuals entering the vehicle ownership set. Based on this, we can establish some features for each risk group.

I assume that risk-averse individuals always purchase insurance and renew their vehicle contracts for as long as they own a vehicle. This necessarily implies they are able to afford it. Vehicle contracts are not cheap in Brazil, especially compared to the mean population income. For vehicles valued up to 60,000 reais, an insurance contract with full coverage can cost, annually, between 3% and 10% of the current vehicle's price. This certainly is a constraint for many Brazilians and represents at least 10.3% of annual per capita household income, or 172% of the minimum wage (in 2020). As a result, I can assume risk-averse agents may also have higher average income and may, consequently, face better credit conditions.

Next, I assume that total repair costs are, on average, the same for individuals buying insurance or not.[13] These costs include maintenance services, parts prices, and any other model-vintage-specific costs.

I also assume that risk-averse individuals, when deciding to replace their current vehicle, tend to buy newer vintages or brand-new vehicles. This restricts the purchasing patterns, having fewer trades from the uninsured fleet to the insured fleet. The assumption here is that it is more likely for a non-scrapped vehicle to leave the insurance database and be bought by a non-risk-averse agent than in the opposite direction.

In Brazil, institutions impose anti-scrapping incentives in the format of tax exemption for older vehicles and the total absence (or support) of any scrappage program. All states in Brazil exempt vehicles from ownership taxes after a certain age threshold. For cars, for instance, the most common cutoff is 15 years, but it can vary from 10 to 25 years. Also, contrary to many developed countries, neither Brazil's federal nor state governments have established any effective scrappage policies aimed at reducing the circulation of older

[13]One could argue that total costs for insured vehicles are higher since they incur into moral hazards and may deteriorate their vehicles much faster or get into accidents more often. However, it is expected for the non-insured fleet to have a significantly older mean fleet age, especially due to anti-scrapping incentives. Older vintage parts may cost more and be harder to find. Hence, the assumption here is that higher costs for non-risk-averse agents are counterbalanced by higher repair frequency for risk-averse individuals.

vehicles.[14]

These anti-scrapping incentives, combined with higher acquisition power (and potentially higher credit availability) from risk-averse agents lead to a scenario where the mean vehicle age for the insured fleet shall be significantly lower than that of the non-insured fleet.

To sum up, a person with risk-averse preferences has the resources to buy insurance and will do so for all the time she owns a vehicle. If the vehicle is not involved in any total loss accident or theft (not truly scrapped),[15] this person may eventually decide to replace it. She will buy a newer vehicle, more likely a brand-new version, or from another risk-averse person, and she will sell her previous vehicle most likely to a non-risk-averse person. Since the number of vehicles on the roads is not exponentially increasing,[16] for each non-scrapped vehicle leaving the insurance database, another vehicle (or a proportional value) may leave the roads and be effectively scrapped. Hence, I expect the turnover for the insured fleet to imply some degree of scrappage (total loss in the insurance database or induced true scrappage in the non-insured fleet).

Because of anti-scrapping incentives for older vehicles, which affects non-insured agents more often, and because risk-averse agents tend to have better economic conditions (income, credit) and may switch vehicles more often (total loss, higher vehicle deterioration), I expect that the insurance database would indeed present higher turnover and consequently stronger scrap elasticity to vehicle prices. Therefore, it could be seen as an upper bound, in absolute terms, for the full fleet scrap elasticity.

[14] In some states or municipalities, we can find policies to limit emissions of certain pollutants. At least up to 2015, vehicles that were not approved in the emission tests, can either have some time to fix it and reduce the emission rates (case of newer vehicles) or are "freed with restrictions" (case of older vehicles). Freed with restriction means reselling the vehicle may be harder and the current vehicle price may fall sharply. Recently, emission laws have become more stringent, but it is out of the scope of this work.

[15] Stolen vehicles in Brazil usually end up in accidents, abandonment, or are scrapped for parts reselling.

[16] According to the total fleet estimations available.

4 Data

The main database comprises the full population of vehicle insurance contracts in Brazil (AUTOSEG), made available by the Private Insurance Superintendence (Susep). Insurance companies in Brazil must report twice a year to the government agency on the contract deals from the previous semester(s). This database is commonly used in financial studies on auto insurance markets, and this may be the first time it is used to understand the turnover and evolution of the fleet.

I aggregated data at the annual level and used one specific semester per report to avoid duplicity problems.[17] Analysis based on annual data helps to minimize potential delays on contracting, renewing or even switching insurance.

Vehicle data is identified by a tag name with full model description and includes insurance and demographics information such as type of insurance coverage, type and monetary value of claims, main driver's age, zip code, amount insured and other insurance information.

I merged fuel efficiency information and other vehicle characteristics obtained from a variety of sources.[18] Fuel prices were obtained from a Petrobras price survey based on a representative set of retailers. In particular, for diesel, I obtained each specific diesel type (S1800/S500, S50/S10) and adjusted the usage according to each vehicle vintage.[19]

The database I use represents the full universe of privately insured vehicles. My measure of scrappage follows a similar definition used by Jacobsen and Van Benthem (2015) and can be understood as the turnover of the insured fleet, i.e., the number of vehicles leaving the insurance database in a given year, compared to the previous year. Mathematically, it is

[17] In the appendix I detail the process and explain the potential issues with duplicity that could arise.

[18] Fuel efficiency came mostly from specialized vehicle websites, vehicle manufacturer manuals, and governmental agencies (IBAMA). For trucks and light trucks, I used specific fuel consumption reported by the Society of Motor Manufacturers and Traders (SMMT). This approach allows me to consider the potential weight carried by a truck and estimate a more precise average fuel consumption per ton per kilometer.

[19] According to Brazilian legislation, diesel vehicles produced until 2011 should use the more pollutant diesel S1800 or S500, but diesel vehicles produced after 2012 were mandated to use only the cleaner versions (S50 and S10). The main difference among different diesel types was especially the amount of sulfur contained in each version. Ultra-low sulfur diesel vehicles (ULSD) cannot use diesel with a high concentration of sulfur, otherwise, they may be subject to mechanical problems and failures. Similarly, high-sulfur diesel vehicles (HSD) are more inefficient if using ULSD and may incur in higher maintenance costs.

defined as:

$$y_{amt} = \frac{n_{am(t-1)} - n_{am}}{n_{am(t-1)}}|_{(t-v)=a} \tag{1}$$

where n_{am} represents the number of vehicles of age a, make-model m in year t in the insurance database. Age is measured as the difference between the year of the contract and the vintage, v, of the vehicle model.

My measure of scrap rate, y_{am} can be more accurately described as the turnover of the privately insured vehicle fleet. The numerator of this expression measures the number of vehicles that were not insured anymore in the current year (leaving the insurance database) and the denominator is the full population of privately insured vehicles in the previous year. This fraction represents the turnover of the privately insured fleet and can be thought of, in a more broad way, as a measure of scrappage.

To understand the idea of fleet turnover as a scrappage, let's see an example. As some vehicles leave the insurance database, being bought by agents that don't buy insurance, it is reasonable to assume that a proportion of older vehicles are being scrapped (the turnover of the insured fleet induces turnover of the non-insured fleet). This assumption implies that the full population of vehicles doesn't grow at the same rate as the sales of new vehicles.[20] A second reason is that this insurance database also contains information on vehicles that were involved in accidents, including those that suffered total loss (truly being scrapped).

Table 10.1 shows the scrap rates for the insured fleet. Two main aspects are relevant here. First, scrap rates are significantly higher than those shown for other markets, such as the US (see the work of Jacobsen and Van Benthem (2015) and Bento, Roth and Zuo (2018)). Second, vehicle scrap rates seem to consistently fall after a vehicle ages 15 years.

Higher scrap rates may be related to the type of database used or safety concerns. In the first case, having vehicle insurance implies having economic conditions to buy the insurance,

[20]This must be true as fleet estimates available correspond to only 56% of the total number of ever registered vehicles.

which can cost, annually, 3% to 10% of the car price. These same agents may also have better credit conditions, being able to replace their vehicles more often. In addition, insured individuals may engage in moral hazard behaviors, which could lead to more accidents, vehicle thefts or faster vehicle deterioration. Regarding safety concerns, there is the fact that Brazil is significantly more violent, including vehicle thefts, than developed countries such as the US.[21]

Figure 11.5 and table 10.1 inform us of the special scrap rate pattern across ages and show us some heterogeneity among manufacturers. This decaying pattern after a vehicle ages 15 years can be associated with some anti-scrapping incentives, such as ownership tax exemption for older vehicles. Each Brazilian state has a different threshold from which older vehicles are exempt from ownership taxes. The average cutoff is around 15 years, and the scrap rates format perfectly captures that information by showing smaller rates for older vehicles.

Lastly, the insurance database allows me to study a series of heterogeneous effects not possible with other types of data. In particular, I have information on the driver's gender and age, and if the vehicle is insured for a firm or personal use.

5 Methodology

Given the assumptions from the previous section, my definition of scrap rate is the change in the size of the insured fleet as defined by equation 1. This statement accommodates two situations: first, when vehicles are effectively scrapped, either by accident resulting in total loss or by theft, and in second place, when a risk-averse agent sells her vehicle to a non-risk-averse person, inducing some other non-risk-averse agent to scrap.

[21] de Lima and Marinho (2017) reports an average of 215 car thefts per 100,000 population for 2012, with a maximum of 737. Another study, from Murray, de Castro Cerqueira and Kahn (2013), reports information from the International Crime Victims Survey (ICVS) showing that Brazil has higher victimization rates than Europe and North America for several crimes, including car theft. In addition, statistics compiled by the Nation Master database shows that Brazilians have approximately 72% more worries about car theft than Americans.

My objective in this work is to understand how price changes affect the turnover of the fleet, i.e., how vehicle prices affect the decision of scrapping or selling used vehicles. I proceed with a panel instrument variables approach using as an instrument a measure of cost per distance traveled. This instrument is defined as:

$$RPK_{mt} = \frac{FuelPrice_t}{KPL_m} \tag{2}$$

Where RPK represents the expected amount of Reais per kilometer traveled, $Fuel\,Price$ is the current retailer fuel price per liter,[22] and KPL represents the respective vehicle fuel efficiency, measured in kilometers per liter. In sum, the instrument can be understood as a measure of how the cost of driving is reduced due to fuel efficiency.

The baseline model is estimated using 3. Here, Y_{amt} represents the scrap rate, P_{amt} is the used vehicle price, and α_{am} and α_{at} represent model-by-age and age-by-year fixed effects, respectively. This is a similar approach applied by Jacobsen and Van Benthem (2015) for the US market.

$$ln(Y_{amt}) = \gamma_1 ln(\hat{P})_{amt} + \alpha_{am} + \alpha_{at} + \epsilon_{amt} \tag{3}$$

$$ln(P_{amt}) = \Sigma_{m=1}^{M} \beta_m Z_{mt} + \alpha_{am} + \alpha_{at} + \mu_{amt} \tag{4}$$

Similarly to Jacobsen and Van Benthem (2015), I also increase flexibility in the price response β_m by separately interacting each fuel economy with fuel prices. However, different from them, I make this interaction at the manufacturer level and not at the vehicle model level. There are two reasons for this: first, the availability of Brazilian fuel efficiency data is not as rich and detailed by vintage as it seems to be the case for the US fleet. Usually, most brands have few to no fuel economy changes across vintages, presenting significant changes only when a new version of a model is released (and not a new vintage).

[22] Fuel here represents gasoline, diesel, or ethanol. For FFV, I used an average between gasoline and ethanol prices. For hybrid vehicles, I used gasoline prices. Electric vehicles were not significant in the period analyzed and, hence, were left out of this study.

For instance, a vehicle model Ford "Ecosport XLT FreeStyle 1.6" car does 8.8 kilometers per liter of gasoline (and 6.2 per liter of ethanol) in the city, for any vintage between 2007 and 2010. A newer version, Ford "EcoSport Freestyle 1.6", does 10 kilometers per liter of gasoline (or 7 per liter of ethanol). This seems to be a common pattern: newer model versions can be released with improved fuel efficiency, although only in a few cases the same version of a model improves over vintages.

The second reason is because much of the technology employed is manufacturer-specific. For example, when the first flex-fuel vehicles were introduced in 2003, each of the manufacturers developed their own version of the flex-fuel engine. GM Chevrolet was the pioneer, releasing the first-ever FFV in Brazil in March 2003, while Fiat, which was working in parallel to develop the technology, released its first FFV a few months later. Each manufacturer seems to be improving their own technology as a way to differentiate and gain space in the market, so by interacting at this level, I am capturing an average effect of the level of fuel efficiency development that each firm was able to achieve.

5.1 First Stage or The Effect of Fuel Prices on Used Car Values

One crucial aspect of this work is the mechanism through which used car prices affect scrap rates. As mentioned, this is the first stage of my main econometric approach and, much beyond this layer, understanding the relationship of fuel prices and used car valuation is relevant itself, especially for countries where fuel price controls are so widely used as is the case for Brazil.

As discussed in section 2, Brazilian governments used the percentage of anhydrous ethanol in the official gasoline blend as an indirect instrument to curb inflationary pressures. Other policy instruments often used are federal taxes (IPI, PIS/COFINS, and CIDE). Since Brazil is the major stockholder of Petrobras, controlling prices directly at the refinery level has also been another source of exerting its influence over fuel prices.

Fuel prices have two important impacts on the fleet. First, it directly impacts consumers' budgets, according to each specific vehicle's efficiency and considering the amount of kilometers driven. If the amount to be driven is kept fixed, at least in the short term, either because public transportation is not an optimal substitute or because consumers have fixed routes they need to travel every day, then vehicle efficiency becomes the main driver to explain the distributional effects of fuel prices shocks.

The second impact is indirect, occurring through the used car market. As fuel prices increase, fuel guzzlers tend to devalue relatively more than fuel-sipper vehicles. In other words, as gasoline price increases, vehicles of lower fuel efficiency tend to lose more market value. For the same vehicle model, it is reasonable to assume that, all aspects controlled, as vehicles age, the constant use leads to natural deterioration of the mechanical parts, leading to more pollution and potentially higher consumption (less efficiency) (Chiang et al. (2008), Harrington (1997)). This would imply some level of fuel economy deterioration for the same vehicle of different vintages. Consequently, older vintages tend to devalue more to fuel price increases.

Considering these aspects, my approach for the first stage uses model-by-age and age-by-year fixed effects to partial out all these potential confounds and identify the true differential impact of fuel price increases through varying fuel economy levels. The idea is that, controlling by model-by-age, a shock in fuel prices will affect each vehicle model of a certain age differently, according to its fuel efficiency level. On the other hand, age-by-year fixed effects allow me to control for any other characteristics that are specific per year and age (or vintage) and affect all vehicles similarly. Since age, year and vintage are, by construction, collinear, these fixed effects also control for specific vintage confounds.

The regression to be estimated is then represented by equation 4. As mentioned, fuel prices, represented by the term Z_{mt}, are weighted by fuel economy. I use dummy interactions at the make level to add flexibility to the model and estimate an average impact by the manufacturer. The results can be seen in the figure 11.6. I didn't impose any specific restriction on the parameters, so negative or positive impacts depends on the average level of the manufacturer left out (baseline options). The relevant aspect is the magnitude of the impacts.

I also follow Busse, Knittel and Zettelmeyer (2013) and Jacobsen and Van Benthem (2015) and estimate a used car price model based on the quartile of fuel economy. Table 10.2 presents such results. For each $1 Real (1 BRL) increase in fuel prices, used vehicles in the most efficient quartile increase their valuation in $1,190 Reais compared to the less efficient quartile. This effect is significant, in line with the literature, and remains relevant for both newer and older vehicles (columns 3 and 4).

To complement this analysis and link to the study of scrap rates, in figure 11.7 I show estimates from the reduced form, investigating fuel price impacts on scrap rates. Again, my assumption is that controlling for the model-by-age and age-by-year fixed effects, the fuel impact captured in the reduced form comes through, and only through, its impact on car prices.

5.2 Identification

For the identification of the scrap elasticity, I need both relevance and exclusion conditions to be satisfied. The relevant condition refers to a strong first stage, evidenced by the regression of used car prices on fuel costs. The exclusion restriction requires that fuel costs affect scrap rates only through used car prices.

For the relevance assumption, the study on the impact of fuel prices on section 5.1 evidences a strong first stage, represented in the regression by quartile of fuel economy and by the graph with the coefficients of the make-dummy interactions with fuel price (figure 11.6).

For the exclusion restriction, the key element is in the fixed effects used in the model. For the efficiency-weighted fuel prices to be a good instrument, it is necessary that any unobservable confound to be partial out, so the variation remaining explains scrap rates only through the effects of used car prices. To control for these unobservables, the set of model-by-age and age-by-year fixed effects play a key role: they absorb the impact of factors affecting the physical scrap rates (mechanical costs, parts prices) and any make-model-vintage specific costs (quality of certain vintage, strikes and other vintage-year specific shocks). By controlling for these unobserved factors, the variation left is the effect of fuel price shocks affecting scrap rates via used car prices according to each specific model efficiency.

The main idea behind this approach is that inefficient vehicles are more affected by fuel shocks, and may devalue more when fuel price increases, relative to new vehicles. For instance, an increase of one real (1 BRL) in gasoline prices may have a greater effect on a "Fiat - Palio ELX/ 500 1.0 4p" that has a fuel efficiency of 10.7 kilometers per liter than on a "Fiat - Palio EDX 1.0 mpi 4p" which does 13.2 kilometers per liter in the city. The owner of the former vehicle version will have a greater impact on her budget than the latter, provided the same amount of kilometers traveled.

In that sense, a common fuel shock affects each vehicle version differently, according to the fuel efficiency level. To isolate this shock from unobservables, I use a set of fixed effects for model-age and year-age. The first set controls for any model-vintage specifics, such as model-specific parts price or repair costs that equally affect all model versions of a given age. The second set controls for year-specific events that affect equally all models of the same age, such as economic conditions (changes in income and credit), yearly changes in the production quality, or any other year-specific factor that affects prices and scrap rates.

The traditional decision problem can better illustrate the link between fuel and used car prices. For example, each year, an individual faces a random repair cost shock (maintenance costs, accidents) and may decide whether to repair and keep the vehicle, repair and sell it, or scrap it. If the repair costs surpass the current vehicle valuation, this individual would be better off by scrapping it. Otherwise, he would keep it or sell it to another individual. Fuel price shocks, in this scenario, could be seen as a specific random maintenance shock. After controlling for unobservables, a fuel price increase would increase costs through the effective fuel economy of the vehicle.

5.3 Sales Tax Reduction Policies

One important policy implemented in Brazil was an IPI sales tax reduction for vehicles. IPI is a tax over all industrialized products and, in the case of vehicles, the actual rates varied according to table 11. The policy implemented at the end of 2008 zeroed the tax for new cars with motors equal to or lower than 1.0 liter and halved the rates for new cars with motors 1.1 to 2.0. The purpose behind this tax reduction was to promote the automobile industry, enhance the economy, and counterbalance the 2008 financial crisis effects.

The first time this policy was implemented, it lasted 13 months (December 2008 to December 2009). The second time it lasted longer, from May 2012 to December 2014. In both cases, this policy was aimed to last a short period of time, but it end up being postponed a few times to keep the incentives over this industry. As mentioned, this policy affected directly the purchase of new cars, whose prices fell considerably in those periods.

Used car prices were affected only indirectly. New cars are technologically more advanced, more reliable, and tend to present better fuel efficiency than older cars. When IPI sales tax rates were reduced, dropping down the price for new cars, a new incentive was created where owners of older, less efficient vehicles saw the opportunity to improve their welfare by switching to newer versions, and scrapping the old ones.

Therefore, even though the policy aimed at the sale of new cars, it also induced an increase in scrappage by creating an incentive for owners of old vehicles to switch to new ones. To capture this feature, I adapted the model as follows:

$$ln(Y_{amt}) = \gamma_1 ln(\hat{P}_{amt}) + \gamma_2 D_{IPI} \times ln(\hat{P}_{amt}) + \alpha_{am} + \alpha_{at} + \epsilon_{amt} \quad (5)$$

$$ln(P_{amt}) = \Sigma_{m=1}^{M} \beta_{m,maker} Z_{amt} + \Sigma_{m=1}^{M} \delta_{m,maker} D_{IPI} \times Z_{amt} + \alpha_{am} + \alpha_{at} + \mu_{amt} \quad (6)$$

Where γ_2 captures the effect of the interaction of a dummy for each year IPI policy was effective and used car prices. To investigate the main population group affected by this policy, on a second version of this model, I further split γ_2 coefficient by interacting this term with dummies for newer or older vehicles.

5.4 Flexible Fuel Vehicles

Flexible fuel vehicles (FFV) were initially introduced in 2003, and gradually absorbed by all manufacturers in Brazil. This new engine allows for the same tank and motor to use any amount of gasoline or ethanol at the same time. By the end of 2006, the four main manufacturers – GM Chevrolet, Fiat, Ford, and Volkswagen – already had the majority of their production with a FFV version available. Other manufacturers followed the same path, with a delay in implementation. Reports from the sector indicate that about 95% of the sales of new cars were FFV by 2010.

A few months after the introduction, the federal government established that FFV vehicles would be subject to the same IPI sales taxes as ethanol vehicles, which were, on average, around 2 p.p. lower than similar gasoline vehicles. When IPI sales taxes were reduced in 2008, it affected all vehicles similarly, zeroing or halving the taxes. Since it is a challenge to differentiate the impacts specific to FFV from those coming from IPI reduction, I will adopt a different approach.

My attempt to understand the introduction of this new technology into the fleet and its impact on scrap rates is to interact with dummy variables for different periods of time. I split my period of analysis into 4 moments:

Introduction (2003 to 2006): period in which the major manufacturers adopted the technology and started replacing their gasoline vehicles with FFV.

Diffusion (2007 to 2010): period in which, associated with IPI sales tax reduction, the FFV technology was vastly promoted and increased its share in the sales of new vehicles, achieving 95% by 2010.

Majority (2011 to 2015): period in which FFV is estimated to become the majority type of vehicle among cars in the actual fleet.[23]

Maturity (2016 to 2020): period in which FFV has become the standard in the market, and no IPI sales tax reduction has been implemented.

I interacted vehicle prices with a dummy for each sub-period to obtain a salience effect of the flex-fuel technology in the overall scrap rates. Because of multicollinearity, I suppressed the interaction for the first period (introduction), making it the baseline for each subsequent period. The regression estimated was:

$$ln(Y_{amt}) = \gamma_1 ln(\hat{P}_{amt}) + \Sigma_{p=2}^{4}\gamma_{2,p} Years \times ln(\hat{P}_{amt}) + \gamma_3 D_{Flex} + \alpha_{am} + \alpha_{at} + \epsilon_{amt} \quad (7)$$

$$ln(P_{amt}) = \Sigma_{m=1}^{M}\beta_{m,maker} Z_{amt} + \Sigma_{m=1}^{M}\delta_{maker,p} Years \times Z_{amt} + \beta_{1,mt} D_{Flex} + \alpha_{am} + \alpha_{at} + \mu_{amt} \quad (8)$$

Where the coefficient of interest is $\gamma_{2,p}$ and the subscript p represents each sub-period of interest. The dummy for flex-fuel was used to accommodate different initial scrap rates for flex-fuel vehicles in comparison with other mono-fuel vehicles.

6 Results

Table 10.3 presents my main estimates for the scrap elasticity, (γ_1), using equation 3. Panel A shows OLS results while panel B uses instrumental variables to account for potential bias. The third panel focuses on all vehicles, which includes pickups, vans, and other light cargo vehicles (commercial vehicles). In this paper, I am not working with trucks, buses, or motorbikes. Appropriate analysis for those categories would require analysis beyond the scope of this work.

Another important restriction regards car prices. The measure of car prices used here is

[23] According to reports from the union of auto parts (Sindipeças), in 2011 the share of FFV in the total fleet was similar to the share of gasoline vehicles, becoming the majority after 2011.

the amount insured, which is highly correlated to the FIPE car price survey. I am limiting my estimations to vehicles evaluated up to 150,000 reais (2020 values). The reason for this is to focus on affordable vehicles, excluding luxury cars and other outliers. Since luxury vehicles represent a small fraction of the fleet, this restriction, even though important, may not affect the elasticities.

The first column is my favorite specification, while columns 3 to 5 extend my main model by interacting with a dummy to identify specific effects from the IPI tax reduction periods. My main elasticity is -0.43, significantly smaller, in absolute values than the -0.71 found by Jacobsen and Van Benthem (2015) for the US market using data for the full fleet. This result seems coherent with the conditions we find in Brazil: practically no incentives for scrappage associated with lower average income and worse credit conditions, making consumers less sensitive to scrapping due to small used vehicle price changes.

6.1 IPI Sales Tax Reductions

As discussed, IPI sales tax affects used vehicle prices only indirectly, by making them less attractive compared to newer, more efficient vehicles. In column three of table 10.3 I present my IPI model. In this version, I interact vehicle prices with a dummy for years with reduced IPI sales tax to identify any differential scrap elasticity when tax reduction policies are in effect.[24] Models 3 and 4 use the same procedure but split the analysis into newer vehicles (aging up to 10 years) and older vehicles (above 10 years).

Policies aimed at reducing the prices of new vehicles seem to be more effective for owners of older vehicles. In column 4, analyzing the interaction dummy for vehicles up to 10 years old, we observe no significant IPI impact on used car prices, and the main scrap elasticity remains at -0.39, similar to the main IPI sales tax model (column 3).

However, the model from the last column shows a significant effect of IPI sales tax

[24]The dummy interaction was built to be one for the years 2009 and 2012 to 2014. I left 2008 out because IPI reduction started only on December 16, so its impact was reduced in that year. I am also not taking into account that 2013 and 2014 were years where the reduction was smaller than in 2008 and 2012. My criteria here is any period where IPI is below the usual tax standard.

reduction over used car prices for owners of vehicles aged 11 years or more. The main scrap elasticity is lowered to -0.30, indicating that owners of old vehicles tend to be less sensitive to price changes and end up scrapping less. This may be a direct implication of the anti-scrapping incentives for older vehicles. Nevertheless, a sales tax reduction policy over new vehicles seems to affect these owners of older vehicles. The interaction dummy shows a significant effect of -0.10, which combined with the main scrap elasticity, brings it back to -0.40, the same level as the IPI model and similar to owners of newer vehicles.

To summarize, the average scrap elasticity for the insured fleet is -0.43. The IPI models show no significant changes for owners of newer vehicles (-0.39) but evidences of a reduction of the elasticity for owners of older vehicles (-0.30). In addition, tax reduction policies applied over new vehicles seem to affect only owners of older vehicles (-0.10), equalling the overall scrap elasticity with newer used vehicles and offsetting any anti-scrapping incentives.

The standard errors for these models are relatively high, so I cannot discard the possibility of the scrap elasticity for columns 4 and 5 being statistically different. Notwithstanding, these results show evidence that: (i) elasticity for older vehicles seems to be more inelastic, reflecting anti-scrapping incentives, and (ii) IPI tax reduction over new vehicles seems to close the gap between older and newer used vehicles, equalizing the scrap elasticity for both groups.

This last result is particularly relevant for policymakers, who can use tax reduction on new vehicles as a mechanism to reduce the amount of less efficient vehicles from the current fleet and, consequently, improve local air pollution.

6.2 Flex Fuel Vehicles

Table 10.4 shows the IV results for flex fuel vehicles (FFV). Since the first reduction of IPI sales tax occurred at the same time most manufacturers have switched to producing FFV, and the second IPI reduction occurred right after FFV became the majority of the fleet, it is a challenge to disentangle one impact from the other. Therefore, the analysis here will contemplate both effects of FFV and IPI tax reduction combined.

Another relevant aspect is that I cannot treat FFV vehicles as a conventional treatment to be studied in this context. The reason for this is that, as FFV technology spreads among manufacturers, it quickly switches production from traditional gasoline engines to flex-fuel, impacting the potential control group (gasoline cars). Cars are not allowed to run by diesel, therefore using diesel cars as a control would not be the most ideal alternative.[25]

In addition, it is expected that FFVs have lower scrap elasticity (in absolute terms) because they are relatively newer cars. Finally, I am not interested in the scrap elasticity of this particular type of new technology, but in the effect it had on accelerating the scrappage or substitution of the older, mono-fuel, technology. The focus of this analysis is, actually, on how this flex-fuel technology induced a faster scrappage of gasoline-driven vehicles.

Given this challenge, the approach I took here was to consider a baseline period and estimate changes in the scrap elasticities as the FFV technology spreads among manufacturers and becomes the new standard for non-diesel vehicles in Brazil.

I set the period from 2003 to 2006 as my baseline period. These years were chosen because FFV was in its initial phase, gradually being adopted by all manufacturers, and consumers were still understanding the new technology and weighing the pros and cons of switching to this type of car.

Next, I set 2007 to 2010 as the "diffusion" period. The IPI tax reduction (December 2008 to December 2009), associated with faster economic growth in the second half of the 2000s, boosted the sales of FFV vehicles and by 2010, 95% of all new car sales were FFV, practically leaving only imported cars as gasoline-only engines. According to the Union of Auto Parts, in 2011 the market share of FFV cars and gasoline cars was similar in the fleet, so I called the next period (2011 to 2015) as "majority". The last period of analysis, entitled "maturity", regards 2016 to 2020, and refers to a period where no IPI sales tax reduction has been implemented and FFV technology has become the standard in the fleet.

[25]Only pickups, commercial vehicles, and trucks can run on diesel, but since these vehicles have a very specific niche (mainly cargo transportation), they may not be a good control for FFV cars.

Column 2 from table 10.4 shows the scrap elasticity for cars for the baseline period to be -0.42. When the diffusion period starts, this elasticity is strengthened by -0.165, summing up to -0.585. The elasticity for the majority period is reinforced by -0.163, resulting in -0.583. Finally, in the last period, maturity, the interaction with price is not statistically significant (-0.002), and the resulting elasticity would return to -0.42.

The last two columns replicate the exercise for flex fuel excluding the years where IPI sales tax reductions were in effect, namely 2009 and 2012 to 2014. The elasticities here are quite close to the first two models, only slightly higher. Considering that IPI tax reduction was applied in years of potential economic downturn as a measure to compensate the automobile sector for a lower level of economic activity, the small change in the elasticities here indicates that the fiscal policy was effective in not weakening the scrappage even in adverse economic periods.

In addition, in table A.5 in the appendix, I re-estimate the same models from table 10.4, but replacing the main efficiency-weighted fuel price instrument by its interaction with the share of flex-fuel vehicles in the registration of new vehicles. The idea was to more accurately account for the acceptance of this new technology in the market. The overall results are quite similar to the ones discussed here.

These results indicate at least three important aspects. First, the introduction of a new technology in the fleet took some time to spread among manufacturers and to be fully accepted by consumers. Second, IPI tax reduction contributed to the further dissemination of flex fuel engine cars by reducing the price of new vehicles and inducing scrappage of old cars. And third, once the tax stimulus ended and the new technology became the standard in the fleet, scrap elasticity tended to return to the baseline period, before the dissemination of the new technology.

The Union of Auto Parts estimates that FFV technology was present in about half of the cars in 2011. This was a relatively fast adoption of new technology, especially if compared to the case of electric vehicles in the US or other developed countries. Fuel consumption also indicates that not only old cars were replaced by FFV, but consumers in fact started using the greener option (ethanol) as a substitute for gasoline.

Certainly, even though cleaner, ethanol is not free of pollutants. However, FFV technology was, on average, also more efficient. Combined with the more frequent use of ethanol, which offsets its GHG emissions via sugarcane plantation, the overall result is a significant reduction of GHG gases generated in the transportation sector.

6.3 Car Ages

In table 10.5 I present results breaking down car age into several brackets. The results here are only suggestive since most standard errors are relatively higher, and I can't rule out that coefficients are different from each other.

What the models suggest here is that cars aging up to 5 years or more than 15 years are less sensitive to car price changes than models aging 6 to 14 years. For he initial period (column 2) it makes sense, considering they are relatively new cars and that most consumers - who made a loan to pay for the vehicle - are probably still paying installments for the purchase. The interesting aspect occurs in column 6.

Cars aged 15 or more usually fall into the ownership exemption bracket, hence their owners have less incentive to scrap. What the model evidences here is precisely this effect: if the vehicle is old enough to obtain exemption from taxes, it also becomes less sensitive to car price changes.

This result has multiple implications. For instance, In 2009, vehicular emissions inspection was introduced in major cities like São Paulo. By then, different policies applied to any vehicle that did not comply with emission levels. For owners of newer vehicles, they had a short window of time to fix any mechanical problem, regularize the emissions levels, and be retested. However, for owners of older cars, they didn't have the same rigor. If the car didn't fall into the permitted emission levels, the vehicle would be released with a stamp warning stating that it was a high pollutant vehicle. The result would be a drastic fall in the car's resale price.

In practice, however, my last model indicates that owners of older vehicles were already less sensitive to car price changes. Given the lack of a policy to enforce the scrappage of such vehicles, if an older vehicle, exempt from ownership tax, falls outside the emission level brackets, its owner would still have an incentive to keep the vehicle, provided that maintenance costs are not impeditive. This occurs because of the lack of a scrappage program, guaranteeing a minimum reward for scrapping, and because of the low average income and restricted access to credit, which difficult the replacement of the vehicle with a newer version.

In summary, the lack of a scrappage program, the low enforcement over older vehicles that don't comply with emission levels, and the exemption of ownership taxes for vehicles aged 15 or more translate into incentives to postpone scrappage. This actually goes in the opposite direction of combating climate change. First, because these older vehicles are, on average, polluting more. And second, because they are less efficient than newer versions.

6.4 Heterogeneous Effects

In this section, I study potential sources of heterogeneous effects from used vehicle prices to scrap rates. In particular, I focus on the analysis of the type of usage (firm versus personal use), gender, and driver age.

6.4.1 Scrap Elasticities by Firm and Personal Usages

Vehicles can be used for either passenger or cargo transportation. In each category, the frequency and intensity of use can determine different patterns of deterioration and accident risks. Therefore, the investigation of this pattern can be interesting, especially if policymakers formulate policies over specific groups, such as facilitating commerce and minimizing transportation costs.

Here my estimates consider all vehicles, which include not only cars, but also pickups, vans, mini-buses, and other light commercial vehicles destined for cargo or passenger transportation.[26]

My analysis does not include large buses or trucks. There isn't sufficient data on buses in the insurance database, and information on fuel efficiency is harder to obtain. Trucks are used for medium and heavy cargo and usually for long-distance transportation. Because of the complexity of this type of vehicle, the specific policies implemented for this category, and other aspects of the segment it represents, it would require other analysis outside the scope of this work.

Table 10.6 shows in panel A results for vehicles used by firms, while panel B shows elasticities for personal usage. The main elasticities are -0.49 for firms and -0.55 for personal use. When split into newer and older vehicles, the scrap elasticity for personal use seems to consistently fall, in absolute terms. For firm use, however, it initially falls for newer vehicles (-0.40) but increases to -0.62 for older vehicles. This pattern could be associated with firms' preference for newer vehicles. Since their use is more intensive, firm vehicles may deteriorate faster, and old versions may be subject to higher maintenance costs, so firms may become more sensitive to price changes, replacing older vehicles more often.

An addendum must be made. Since Uber drivers are autonomous, independent workers, they most probably contract insurance as regular users, not as a firm. Since these driving app services require their drivers to use newer vehicles, it is expected that these drivers would be more price-sensitive. However, without further information, I cannot investigate much more into this aspect.

The interesting aspect here is that firms tend to be more price-sensitive when owning an older vehicle. Policymakers could utilize of this feature to promote cleaner technology or more efficient vehicles aiming to reduce the environmental impact that the intensive use by firms would impose. In fact, this is what happens to the truck category, where, in many government administrations, subsidies to replace older vehicles were offered. Even though I am analyzing the market of light cargo and urban transportation, similar incentives could

[26]Mini-buses are buses with capacity up to 16 passengers. Traditional large buses (capacity above 40 passengers) are not included in this analysis.

be quite effective for this category of agents.

6.4.2 Scrap Elasticities by Gender

Several could be potential reasons for gender to impact scrap rates via used car prices. First, it could be the case that women drive more responsibly, and as a result face less vehicle deterioration or are less involved in accidents. This would lead to a reduction of scrap rates for women and less depreciated car values when compared to men.

Second, it could be that the replacement of an old vehicle is different between men and women. It can be the case that women prefer newer vehicles because they are more reliable and tend to require less maintenance, or it could also be the case that men use cars as a sign of status quo, and in this sense would replace them more often. It can also be that one gender, on average, tends to drive more kilometers than the other.

Each potential reason can lead to a stronger or weaker scrap elasticity, so the answer is not simple and may depend on the characteristics and preferences of drivers in each country or region.

Panel A from table 10.7 shows the results for OLS for cars, while panels B and C shows the result of the second stage for car and all vehicles, respectively. Overall, the elasticities for each type of model is similar between female and male drivers. Any difference here is not statistically significant.

Only in the last model, on panel C, it is possible to see a larger difference between male and female drivers. The difference between panels B and C is the addition of light commercial vehicles.[27] The fact that the elasticity of female drivers is stronger may suggest that women, when operating vehicles destined to commerce (e.g.: vans for transportation of people or cargo) may be more sensitive to car price changes and prefer newer vehicles.

Overall, as mentioned, none of the results are statistically different between male and female drivers, so a common policy that affects the scrappage of older vehicles would be as

[27] Pickups, small passenger vehicles, and other light cargo vehicles.

effective for one group or another.

6.4.3 Scrap Elasticities by Driver Age

Driver age can also be an influence factor on scrap rates and used car prices. Young adults may be less responsible and have fewer drive skills, which would lead to more intense vehicle deterioration or accidents. On the extreme, elderly drivers may be less responsive to events when driving.

Table 10.8 shows the scrap elasticities by driver age. I used four different brackets of age: young adults (aged 18 to 24 years old), adults (aged 25 to 44 years old), middle age adults (aged 45 to 64 years old), and elderly (aged 65 years old or more).

For this analysis in particular, I am focusing only on cars and I added on panel B an analysis under IPI tax reduction, similar to the estimation shown in table 10.3. From panel A, the scrap elasticity for young adults seems to be slightly smaller than for adults aged 25 to 44 years old (-0.31 $\times$ -0.39), even though they are not statistically different from each other. Model 3, however, shows that older adults (45 to 64 years old) are less sensitive to car price changes. Finally, the elderly above 64 years seem to be indifferent to car price changes.

The apparent unresponsiveness of the elderly to car prices could be linked to their purchase of special PCD cars. PCD stands for *people with deficiency* and this is basically a policy to facilitate that people who suffer some sort of deficiency could purchase a vehicle using some fiscal benefits. Among the benefits, there is the exemption of licensing tax, IPI sales tax, ICMS (state tax), and IOF (tax over financial movements and loans). On the other hand, people who are eligible for a PCD car are mandated to replace their vehicles every 4 years, independent of the condition of the vehicle.

Among the criteria for a person to enter this special program are a series of diseases or deficiencies that occur more frequently among the elderly, such as arthrosis, Parkinson's, and vision or auditory deterioration, among many others. As a result of being on PCD, car prices may be a less relevant factor and, since the replacement each 4 years is mandatory, it is possible indeed that they would be unresponsive to car prices.

When we move to panel B, the main elasticities seem to remain quite close to those in panel A, but on moments where IPI tax reductions are effective, each group seems to respond differently. Younger adults show a positive effect (+0.28), which reduces their final elasticity to -0.08. The elderly, on the other extreme, have a significant negative impact of -0.20. Other groups seem to behave as expected with a negative, significant, and less intensive impact.

There is a potential mechanism that could be linking young adults and the elderly in this scenario with IPI tax reduction over new vehicles. First, the part of the elderly group who are not on the PCD program may be taking advantage of the tax reduction to replace their vehicles and buy newer models. This would generate an excess supply of used cars in the market, which would be acquired by new young adults who could be buying their first car.

Since young adults are at the beginning of their careers, they tend to have more credit restrictions and lower income and may take advantage of the excess of used cars at lower prices in the market.

If we take a look at the statistics, we observe that the average car age decreases for the elderly group under tax reduction periods and increases for young adults, corroborating the idea of one group potentially buying used cars from the other.

7 Robustness Check and Consistency

In this section, I present some robustness checks and alternative specifications to show the consistency of my results.

Table 10.9 shows some alternative specifications. Column 1 of table 10.9 presents a model with car prices ranging up to 400,000 Reais. The average valuation for the vehicles in my database is 63,000 Reais, while the valuation only for luxury vehicles is 116,400 Reais. My estimates vary quite smoothly until a ceiling of 400 thousand Reais (see table A.3 in the appendix). Vehicles above this threshold are marginal and represent less than 0.01%.

Next, in column 2, I estimate a model excluding all luxury manufacturers. The result is very similar to my main estimates. Cars from luxury manufacturers in my dataset represent only 1.86%, but their valuation can be worth up to 2.7 million Reais.

Column 3 shows an exercise considering only years with price increases. From 2002 to 2020, only a few years didn't show any price increase in fuel prices at the retailer level.[28] The scrap elasticity increases to -0.497, but it's still within one standard error from my main model.

It is important to notice that fuel price behavior at the retailer level may be different from its behavior at the distribution and refinery segments. As mentioned, Brazil has a long history of intervening in the economy to minimize or even avoid large fuel price fluctuations. In particular, during the period of 2011 to 2014, the government imposed a price ceiling on Petrobras refinery prices, controlling very closely any production price increases. To test the sensitivity of my results to this period, I estimated model 4 in table 10.9, excluding the years 2011 to 2014. The result is an elasticity slightly smaller than my main specification, but still within one standard error interval.

In table 10.10 I test several different sets of fixed effects. Column 1 is my main specification. Models 2 to 4 are quite similar to the main version and all fall within one standard error. the last two columns include interactions of model and vintage, and the resulting elasticities are stronger. Yet, they fall within two standard errors and a hypothesis test cannot rule out they are statistically different from my main specification.

8 Policy and Discussions

In this section, I discuss some potential reasons for the success of the flex-fuel technology, as well as the results from the sales tax policies, and potential implications for electric vehicles.

Flex-fuel vehicles were introduced in a moment where both consumers and the market

[28] These years are: 2002, 2007, 2008, 2019, and 2020.

presented some features and aspects that favored the new technology release and adoption. As mentioned in section 2, there was a huge promotion of ethanol-driven vehicles in the 1980s, lasting until the mid-1990s. Among the consequences of this phase, was the adoption, on practically all fuel retailers, of pumps for providing ethanol. Even though ethanol use in vehicles dropped significantly since 1990, this alternative fuel was still available in most retailers around the country by the time flex-fuel vehicles were introduced in the market.

The relative success of ethanol-driven vehicles in the 1980s was mostly associated with a series of subsidies and incentives given in those years. With the introduction of flex-fuel vehicles, ethanol became once more a viable choice because the new technology also improved fuel efficiency, which partially compensated for the reduction of subsidies. Also, during the periods with gasoline price shocks in the second half of the 2000s, having a vehicle that could easily substitute the fossil fuel option for a cheaper energy source was another advantage of flex-fuel vehicles. Considering the total fleet estimates by age from the 2023 report from Associação Nacional dos Fabricantes de Veículos Automotivos (2023), I estimate that the diffusion and majority phases of the flex-fuel era were responsible for an additional 465,000 vehicles scrapped per year.

Regarding the sales tax reductions, implemented between December of 2008 and December of 2009, a few aspects of the government actions should be emphasized. First, the reduction of taxes on new vehicles was a policy aimed to counterbalance the economic downturn resulting from the financial crisis that hit the US markets in 2008. Second, the tax reduction was supposed to last only three months, ending between February and March of 2009. However, this policy was renewed several times, as expressed by the decrees in column two of table A.2. Newspapers from 2009 recurrently reported consumer rushes towards the purchase of new cars close to each supposed ending of the policy, right before it was renewed.

When a similar policy was implemented in 2012, the core intention was similar: stimulate the economy by inducing consumer expenses and helping the automobile industry. However, not only consumers were already aware of potential delays in ending the policy, but also the government established a timeline for the tax to gradually return to normal levels.

There is another reason for which the tax reduction policy from 2012 to 2014 was less effective than the 2008 to 2009 policy. During the period of 2011 to 2014, the government imposed a gasoline price ceiling on the Petrobras refinery prices. The intention was to curb domestic inflation and avoid strong readjustment of prices due to peaks in international oil prices in those years. With a gasoline price less expensive than it should have been, the relative ethanol to gasoline price was such that consuming gasoline had a better cost-benefit, which led consumers to substitute back from ethanol to gasoline as seen in figure 11.1.

If an increase in fuel prices leads consumers to increase their valuations on the most efficient vehicles, a decrease in fuel prices may not induce them to replace their used and less efficient vehicles. Hence, the second reduction of sales tax may have been, at least partially, counterbalanced by the gasoline price ceiling policy between 2012 and 2014. On average, considering both periods with sales tax reductions, and based on its salience effect (interaction dummy in the table 10.3) and the Associação Nacional dos Fabricantes de Veículos Automotivos (2023) report, I estimate that tax reduction policies were responsible for additional 185,000 vehicles scrapped per year.

Recently, the government tried to implement another sales tax reduction, focused on popular vehicles (mainly 1.0 engine types). This policy was not as successful as previous tax reductions. Even though the period of this new policy (2023) is outside of my period of analysis, a few ideas for future research can be discussed here. The Brazilian automotive market has seen a huge surge of SUVs and more potent vehicles, and the introduction of other technologies such as electric vehicles. By implementing a policy focused on popular 1.0 engine vehicles, the government may have missed the target, offering subsidies on segments that consumers may not have as much interest as in the past. Once more, this is a conjecture, and specific studies shall be done to confirm or refute this idea.

Finally, on the implementation of electric vehicles (EV), a few lessons can be driven from past experience. First, a sales tax reduction on the new technology may help promote it in its initial phases. Second, electric vehicles face a restriction that flex-fuel vehicles don't: recharging stations are still rare and too slow. An important restriction to EVs in Brazil, especially in major cities, is the lack of infrastructure in houses and apartment buildings to adapt domestic recharging stations. On top of that, there aren't enough recharging stations in the major cities, and even less in the countryside and smaller municipalities.

In addition to this, the actual technology for recharging EVs faces a trade-off between recharging speed and location (Dorsey, Langer and McRae (2022)). Faster recharge stations are more expensive, but investing in locations with cheaper versions may impose a longer waiting time for recharging for consumers.

The challenges for promoting EVs may be one of the most important topics in the next few years. However, even though Brazil has a great advantage in having most of its electricity produced by hydroelectric sources, the continuous provision of electricity to all parts of the country, and the expansion of feasible recharging stations may impose obstacles that future governments have to face.

9 Conclusion

In the discussion on potential ways to minimize climate change and diminish the amount of greenhouse gas emissions, policies aimed at replacing fossil fuel dependence or reducing the negative effects of its usage are all welcome. In the transportation sector, this discussion translates into using cleaner technologies or switching to cleaner alternative fuels. In this sense, the study of the used car price elasticity of scrappage plays a central role in meeting climate goals.

In this work, I estimate the used vehicle price elasticity of scrappage for Brazil. The relevance of the study is multiple. First, it is the first of the kind for an emerging country with a sizeable transportation sector. Second, the results may help design policies to replace old vehicles, introduce new technologies in the fleet, and ultimately promote cleaner urban environments.

My main model estimates an impact of -0.43, which is significantly lower than the impact found for developed countries. Differently from these other works, and in the absence of better data, I work with a restricted sample that comprehends the universe of the privately insured vehicles, and about one-third of the full fleet. Nevertheless, under some assumptions, I discuss how my results can be seen as an upper bound, in absolute terms, to the full fleet scrap elasticity.

My results may be in line with characteristics usually found in many emerging countries, such as lower average income and significant income inequality, credit restrictions, anti-scrapping incentives, and the absence of active scrapping programs.

Next, I study the impacts of Brazilian tax reduction policies for new vehicles and how this impacted the scrap elasticity for used vehicles. My main model shows that, on average, owners of cars aged 10 years or more are the most affected by these policies. This is a strong result and it can help design policies to promote the replacement of older, inefficient, and more pollutant vehicles.

I split my database into four sub-periods to analyze how the evolution of the flex fuel vehicle technology (FFV) altered the overall scrap elasticity. I establish an introduction moment when FFV was first released, and compare the subsequent periods until the moment this new technology became the new standard of vehicles in Brazil. My results here show that new technologies do affect the scrappage of old vehicles but any impact vanishes once the current fleet completely absorbs these innovations. Also, tax reduction policies greatly benefit the diffusion of these new technologies.

Finally, I also investigate a series of heterogeneous effects related to firm and personal use of vehicles, gender, and driver ages. My results show that agents can vary largely in their preferences, depending on the purpose of use and driver's age. I found no strong evidence of differences between male and female drivers.

My results can be applied to a variety of policies, supporting policymakers to focus on certain groups or agents and calibrate the expected impacts over the fleet. It may also help in planning on promoting and subsidizing new and cleaner technologies to be introduced in the fleet (e.g. electric vehicles). In focusing on environmental aspects, my work can be used for the discussion of regulation enforcement and calibration, helping public agents determine the next steps in promoting greater fuel efficiency and controlling GHG emissions in the current and next generation of vehicles.

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10 Tables

Table 10.1: Scrap Rates and Used Car Prices by Age

	All Vehicles			All Vehicles			All Vehicles	
Age (years)	Scrap Rate (percent)	Car Price ($ Reais)	Age (years)	Scrap Rate (percent)	Car Price ($ Reais)	Age (years)	Scrap Rate (percent)	Car Price ($ Reais)
1	7.43	50,375	11	23.72	22,835	21	16.37	9,974
2	9.92	49,514	12	23.22	21,074	22	17.16	9,280
3	13.33	44,016	13	23.06	19,344	23	18.39	8,901
4	15.56	40,402	14	23.26	17,648	24	17.86	8,423
5	16.01	37,147	15	23.88	16,015	25	17.78	8,112
6	16.94	34,292	16	23.68	14,594	26	18.56	7,825
7	18.20	31,688	17	22.65	13,504	27	18.18	7,311
8	19.66	29,058	18	21.11	12,594	28	15.29	6,861
9	21.68	26,912	19	18.10	11,325	29	14.29	6,421
10	22.74	25,294	20	17.30	10,627	30	11.70	6,180

Table presents median values of scrap rates and vehicles prices. Trucks, buses and motorbikes are not included in the analysis.

Table 10.2: Used Vehicle Price Elasticity of Scrappage

	All Ages	up to 10 years	above 10 years
Fuel Price × Quartile 2	320.9**	604.7**	652.2***
	(159.4)	(258.7)	(136.2)
Fuel Price × Quartile 3	1089.6***	1885.1***	279.4***
	(128.4)	(250.5)	(97.4)
Fuel Price × Quartile 4	1190.7***	1988.2***	538.8***
	(144.8)	(266.5)	(115.9)
N	36,550	17,060	17,476

Notes: The dependent variable is vehicle used car prices. The coefficients represent the effect of fuel price by quartile. Additional controls used: dummies for vehicle types (pickups, other commercial vehicles) and dummies for cylinder size (proxy for horsepower). These regressions are a summary manner to express the first stage: fuel prices have a significant impact on used car prices, and increase as vehicles become more efficient. Models are clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.3: Used Vehicle Price Elasticity of Scrappage

	Model 1 Main	Model 2 IPI tax	Model 3 up to 10 years	Model 4 above 10 years
Panel A: OLS models for cars				
Scrap Elasticity	-0.1116***	-0.0973***	-0.0573*	-0.1465***
	(0.0202)	(0.0210)	(0.0313)	(0.0261)
Scrap Elasticity ×		-0.0531***	-0.0336	-0.0715***
Tax Reduction dummy		(0.0176)	(0.0265)	(0.0225)
N	31,281	31,281	16,246	15,035
Panel B: IV models for cars				
Scrap Elasticity	-0.4337***	-0.4035***	-0.3933***	-0.3014***
	(0.0678)	(0.0655)	(0.0802)	(0.0753)
Scrap Elasticity ×		-0.0647***	-0.0261	-0.1043***
Tax Reduction dummy		(0.0222)	(0.0337)	(0.0279)
N	31,162	31,162	16,242	14,920
F-Stat	161.43	651.83	3,890.92	471.92
Panel C: IV models for all vehicles				
Scrap Elasticity	-0.5493***	-0.4911***	-0.4657***	-0.3378***
	(0.0520)	(0.0510)	(0.0593)	(0.0698)
Scrap Elasticity ×		-0.1150***	-0.0792**	-0.1451***
Tax Reduction dummy		(0.0222)	(0.0330)	(0.0275)
N	39,736	39,736	20,654	19,082
F-Stat	143.72	122.57	189.29	73.09

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. The last two columns represent the IPI car sales tax models split into vehicles with less or more than ten years. A dummy for all periods with IPI car sales tax reduction was interacted with prices to estimate any salience effect from the tax policy. Third panel regressions also include pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.4: Used Vehicle Price Elasticity of Scrappage

	Full Sample		Excluding 2009, 2012-2014	
	Cars	All Vehicles	Cars	All Vehicles
Introduction (2003 to 2006)				
Scrap Elasticity	-0.4205***	-0.4013***	-0.4345***	-0.4609***
	(0.0661)	(0.0555)	(0.0713)	(0.0611)
Diffusion (2007 to 2010)				
Scrap Elasticity x	-0.1645***	-0.2464***	-0.2047***	-0.2789***
dummy 2008 to 2010	(0.0429)	(0.0407)	(0.0459)	(0.0437)
Majority (2011 to 2015)				
Scrap Elasticity x	-0.1627***	-0.2358***	-0.2502***	-0.2723***
dummy 2011 to 2015	(0.0434)	(0.0407)	(0.0495)	(0.0467)
Maturity (2016 to 2022)				
Scrap Elasticity x	-0.0017	-0.0486	-0.0328	-0.0725
dummy 2016 to 2020	(0.0456)	(0.0430)	(0.0485)	(0.0456)
N	31,135	39,704	23,192	29,502
F-Stat	336.20	110.48	221.12	76.84

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Dummies for each sub-period (diffusion: 2008 to 2010; majority: 2011 to 2015; maturity: 2016 to 2020) were interacted with used car prices to capture salience effects as flex fuel vehicles increase their participation in the total fleet. The last two columns exclude the years of 2009 and 2012 to 2014, which represent years where the federal government implemented reduced sales taxes for new vehicles. Besides cars, regressions from the columns "all vehicles" also include pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.5: Used Vehicle Price Elasticity of Scrappage

	All ages	Age 1-5	Age 6-9	Age 10-14	Age 15+
Panel A: OLS, Cars					
Scrap Elasticity	-0.1116***	-0.0216	-0.0753*	-0.1639***	-0.1726***
	(0.0202)	(0.0548)	(0.0407)	(0.0333)	(0.0337)
N	31,281	6,263	8,012	8,531	8,475
Panel B: IV, Cars					
Scrap Elasticity	-0.4337***	-0.3136**	-0.3677***	-0.3602***	-0.2459**
	(0.0678)	(0.1315)	(0.1135)	(0.0909)	(0.1012)
N	31,162	6,263	8,010	8,510	8,374
F-Stat	161.43	222.55	313.34	148.99	46.73
Panel C: IV, All Vehicles					
Scrap Elasticity	-0.5493***	-0.4328***	-0.5022***	-0.4534***	-0.4794***
	(0.0520)	(0.0945)	(0.0814)	(0.0826)	(0.1051)
N	39,736	8,242	9,959	10,679	10,851
F-Stat	143.72	201.49	167.81	118.89	52.86

Notes: The dependent variable is vehicle scrap rates by age group. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Third panel regressions also include pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.6: Used Vehicle Price Elasticity of Scrappage by Usage

	Model 1	Model 2	Model 3
Panel A: Scrap Elasticity - Firm Use			
	Main	up to 10 years	above 10 years
Baseline	-0.4900***	-0.3960***	-0.6210***
	(0.0685)	(0.0701)	(0.1637)
N	27,070	17,813	9,194
F-Stat	132.64	156.75	48.56
Panel B: Scrap Elasticity - Personal Use			
Baseline	-0.5535***	-0.4757***	-0.4669***
	(0.0572)	(0.0685)	(0.0715)
N	37,507	19,592	17,915
F-Stat	137.69	237.38	60.65

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. The first panel represents vehicles registered for firm use. The second panel is registered by personal use. These regressions include all vehicles, i.e., cars pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.7: Used Vehicle Price Elasticity of Scrappage by Gender

	Model 1 Male	Model 2 Female
Panel A: OLS models for cars		
Scrap Elasticity	-0.0488*	-0.0586**
	(0.0268)	(0.0222)
N	23,871	28,144
Panel B: IV models for cars		
Scrap Elasticity	-0.3219***	-0.3068***
	(0.0873)	(0.0713)
N	23,804	28,058
F-Stat	86.03	115.50
Panel C: IV models for all vehicles		
Scrap Elasticity	-0.4128***	-0.4949***
	(0.0780)	(0.0572)
N	29,181	35,455
F-Stat	90.31	140.78

Notes: The dependent variable is vehicle scrap rates by gender. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Third panel regressions also include pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.8: Used Vehicle Price Elasticity of Scrappage for Cars

	Model 1 18 to 24	Model 2 25 to 44	Model 3 45 to 64	Model 4 64 or more
Panel A: Scrap Elasticity - Cars				
Scrap Elasticity	-0.3064**	-0.3892***	-0.1713*	-0.2195
	(0.1312)	(0.0908)	(0.1016)	(0.1697)
N	10,361	14,404	11,733	9,558
F-Stat	86.19	135.85	100.37	21.25
Panel B: Scrap Elasticity - Cars				
Scrap Elasticity	-0.3572***	-0.3601***	-0.1706*	-0.1426
	(0.1293)	(0.0878)	(0.0975)	(0.1453)
Scrap Elasticity ×	0.2809***	-0.0831**	-0.1220***	-0.1969***
Tax Reduction dummy	(0.0665)	(0.0366)	(0.0367)	(0.0470)
N	10,387	14,474	11,856	9,641
F-Stat	89.52	143.95	120.77	1,883.68
Panel C: Summary Statistics				
Under Tax Reduction (average of 2009 and 2012 to 2014)				
Car Age (years)	7.1	9.4	10.3	11.0
Car Price (BRL '000)	43.6	49.0	47.5	41.0
Scrap Rate (percent)	27.2	29.2	24.0	17.0
Under No Tax Reduction (other years)				
Car Age (years)	7.0	9.7	10.6	11.2
Car Price (BRL '000)	42.5	43.6	41.9	37.1
Scrap Rate (percent)	24.8	26.6	21.2	14.7

Notes: The dependent variable is vehicle scrap rates by driver age group. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.9: Used Vehicle Price Elasticity of Scrappage

	Model 1 up to $400k	Model 2 No Luxury	Model 3 Fuel Increase	Model 4 Excluding 2011-2014
Panel A: IV models for cars				
Scrap Elasticity	-0.3822***	-0.4502***	-0.4968***	-0.3914***
	(0.0676)	(0.0798)	(0.0785)	(0.0750)
N	33,238	25,063	24,250	23,115
F-Stat	160.76	161.27	118.95	121.23
Panel B: IV models for all vehicles				
Scrap Elasticity	-0.5132***	-0.5901***	-0.5420***	-0.5233***
	(0.0511)	(0.0602)	(0.0597)	(0.0585)
N	41,862	33,014	30,997	29,492
F-Stat	139.79	141.01	111.69	118.03

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Second panel regressions also include pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 10.10: Used Vehicle Price Elasticity of Scrappage

Panel A: IV Models						
	Main	Model 2	Model 3	Model 4	Model 5	Model 6
Scrap elasticity	-0.4337***	-0.3909***	-0.4033***	-0.3716***	-0.5744***	-0.5484***
	(0.0678)	(0.0663)	(0.0655)	(0.0647)	(0.0784)	(0.0869)
N	31,162	31,472	31,472	31,182	31,257	31,239
F-Stat	161.43	256.22	340.56	345.93	138.68	163.97
Fixed Effects						
Model		X	X			
Age		X		X		
Vintage			X		X	
Year		X	X	X	X	
Model-by-Age	X			X		
Model-by-Vintage					X	X
Age-by-Year	X					
Vintage-by-Year						X

Notes: The dependent variable is vehicle scrap rates by age group. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Each column shows a regression using a different set of fixed effects. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

11 Figures

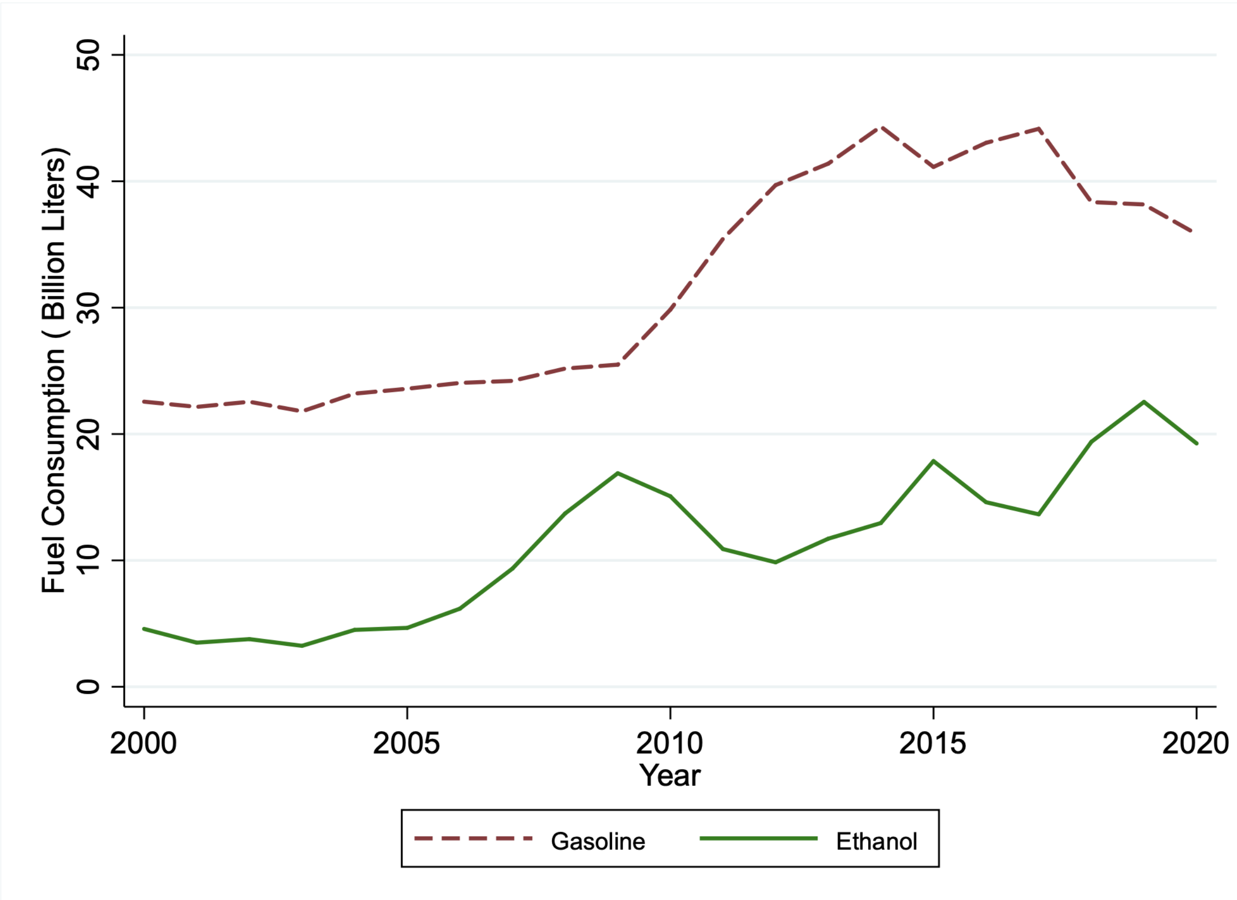

Figure 11.1: Fuel Consumption: Gasoline and Ethanol

Notes: Leading up to 2003, ethanol consumption was declining and limited to the very few ethanol-driven vehicles produced until the previous decade. After 2003, with the introduction of flex fuel vehicles (FFV), ethanol consumption became once more a viable option, specially in moments of gasoline price increase. The graph shows a continuous increase of ethanol consumption up to 2009, moment when the FFV fleet reached around 40% of the total fleet according to market analysis reports. From this point on, ethanol became an effective substitute to gasoline and started responding more effectively to gasoline price fluctuations.

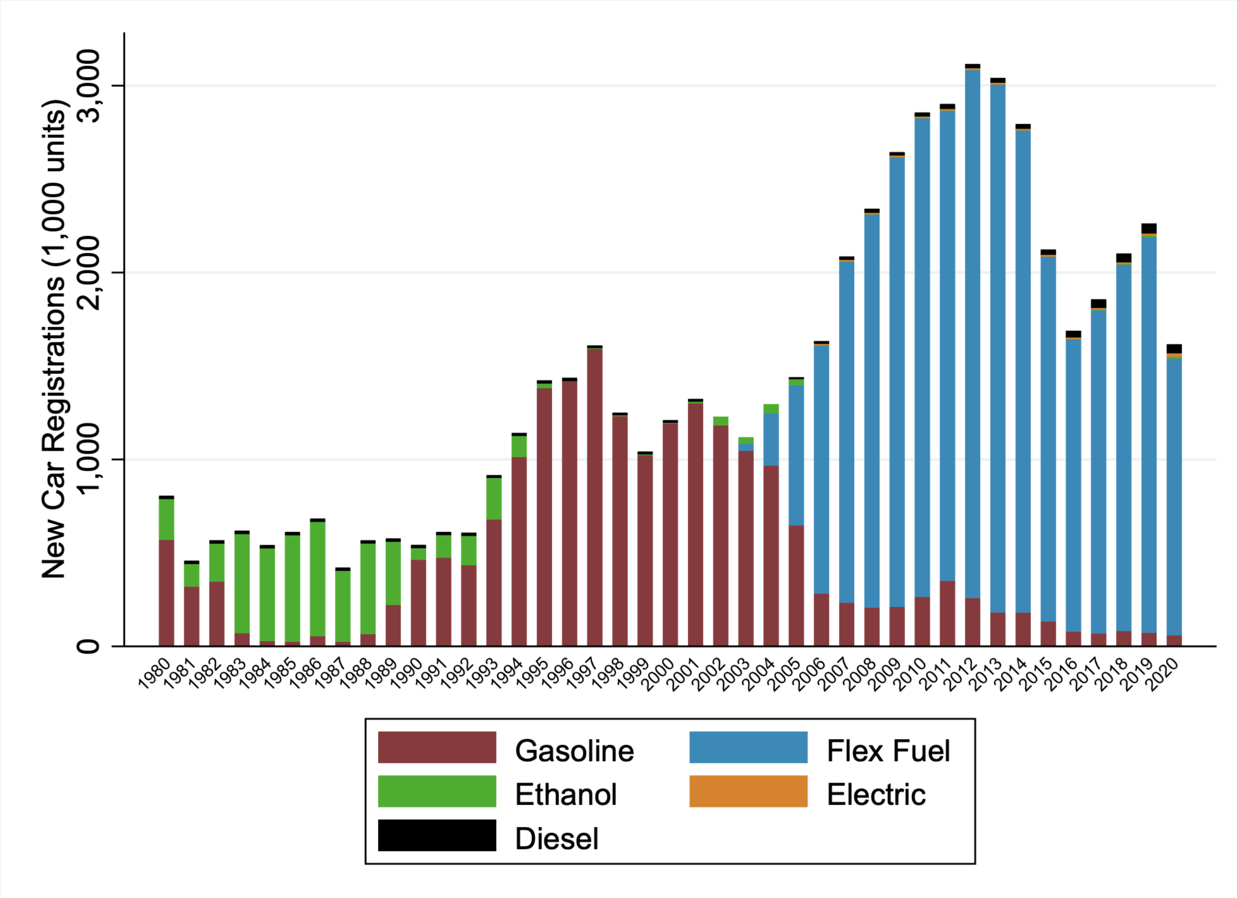

Figure 11.2: Car Registrations by type of Fuel

Notes: This figure shows the evolution of Brazilian new car registrations by type of fuel. Ethanol-driven cars represented a significant portion of the new registrations between their first release in 1980 and the beginning of the 1990s. The fast adoption of flex fuel vehicles by the major manufacturers between 2003 and 2005 led to an increasing substitution of gasoline-driven cars by the bi-fuel technological version in the following years. Data source: Anfavea.

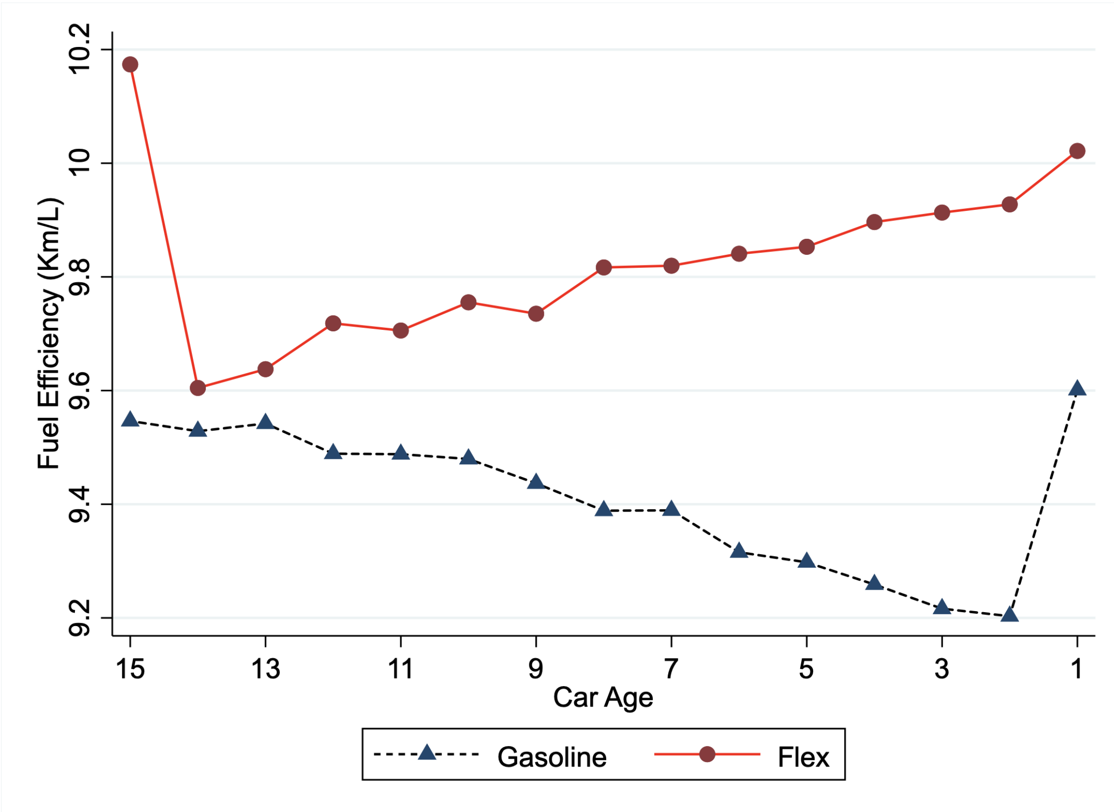

Figure 11.3: Fuel Efficiency of Gasoline and Flex Fuel Vehicles by Age

Notes: This figure displays the evolution of fuel economy by vehicle age and type of technology. After the initial year, flex fuel technology gradually replaced traditional gasoline-only engines. Manufacturers invested in this new FFV to improved its efficiency over time.

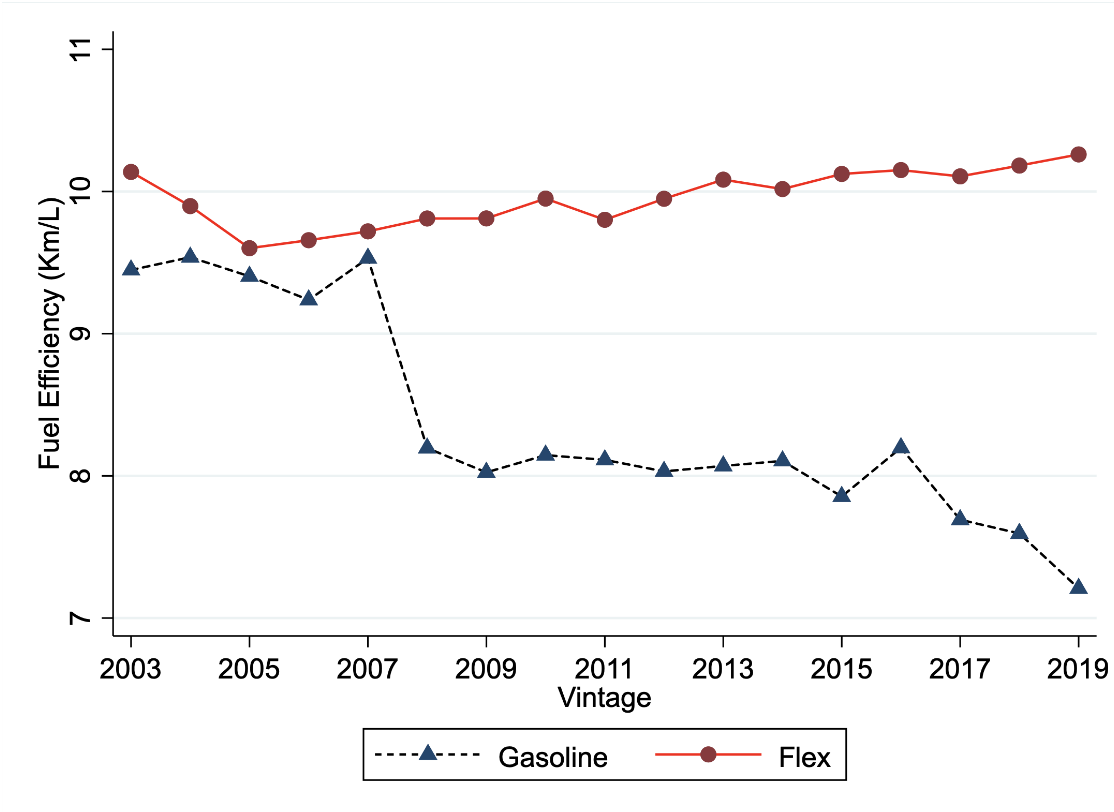

Figure 11.4: Fuel Efficiency of Gasoline and Flex Fuel Vehicles by Vintage

Notes: This figure shows the evolution of fuel economy by vehicle vintage and type of technology. After flex fuel vehicles were introduced in the market in 2003, the four main manufacturers quickly switched their production from gasoline-only to the new bi-fuel technology. In the period of 2006 to 2007, other smaller manufacturers entered the FFV market and most of the production of gasoline-only vehicles were replaced by the bi-fuel vehicles. At this point, the gasoline models left in the market had a significant lower fuel economy level.

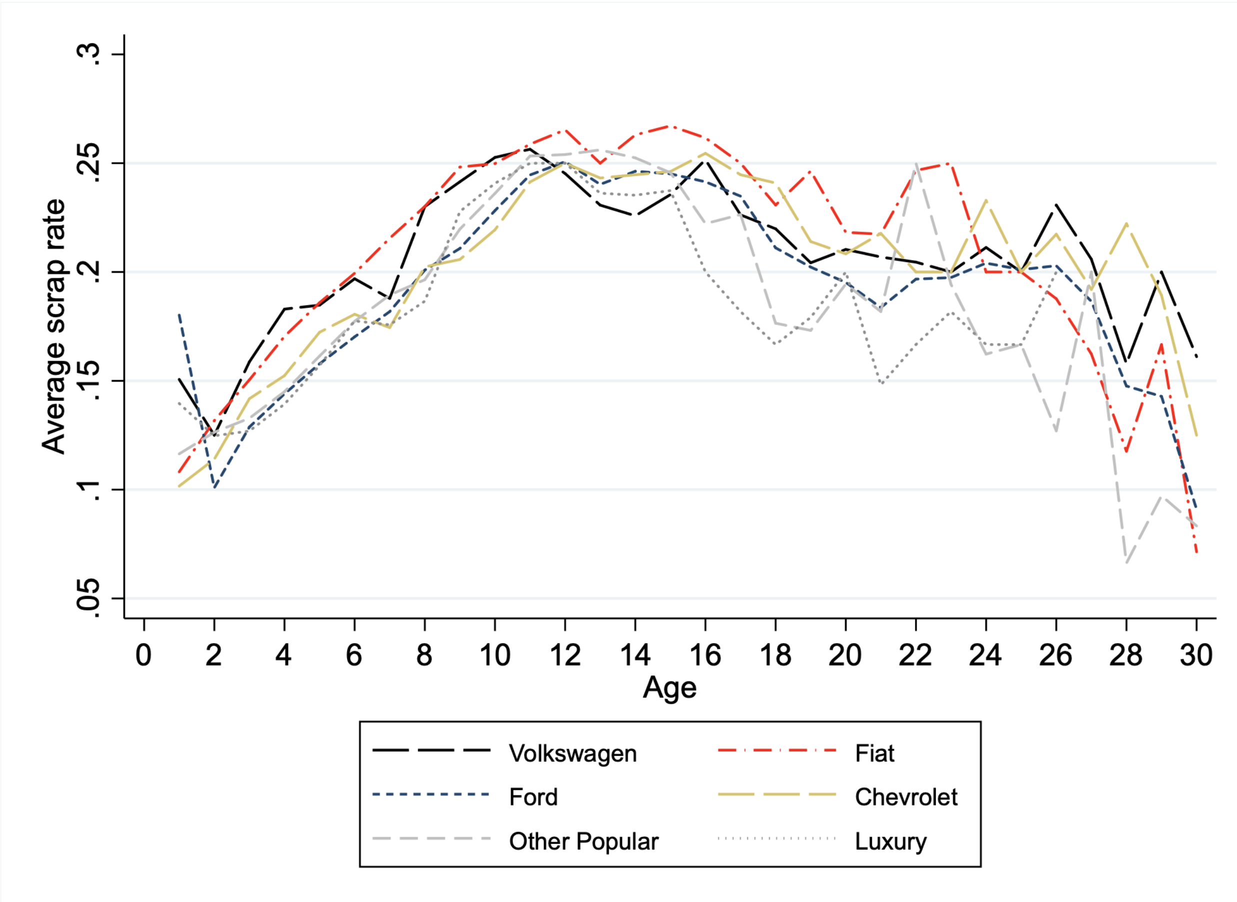

Figure 11.5: Median Scrap Rates by Vehicle Age and Maker

Notes: This figure shows the median scrap rates by vehicle age. Opposite to many other countries, the pattern of scrap rates for Brazil presents a decay after vehicle ages 15 years. This behaviour could be associated to the anti-scrapping incentives that Brazilian institutions impose, such as ownership tax exemptions for older vehicles (aging more than 15 years, on average) and the lack of federal programs mandating or incentivizing scrappage of older vehicles.

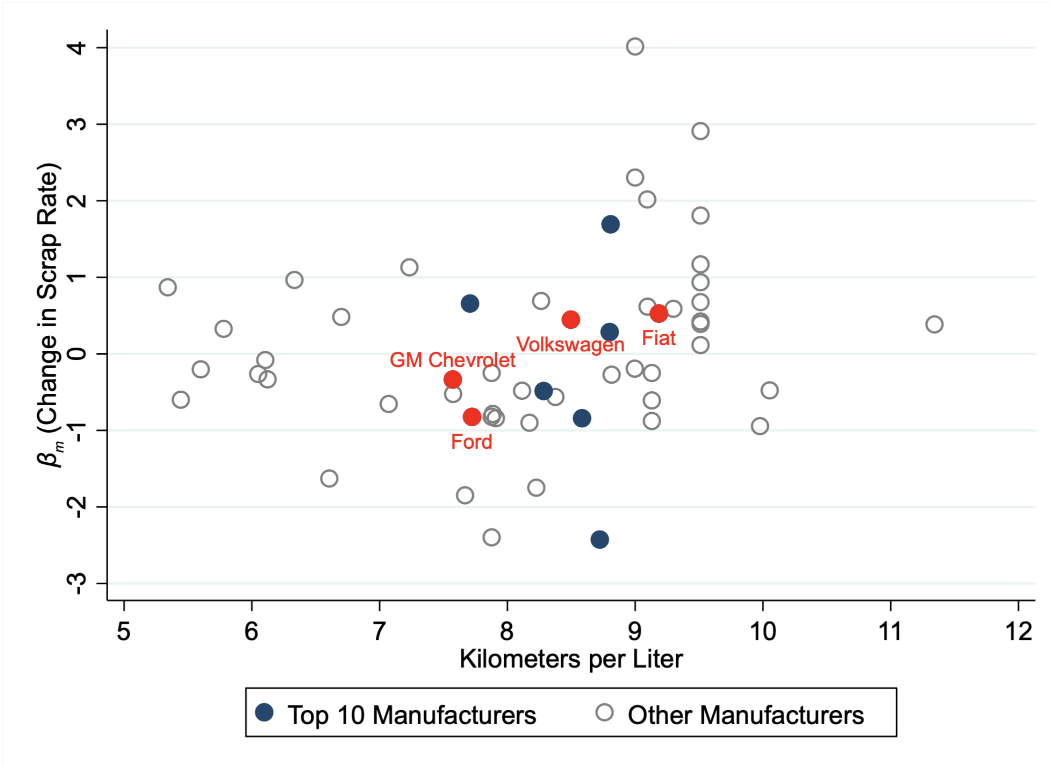

Figure 11.6: Coefficients from the First Stage

Notes: This figure represents the coefficients of the regression of car prices on efficiency-weighted fuel prices. This is the first stage of the main instrumental variable regression of scrap rates on car prices. The figures highlights the top 10 major manufacturers and, among them, the four principal producers. This last group had above 80% participation in the new vehicle registrations in 2003.

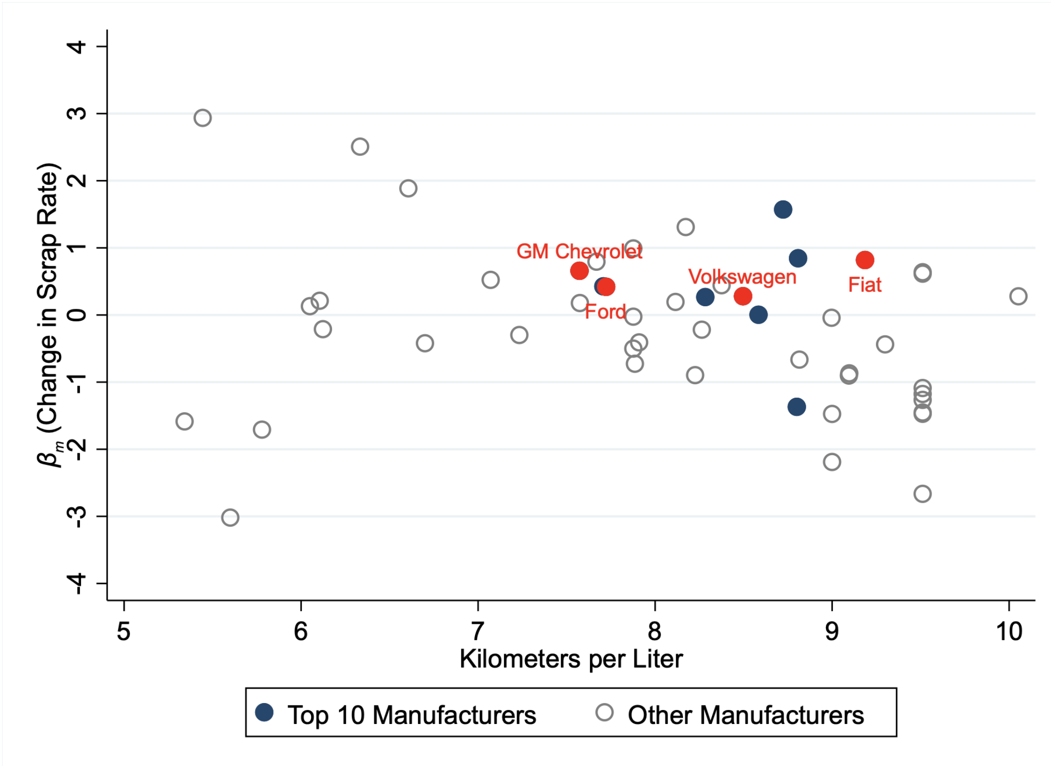

Figure 11.7: Coefficients from the Reduced Form

Notes: This figure shows the coefficients of the reduced form and represents the regression of scrap rates on efficiency-weighted fuel prices. The figures highlights the top 10 major manufacturers and, among them, the four principal producers. This last group had above 80% participation in the new vehicle registrations in 2003.

Appendix A.1

Autoseg (SUSEP) Database and Adjustments

Private insurance companies in Brazil must report regularly to the Private Insurance Superintendence Agency (SUSEP) a series of information regarding new insurance contracts and any changes related to them. Vehicle insurance, in particular, is reported twice a year to SUSEP with information regarding the previous semester. However, it is also common practice to report information regarding two other past semesters, including any changes that occurred since the last report.

The selection of the data to be used in the work took a few initial steps. First, I selected only rows related to the full coverage of the vehicle. I am interested in those cases where any sort of accident (partial or total loss), fire, or theft can be covered. Second, I selected contract endorsements that indicate no changes to the contract. This means I am selecting each contract only once, avoiding duplicity. Usually, when there is a claim or any other change in the contracts, a new observation (row) is added describing the changes. To avoid duplicity, I have to select contracts with no endorsement changes at all.

Next, for each specific semester, I selected data from one and only one database. To illustrate this point, I report in table A.1 the number of unique contracts by semester by submission period for the year 2008. Column 1 refers to SUSEP terminology given to each database and column 4 identifies the approximate period of submission. For example, databases ending in "A" (2008A, 2009A, 2010A) refer to data delivered around the end of the first semester of the year, usually with information up to the second semester of the previous year.

A quick reading of this table informs us, for instance, that the data reported in June 2009 (file 2009A) has information on 4.153 million new contracts for the first semester of 2008 and 4.591 million new contracts for the second semester of 2008.

Two aspects of the database make the comparison harder. First, the data is anonymous, which means I cannot identify each specific insurer (vehicle owner) and the mask used is unique per submission, which means I cannot merge data between two submissions.

To avoid duplicity, in this case, I opted, by semester, to use the data from the file with a higher number of contracts registered. The variations among submissions may be due to canceled contracts, new contracts now informed in previous submissions, or any mistakes made during submissions. By selecting the highest number per semester I am obtaining the highest number of vehicles that, at least for a full semester, had an active insurance contract.

Table A.4 estimates the main model using different combinations of these datasets. Column two uses the preferred database, which selects the semester with the highest number

Table A.1: Insurance Data Submitted

Reference year: 2008

	Semester		Database
	First	Second	Submission
2008A	7,192	1	June 2008
2008B	4,800,646	10,034	December 2008
2009A	4,153,021	4,591,425	June 2009
2009B	4,362,782	4,834,484	December 2009
2010A	80,264	4,130,815	June 2010

Source: Autoseg (SUSEP)

of contracts, while columns three and four select from submissions in the first and second semesters, respectively, and for the first time the semester dataset is complete. Column 5 selects data from the most recent semester for which data is complete, no matter if it is the June or December submission. The results show scrap elasticities that are consistent, and independent of the database chosen. Each scrap coefficient falls within one standard error interval from the main model, so there is no strong evidence that the different choices made about the dataset should affect the estimations in this paper.

Notes: This table represents the amount of contracts from 2008 reported by the insurance firms in different semesters. Typically, insurance firms submit data to the federal agency (SUSEP) twice a year, and the information submitted usually comprises data from the past three years. In this table I show how specific information from each submission for each semester of the year can vary. I associate this variation to a potential update of number of contracts that were effective in each semester.

Table A.2: IPI Tax for New Vehicles

Period		Cars						Commercials	Trucks
Start:	Decrees	Gasoline up to 1.0	Ethanol / FFV up to 1.0	Gasoline 1.1 to 2.0	Ethanol / FFV 1.1 to 2.0	Gasoline 2.1 or more	Ethanol / FFV 2.1 or more	Light	Chassi
Dec/2001	4070/2001	10.0	10.0	25.0	25.0	25.0	25.0	10.0	5.0
Dec/2002	4542/2002	9.0	9.0	15.0	13.0	25.0	20.0	10.0	5.0
Aug/2003	4800/2003	5.0	5.0	12.0	9.0	25.0	20.0	6.0	5.0
Nov/2003	4902/2003	6.0	6.0	13.0	10.0	25.0	20.0	7.0	5.0
May/2004	5058/2004	7.0	7.0	13.0	11.0	25.0	18.0	8.0	5.0
Dec/2008	6890/2009	0.0	0.0	6.5	5.5	25.0	18.0	1.0	0.0
Oct/2009	6890/2009	1.5	0.0	8.0	6.5	25.0	18.0	1.0	0.0
Nov/2009	6890/2009	3.0	0.0	9.5	7.5	25.0	18.0	1.0	0.0
Dec/2009	6890/2009	5.0	3.0	11.0	7.5	25.0	18.0	1.0	0.0
Jan/2010	6890/2009	7.0	3.0	13.0	7.5	25.0	18.0	4.0	0.0
Apr/2010	6890/2009	7.0	7.0	13.0	11.0	25.0	18.0	4.0	0.0
May/2012	7725/2012	0.0	0.0	6.5	5.5	25.0	18.0	1.0	0.0
Jan/2013	7725/2012	2.0	2.0	8.0	7.0	25.0	18.0	2.0	0.0
Jan/2014	8168/2013	3.0	3.0	10.0	9.0	25.0	18.0	3.0	0.0
Jan/2015	8168/2013	7.0	7.0	13.0	11.0	25.0	18.0	8.0	0.0
Mar/2022	10979/2022	5.7	5.7	10.6	9.0	20.4	14.7	6.5	0.0
Abr/2022	11055/2022	5.7	5.7	10.6	9.0	20.4	14.7	5.2	0.0
Aug/2022	11055/2022	5.3	5.3	9.8	8.3	18.8	13.5	5.2	0.0

Imported vehicles had a 30p.p. increase in (IPI) sale taxes beginning in middle December 2011 (not shown in this table). Rules for avoiding this increase in taxation included having a significant percentage of the vehicle produced in Brazil, among other requirements.

Table A.3: Used Vehicle Price Elasticity of Scrappage

Panel A: All Cars					
	up to 150k	up to 300k	up to 400k	up to 500k	any price
Scrap elasticity	-0.4337***	-0.4175***	-0.3822***	-0.3008***	-0.1058*
	(0.0678)	(0.0674)	(0.0676)	(0.0669)	(0.0621)
N	31,162	32,926	33,238	33,387	33,525
F-Stat	161.43	160.21	160.76	161.86	127.80
Share of Total (%)	99.50	99.93	99.97	99.99	100

Panel B: Popular Cars					
	up to 100k	up to 150k	up to 200k	up to 300k	any price
Scrap elasticity	-0.4670***	-0.4502***	-0.4504***	-0.4544***	-0.4430***
	(0.0849)	(0.0798)	(0.0801)	(0.0814)	(0.0808)
N	24,059	25,063	25,393	25,560	25,585
F-Stat	176.19	161.27	164.77	165.64	166.09
Share of Total (%)	98.85	99.80	99.94	99.99	100

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Panel A focuses on all light-duty cars, popular or luxury, while panel B focuses only on popular cars. Pickups, vans, minibuses and other light commercial vehicles are not included in these estimations. The "share of total" row represents the amount of vehicles in each valuation category, compared to the total number of vehicles in my database. Clustered on make-model-(car age) and tax brackets
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.4: Used Vehicle Price Elasticity of Scrappage

	Model 1 Main	Model 2 Report A	Model 3 Report B	Model 4 Most Recent
Panel A: OLS models for cars				
Scrap Elasticity	-0.1116***	-0.1091***	-0.1040***	-0.1076***
	(0.0202)	(0.0179)	(0.0200)	(0.0193)
N	31,281	30,616	31,431	30,508
Panel B: IV models for cars				
Scrap Elasticity	-0.4337***	-0.4557***	-0.4953***	-0.3951***
	(0.0678)	(0.0624)	(0.0634)	(0.0577)
N	31,162	30,497	31,195	30,323
F-Stat	161.43	198.67	159.98	193.33
Panel C: IV models for all vehicles				
Scrap Elasticity	-0.5493***	-0.5789***	-0.6090***	-0.5419***
	(0.0520)	(0.0486)	(0.0525)	(0.0472)
N	39,736	38,872	39,661	38,620
F-Stat	143.72	133.83	156.36	177.02

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. Panel A focuses on light-duty cars, while panel C focus on all vehicles, which include pickups, vans, minibuses and other light commercial vehicles. Clustered on make-model-(car age) and tax brackets.

Each column represents a different combination of the potential datasets submitted to the governmental agency. Insurance firms must submit twice a year (June and December) a dataset with all vehicle contracts from the past three semesters. This create an overlapping of information on each semester. To avoid duplicity of information, I aggregate only one set of information per semester to obtain the annual vehicle fleet. Each column in this table uses a different set of data as follows: column "Main" uses data from the dataset with more information for each semester (this is the database all the estimation in the paper are based upon); column "Report A" uses data from the first semester for which database A (submitted in June) is complete; column "Report B" uses data from the first semester for which database B (submitted in December) is complete; and column "Most Recent" uses data from the most recent semester for which database (June or December) is complete.

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.5: Used Vehicle Price Elasticity of Scrappage

	Full Sample		Excluding 2009, 2012-2014	
	Cars	All Vehicles	Cars	All Vehicles
Introduction (2003 to 2006)				
Scrap Elasticity	-0.4114***	-0.4104***	-0.4191***	-0.3651***
	(0.0727)	(0.0609)	(0.0783)	(0.0712)
Diffusion (2007 to 2010)				
Scrap Elasticity x	-0.1625***	-0.2086***	-0.1971***	-0.4145***
dummy 2008 to 2010	(0.0429)	(0.0410)	(0.0457)	(0.0735)
Majority (2011 to 2015)				
Scrap Elasticity x	-0.1629***	-0.1970***	-0.2467***	-0.3496***
dummy 2011 to 2015	(0.0433)	(0.0411)	(0.0497)	(0.0591)
Maturity (2016 to 2022)				
Scrap Elasticity x	-0.0020	-0.0070	-0.0303	-0.1468**
dummy 2016 to 2020	(0.0461)	(0.0440)	(0.0489)	(0.0577)
N	31,135	39,704	23,192	29,178
F-Stat	291.92	93.85	195.05	92.24

Notes: The dependent variable is vehicle scrap rates. The scrap elasticity represents the used car price elasticity of scrappage. The instrument for used for car prices is fuel prices weighted by vehicle efficiency. For each sub-period (diffusion: 2008 to 2010; majority: 2011 to 2015; maturity: 2016 to 2020), the average share of flex fuel vehicles (FFV) in the new vehicle registrations were interacted with used car prices to capture salience effects as FFV increase their participation in the total fleet. The last two columns exclude the years of 2009 and 2012 to 2014, which represent years where the federal government implemented reduced sales taxes for new vehicles. Besides cars, regressions from the columns "all vehicles" also include pickups, vans, minibuses and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Appendix B.1

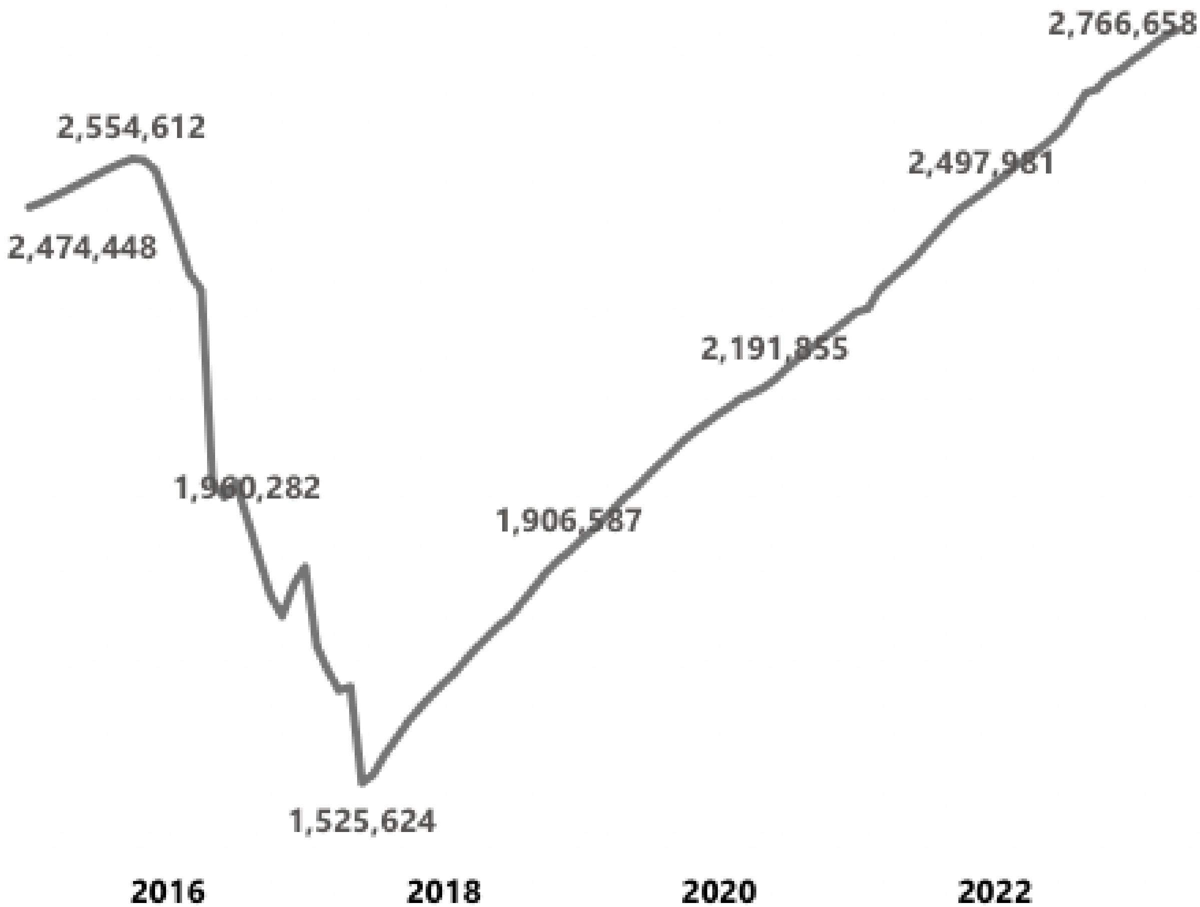

Figure B.1: Mandatory Truck Registration Renewal

Notes: This figure shows the evolution of truck registration numbers. Between 2016 and 2018, truck owners were mandated to renew their vehicle registration. This resulted in the drop in the official numbers as seen in the figure. Registration records usually only accumulates new registration and never deducts trucks that were scrapped and are not in the actual fleet anymore. This mandatory renew of the register was the first in the category and evidences the overestimation of official records.

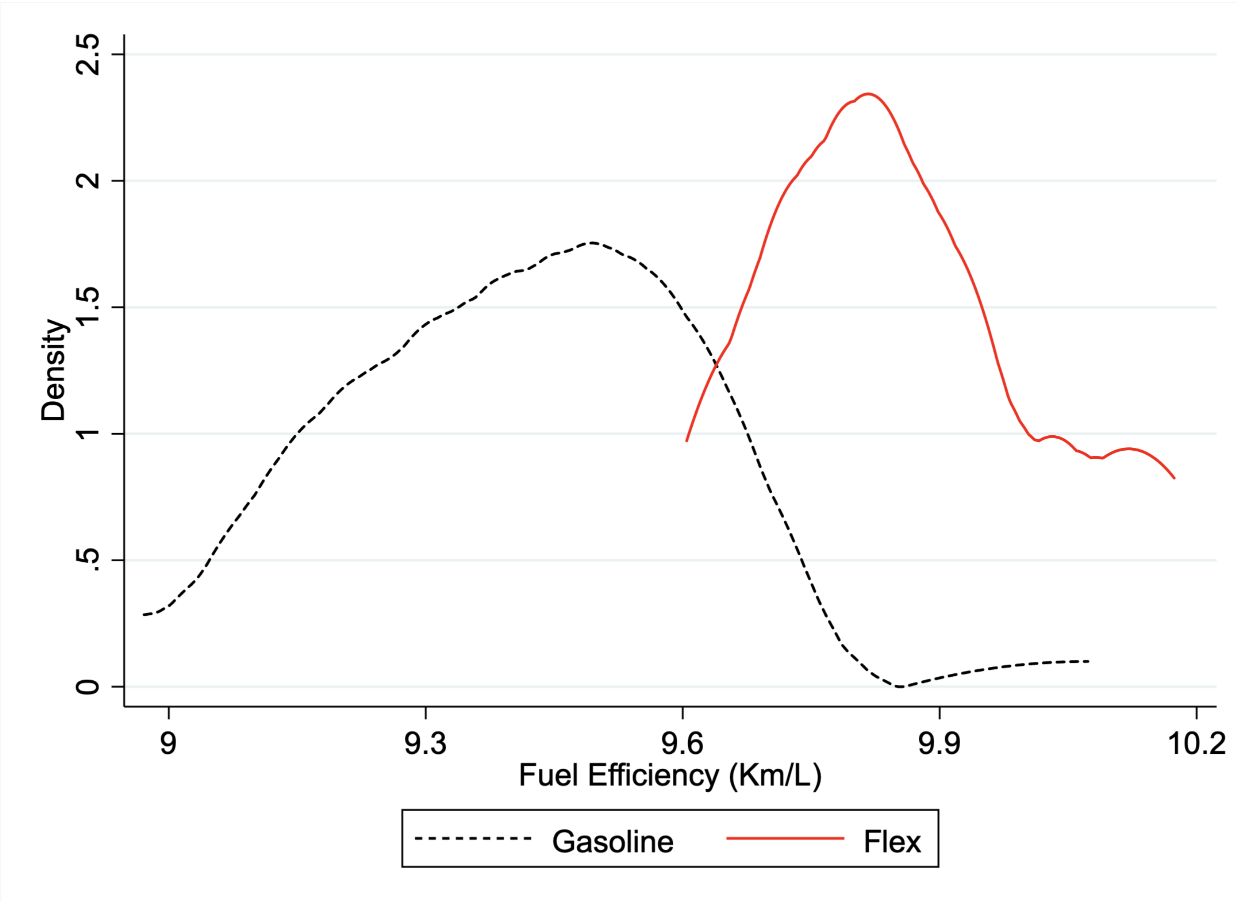

Figure B.2: Fuel Efficiency of Gasoline and Flex Fuel Vehicles - Density

Notes: This figure represents the density of vehicles by level of fuel economy and type of engine.