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 a 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 instrument a measure of fuel prices weighted by fuel efficiency, I found Brazilian'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

JEL Codes: L62, Q48, Q52, Q55

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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less efficient but also the most pollutant, and several policies can be used to accelerate the elimination of these outdated vehicles, replacing them for more efficient and sustainable versions (Jacobsen et al.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, trying to understand how the adoption of this new technology induced older vehicles 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 the 2020. This information represents about one third of the total fleet.[2] While my work is restricted to

[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 private insured vehicles (38.1 million cars as of 2020). The problem of using

the universe of vehicles with private insurance, I discuss how, 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 its 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, specially 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 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 into newer and older vehicles,[4] I found evidence of older cars becoming more sensitive to tax

Brazilian official records is that they only accumulates registration over the years, never excluding vehicles that were scrapped or incurred in total loss accidents, resulting in 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.

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

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. 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 used vehicle price elasticity of scrappage for Brazil or any 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 conditions, such as lower average income, credit restrictions and anti-scrapping incentives.

Second, my works contributes to the literature on the impacts of fuel prices on used car

[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 induces scrappage of older vehicles.

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 8 I show some robustness checks 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 main fuel in Otto cycle engines to reduce dependence on imported fossil fuel and diminish environmental impacts (Bajay (2004)). Even though ethanol-driven vehicles had only a temporary success, fading out along the second half of 1990s, the anhydrous ethanol was widely successful and was widely used, specially after 2000, as a policy instrument to either diminish pollution in major cities or to control for gasoline price fluctuations.

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

To understand the movements on the demand side, consider the decision concerning the purchase of a new car. Consumers are usually unaware of all the relevant information before they purchase and experience the vehicle. For instance, comfortability, effective fuel efficiency and driveability are some aspects that vary by individuals' perception and can only be fully assessed after purchasing and experiencing the car. Because of this aspect that

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

turns it into an experience good, when deciding to buy a new vehicle, consumers may rely on extra source 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 indicate that consumers quickly adhere 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 was flex fuel. Flex fuel vehicles revolutionized the market in at least two ways. First, it 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, it brought a significant increase in overall fuel efficiency as can be seen in figures 11.4 and 11.3.

2.2 Vehicle Registrations in Brazil

Official vehicle registration numbers in Brazil are highly overestimated. The main reason for this is 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

[7] According the ANFAVEA (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.

trucks in 2016 to 1.53 million trucks in 2018, indicating that old number were at least 67% higher than the actual truck fleet (see figure B.1).

On insured vehicle data, two main sources exist. First, there is the mandated government-issued insurance, which actually only covers some medical costs in case of accidents and up to a small amount of expenses. Second, there is information from private insurance firms, which must report to the government on new contracts each year. The former is not made publicly available and, technically, covers the full fleet. The second is made publicly available, but roughly covers one third of the fleet.

It is important to emphasize that not all vehicles in Brazil are mandated to have the "traditional" private insurance. This is the type of insurance that covers repairs, accidents, thefts and even total loss are all private contracts. For instance, while the union of auto parts (Sindipeças) estimates[9] that the actual car fleet is about 38.0 million (or 45.9 million for all vehicles), the total number of insured vehicles with full coverage is about 13.4 million cars in 2020.

This discrepancy between full fleet estimates and insured fleet is reflected on scrap rates. By defining scrap rates as the number of vehicles leaving the fleet database, compared to the previous year, two problems may arise. First, the level of the data is relevant, either for a comparison basis or for the amount of vehicles exiting the fleet. Hence, with one third of the fleet - case of the insured database - it expected that these scrap rates will be higher than if using the full fleet database. The second reason is that, by focusing on private insured vehicles, which are usually costly contracts in Brazil, some sort of selection towards vehicle owners with higher income can be happening.

In section **??** I explore some assumptions under which I believe that, given the characteristics of the contracts I observe and assumptions over 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.

[9] 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.

3 Conceptual Framework

Before I delve more into the data aspects and develop the main econometric 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 synonym to scrappage.

3.1 Main Assumptions

The insurance database, as mentioned, corresponds to about one third of the actual fleet. In principle, the turnover of this particular fleet may not reflect accurately the turnover of population of the 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 lead to a total loss of the vehicle, which ends up being scrapped.[10] Considering the potential moral hazard created by the insurance contract, these accidents, and therefore the true scrappage in this database, are expected to be overrepresented compared to the non insured fleet. This could cause a bias towards higher scrap rates, as mentioned before.

The second assumption I make regards risk-averse and non-risk averse agents. I assume the first group will always buy insurance, while the second will never buy it. I also assume agents don't switch their risk preferences.[11] This basically means the increase of both insured and uninsured fleet over time is due to new individuals entering the vehicle ownership set. Based on this, we can establish some features for each risk group of agents.

In this scenario, I assume that risk averse individuals always buy and renew their vehicle contracts as long as they own a vehicle. This necessarily implies they are able to afford for

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

[11] 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 towards the scrap rates of the non-insured fleet. In this sense, the scrap rates of insured and uninsured fleet tend to converge to a common denominator.

it. Vehicle contracts are not cheap in Brazil, specially 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). Hence, I 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.[12] 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 less 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 the opposite direction.

To reinforce this assumption, I need to discuss the anti-scrapping incentives in Brazil. There are at least two main incentives: the ownership tax exemption for older vehicles and the lack of policies or government support to buy and scrap old vehicles. All states in Brazil exempt vehicles from ownership taxes after 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 or state governments have established any effective scrappage policies aimed to reduce older vehicles from circulating.[13]

These anti-scrapping incentives, combined with higher acquisition power (and potential

[12] 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, specially 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.

[13] 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.

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[14] (not truly scrapped), 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 amount of vehicles in the roads are not exponentially increasing[15], 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.

4 Data and Other Assumptions

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

[14]Stolen vehicles in Brazil usually end up in accidents, abandonment or are scrapped for parts reselling.
[15]According the the total fleet estimations available.

evolution of the fleet.

I aggregated data at annual level and used one specific semester per report to avoid duplicity problems[16]. 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 also includes other insurance and demographics data 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.[17] 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.[18]

The database I use represents the full universe of private insured vehicles. My measure of scrappage follows 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 compared to the previous year. Mathematically, it is 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 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

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

[17]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 potential weight carried by a truck and estimate a more precise average fuel consumption per ton per kilometer.

[18]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 specially the amount of sulfur contained in each version. Ultra low sulfur diesel vehicles (ULSD) cannot use diesel with 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.

private insured vehicle fleet. The numerator of this expression measures the amount of vehicles that were not insured anymore in the current year (leaving the insurance database) and the denominator is the full population of private insured vehicles in the previous year. This fraction represents the turnover of the private insured fleet and can be thought, in a more broad way, as a measure of scrappage.

To understand the idea of fleet turnover as 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[19]. A second reason is that this insurance database also contains information on vehicles that were involved in accidents, including those which led to a 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 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, 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 US[20].

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

[20]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

Figure 11.5 and table 10.1 informs us on 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 to 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 cuttoff 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 data. In particular, I have information on 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 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 sell her vehicle to a non-risk averse person, inducing some other non-risk averse agent to scrap.

My objective in this work is to understand how price changes affects 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 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, $Fuel\,Price$

Nation Master database shows that Brazilians have approximately 72% more worries about car theft than Americans.

is the current retailer fuel price per liter[21] and KPL represents the fuel efficiency, measured in kilometers per liter. In sum, the instrument can be understood as a measure on how 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 manufacturer level and not at 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).

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.

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

For example, when the first flex fuel vehicles were introduced in 2003, each of the manufacturers developed their own version of 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 two months after. 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, specially for countries where fuel price controls are so widely used as it 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 on 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 over the fleet. First, it directly impacts consumers' budget, according to each specific vehicle 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 everyday, then vehicle efficiency becomes the main driver to explain the direct impact of fuel prices.

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 a natural deterioration of the mechanical parts, leading to more pollution and potential 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 certain age differently, according to its fuel efficiency level. On the other hand, age-by-year fixed effects allows me to control for any other characteristics that are specific per year and age (or vintage) and affects all vehicles similarly. Since age, year and vintage are, by construction, collinear, these fixed effects also controls for specific vintage confounds.

The equation to be estimated is then represented by 4. As mentioned, fuel prices, represented by the term Z_{mt}, is weighted by fuel economy. I use dummy interactions at the make level to add flexibility to the model and estimate an average impact by manufacturer. The results can be seen in the figure 11.6. I didn't impose any specific restriction to 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 an used car price model based on 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 remain relevant for both newer and older vehicles (columns 3 and 4).

To complement this analysis and link to the study of scrap rates, on figure 11.7 I show estimates from the reduced form, investigating fuel price impacts on scrap rates. Again, my assumptions is that, controlling for the model-by-age and age-by-year fixed effects, the fuel impact captured here 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 via 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 greater effect on a "Fiat - Palio ELX/ 500 1.0 4p" that has 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 in her budget than the latter, provided the same amount of kilometers travelled.

I 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 affects all model versions of a given age. The second set controls for year-specific events that affects equally all models of 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, in each year, an individual face 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 surpasses 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 Tax Reduction Policies

One important policy implemented in Brazil was an IPI 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 in the end of 2008 zeroed the tax for new cars with motor equal or lower than 1.0 liter, and halved the rates for new cars with motor 1.1 to 2.0. The purpose behind this tax reduction was to promote the automobile industry, enhancing 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 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 the incentive for owners of old vehicles to switch for new ones. To capture this feature, I adapted the model as follows:

$$ln(Y_{abt}) = \gamma_1 ln(\hat{P})_{abt} + \gamma_2 D_{IPI} * \hat{P}_{abt} + \gamma_3 IPI + \alpha_{ab} + \alpha_{at} + \epsilon_{abt} \tag{5}$$

$$ln(P_{abt}) = \alpha_{ab} + \alpha_{at} + \Sigma_{m=1}^{M} \beta_{bm} Z_{abt} + \Sigma_{m=1}^{M} \delta_{bm} D_{IPI} * Z_{abt} + \mu_{abt} \tag{6}$$

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 indicates 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 taxes as ethanol vehicles, which were, on average, around 2 p.p. lower than similar gasoline vehicles. When IPI 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 for 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 over scrap rates is to interact 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 to FFV.

Diffusion (2007 to 2010): period in which, associated with IPI 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[22]

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

In terms of estimation method, I pursued a similar approach developed for IPI tax: interactions of dummies for each period with used vehicle prices. Because of multicollinearity, I suppressed the interaction for the first period (introduction), making it be the baseline for each subsequent period.

[22]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.

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 focus 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 motorbike. 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 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 vehicle represent a small fraction of the fleet, this restriction, even though important, may not affect much the elasticities.

The first column is my favorite specification, while columns 3 to 5 extends my main model by interacting 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 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 Tax Reductions

As discussed, IPI tax affects used vehicle price only indirectly, by making them less attractive compared to newer, more efficient vehicles. On column three of table 10.3 I present my IPI model. I this version, I interact a dummy for years with reduced IPI tax and vehicle prices to identify any differential scrap elasticity when tax reduction policies are in effect.[23] Models 3 and 4 use the same procedure, but split the analysis in newer vehicles (aging up to 10 years) and older vehicles (above 10 years).

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

However, the model from the last column shows significant effect of IPI tax reduction over used car prices for owners of vehicles aging 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 tax reduction policy over new vehicles seem to affect these owners of older vehicles. The interaction dummy shows a significant effect of -0.10, which combined to the main scrap elasticity, brings it back to -0.40, 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 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.

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

[23]The dummy interaction was built to be one for years 2009 and 2012 to 2014. I left 2008 out of because IPI reduction started only in 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 2008 and 2012. My criteria here is any period where IPI is below the usual tax standard.

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 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 because, 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 possible.[24]

In addition, it is expected that FFV have lower scrap elasticity (in absolute terms) because they are relatively newer cars. And this is actually not the information of interest here. The focus should actually be on how this new technology induced a faster scrappage of the old technology.

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 become 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.

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

Next, I set 2007 to 2010 as the "diffusion" period. The IPI tax reduction (December 2008 to December 2009) 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 tax reduction has been implemented and FFV technology has become the standard in the fleet.

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 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 indicate that the fiscal policy was effective in not weakening the scrappage even in adverse economic periods.

In addition, on table A.2 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 tend 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 a new technology, specially if compared to the case of electric vehicles in 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 more frequent use of ethanol, which offsets its GHG emissions via sugarcane plantation, the overall results is a significant reduction of GHG gases generated in the transportation sector.

6.3 Car Ages

On table **??** 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 prices 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 aging 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, they also become 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, regularizing 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 resale price.

In practice, however, my last model indicate that owners of older vehicles were already less sensitive to car price changes. Given the lack of a policy to enforce the scrappage such vehicles, if an older vehicle, exempt of ownership tax, fall outside the emission level brackets, its owner would still have 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 for a newer version.

In summary, the lack of a scrappage program, the low enforcement over older vehicles that doesn't comply with emission levels, and the exemption of ownership taxes for vehicles aging 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.

7 Heterogeneous Effects

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

7.1 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, specially if policymakers formulate policies over specific groups, such as facilitating commerce and minimizing transportation costs.

Here my estimates consider all vehicles, which includes not only cars, but also pick-ups, vans, mini-buses[25] and other light commercial vehicles destined for cargo or passenger transportation.

My analysis does not include large buses nor trucks. There isn't sufficient data on buses in the insurance database, and information on fuel efficient 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 and 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. 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 to 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 an insurance as a regular user, not as a firm. Since these driving app services require their drivers to use newer vehicles, it is expected that these drivers would

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

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 be quite effective for this category of agents.

7.2 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 faces 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 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, tend to drive more kilometers than the other.

Each potential reason can lead to a stronger or a 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 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.footnotePickups, small passenger vehicles and other light cargo vehicles. 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 affect scrappage of older vehicles would be as effective for one group or another.

7.3 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 less 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 on 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 seem to be slightly smaller than for adults aging 25 to 44 years-old (-0.31 $\times$ -0.39), even though they are not statistically different from each other. Model 3, however, show that older adults (45 to 64 years-old) are less sensitive to car price changes. Finally, elderly above 64 years seem to be indifferent to car price changes.

On the apparent unresponsiveness of elderly to car prices, this 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 exemption of licensing tax, IPI tax, ICMS (state tax) and IOF (tax over financial movements and loans). On the other hand, people who are eligible for a PCD car is 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 elderly, such as arthrosis, Parkinson, 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 seem to respond differently. Younger adults show a positive effect (+0.28), which reduces their final elasticity to -0.08. 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 elderly in this scenario with IPI tax reduction over new vehicles. First, the part of the elderly group who are not on PCD program may be taking advantage of the tax reduction to replace their vehicles and buy newer models. This would generate an excess of 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 in 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 on the statistics, we observe that the average car age decreases for the elderly group under tax reduction periods and increases fro young adults, corroborating the idea of one group potentially buying used cars from the other.

8 Robustness Check and Consistency

In this section I present some robustness check and alternative estimations to show how my main results are consistent across different specifications. Table 10.9 show some alternative specifications.

Column 1 of table 10.9 has model with car prices ranging up to 500 thousand 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.1 in the appendix). Vehicles above 500 thousands are marginal and represent less than 0.01%.

Next, on column 2, I estimate excluding all luxury manufacturers. The result is very similar to my main estimates. Luxury cars in my dataset represents 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 increase. From 2002 to 2020, only a few years[26] didn't show any price increase in fuel prices at the retailer level. The scrap elasticity increases to -0.497, but it's still within one standard deviation from my main model.

If, on the hand, fuel prices at teh retailer level increased almost all years during the period of analysis, the same is not true for refinery's or distributors' prices. 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 relevance of this period, I estimated model 4 in the table 10.9. The result is an elasticity slightly smaller than my main specification, but still within one standard deviation interval.

On 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

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

deviation. the last two columns includes interactions of model and vintage, and the resulting elasticities are stronger. Yet, they fall within two standard deviations and a hypothesis test cannot rule out they are statistically different from my main specification.

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 work, and in the absence of better data, I work with a restricted sample that comprehends the universe of the private 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 aging 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 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 purpose of use and driver age. I found no strong evidence of differences between male and female drivers.

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

Panel A: Scrap Elasticity - Firm Use			
	Model 1	Model 2	Model 3
	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 vehicle 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

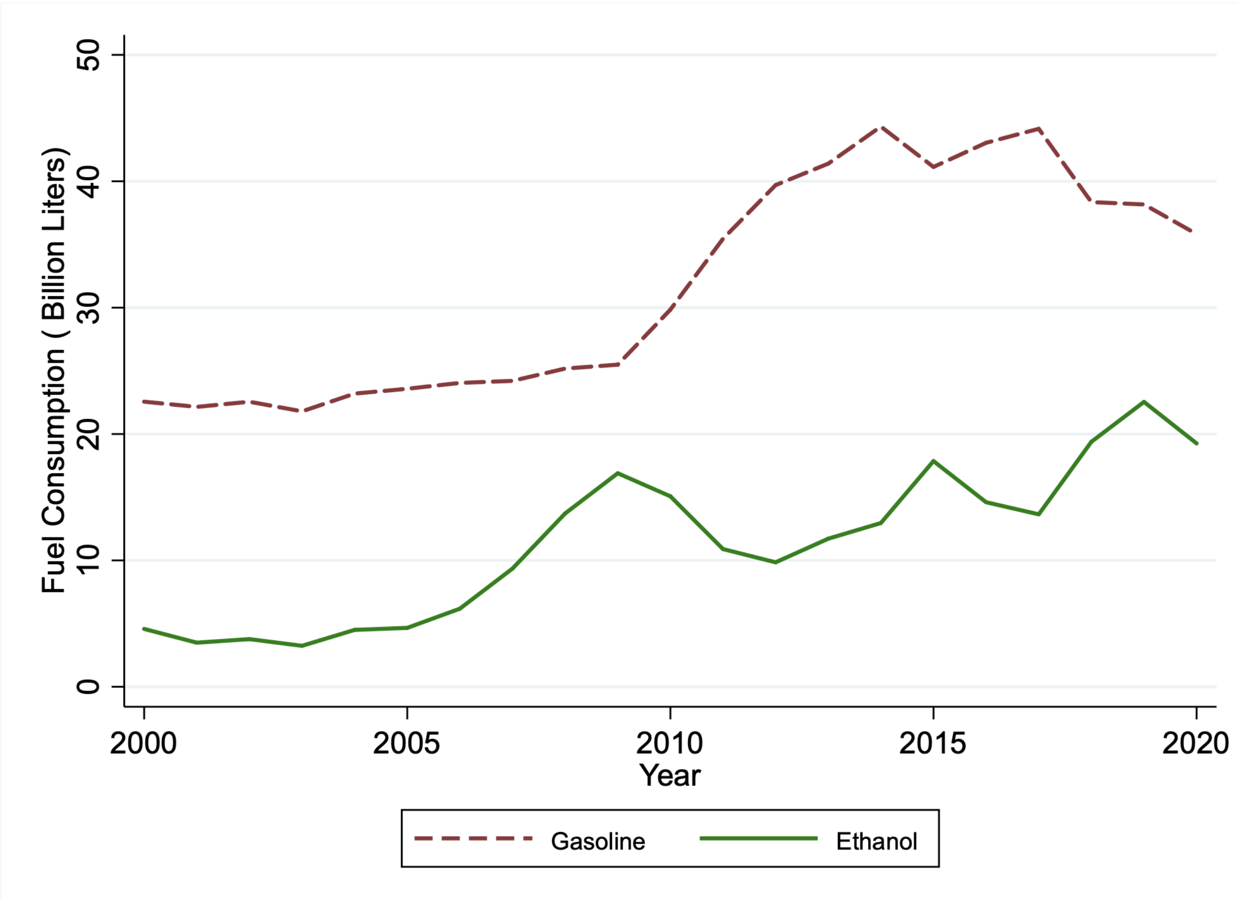

Figure 11.1: Fuel Consumption: Gasoline and Ethanol

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.

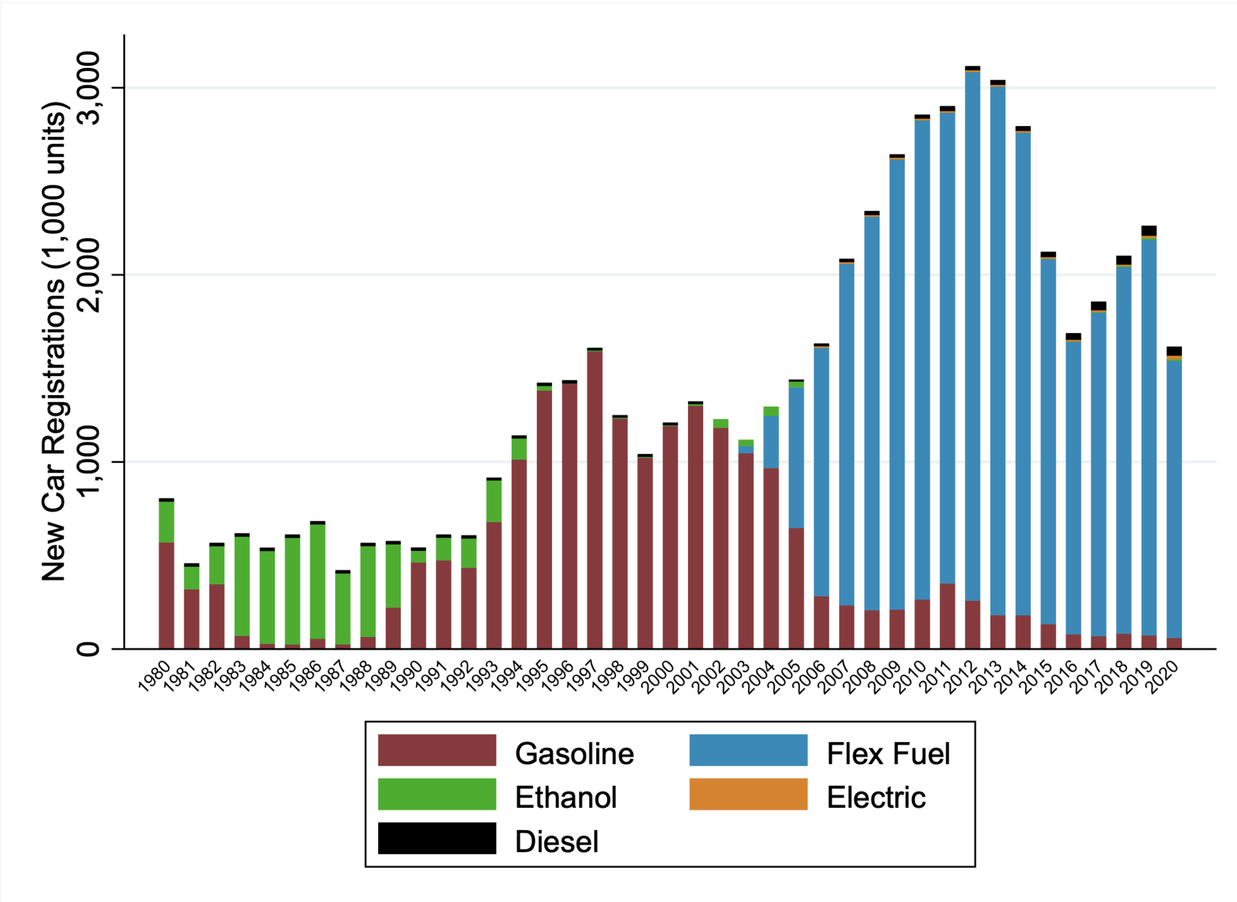

Figure 11.2: Car Registrations by type of Fuel

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.

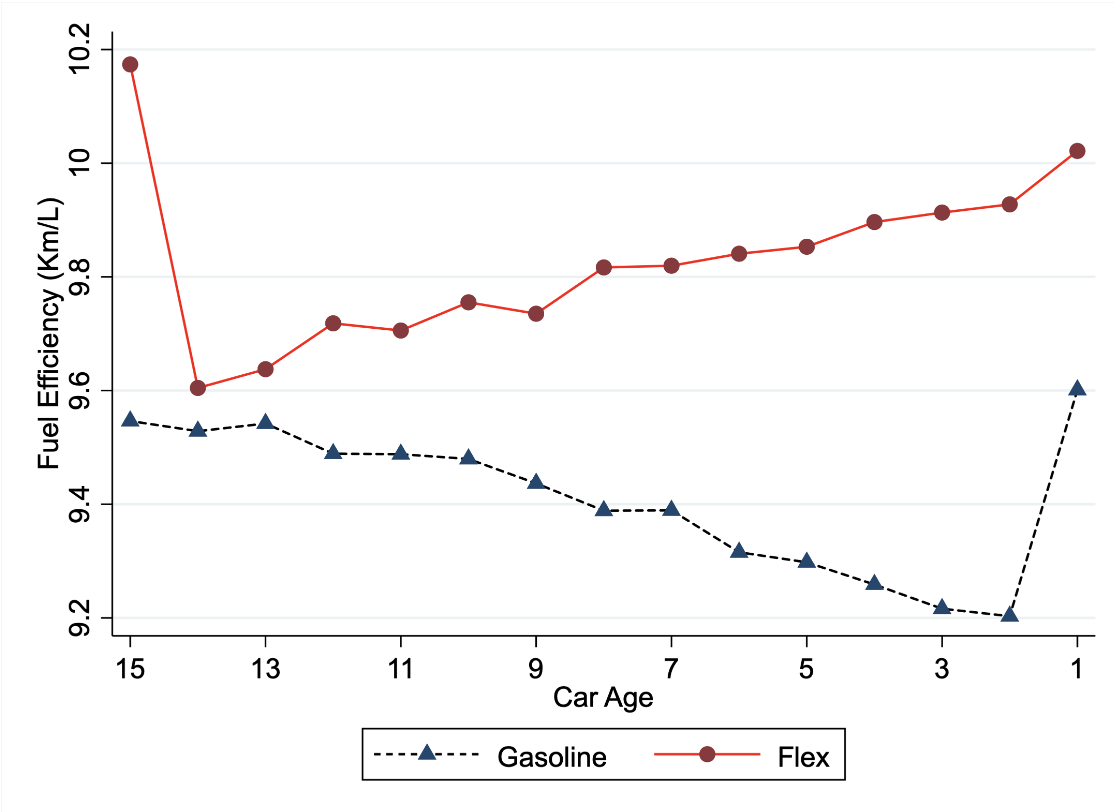

Figure 11.3: Fuel Efficiency of Gasoline and Flex Fuel Vehicles by Age

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.

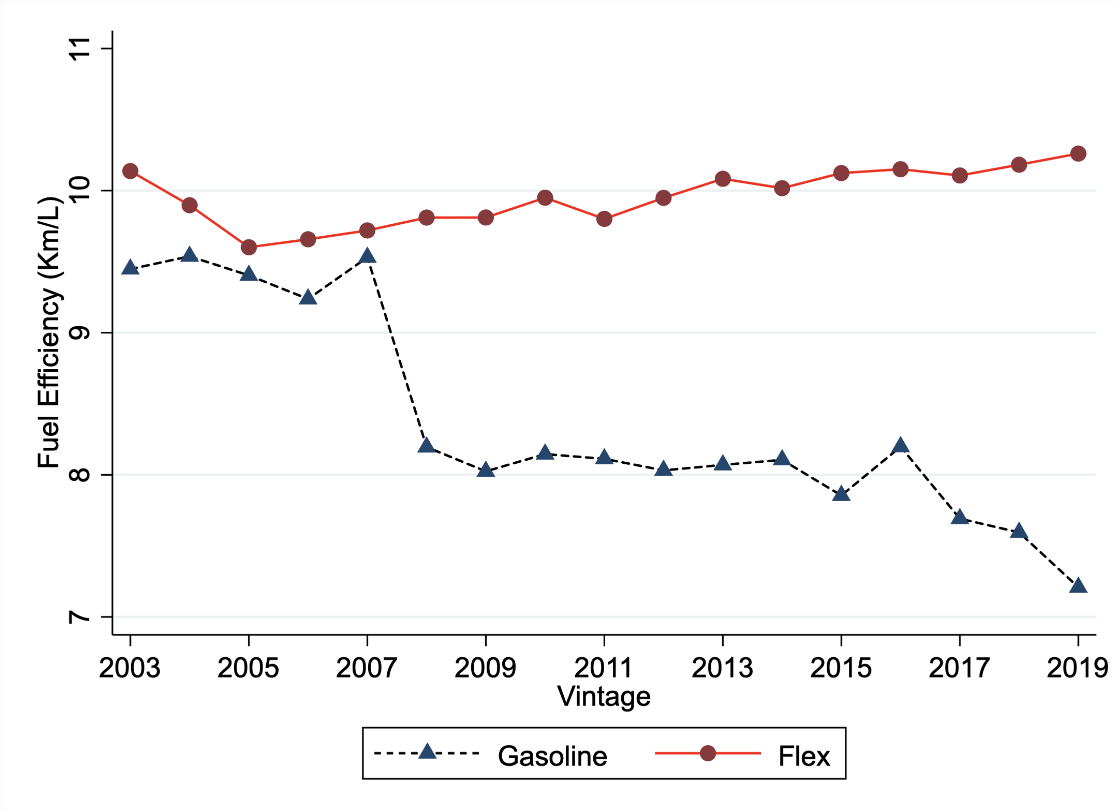

Figure 11.4: Fuel Efficiency of Gasoline and Flex Fuel Vehicles by Vintage

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.

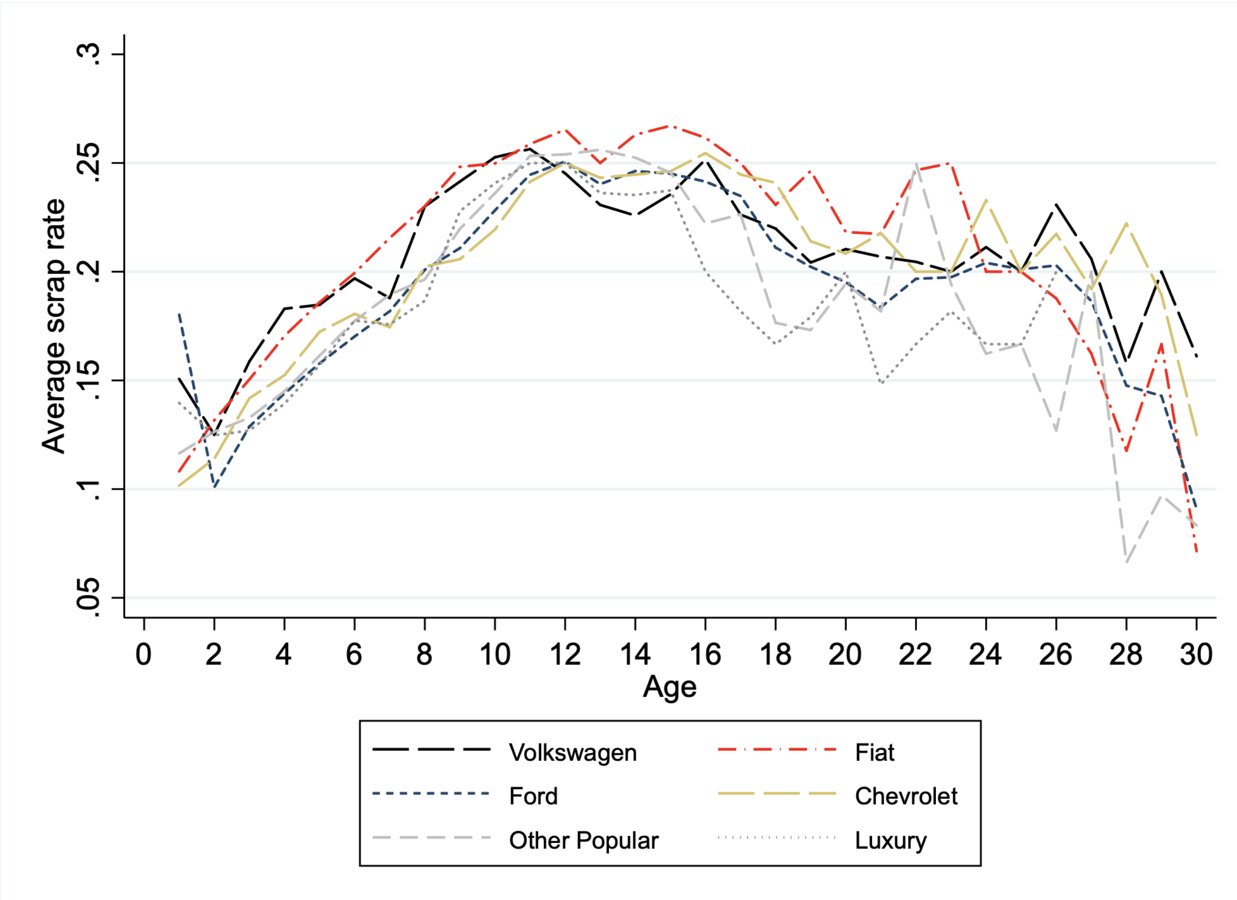

Figure 11.5: Median Scrap Rates by Vehicle Age and Maker

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.

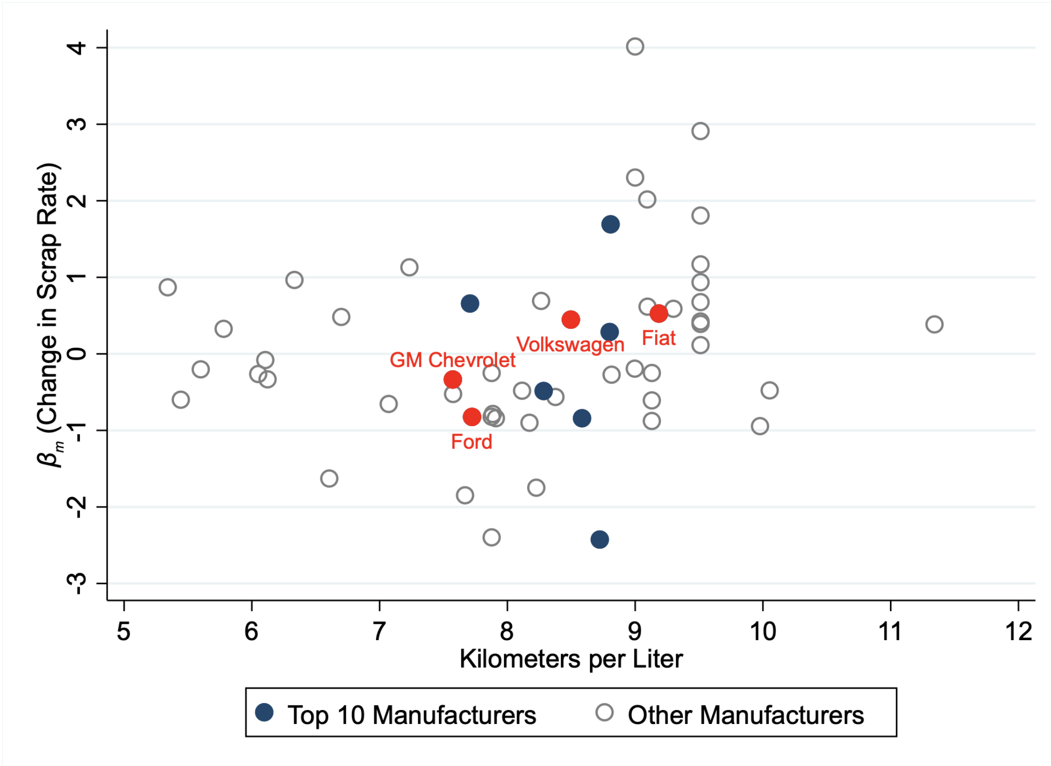

Figure 11.6: Coefficients from the First Stage

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.

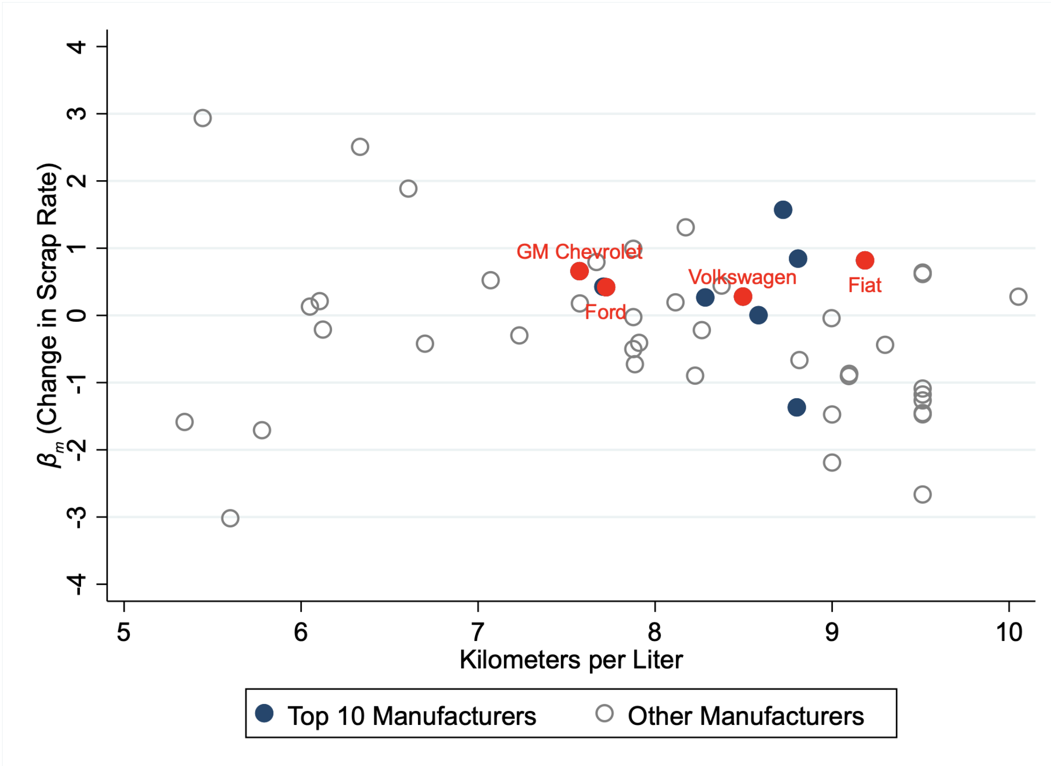

Figure 11.7: Coefficients from the Reduced Form

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.

The 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 chances that occurred since last report.

The selection of the data to be used in work took a few initial steps. Firstly, I selected only rows related to 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. 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 endorsements changes at all.

Next, for each specific semester, I opted to obtain data from one and only one database. To illustrate this, I report on table A.1 the amount 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) refers to data deliver 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 should inform 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 makes the comparison harder. First, the data is anonymous, which means I cannot identify each buyer (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 higher number of contracts registered. the variations among submissions may be due to cancelled contracts, or new contracts now informed in previous submissions, or any mistakes done during submission.

Since I cannot be sure the reason for such variability and all I can do is, by semester, see which contracts were firmed and were active in that period, 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.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)

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.

Appendix A.2

Table A.1: IPI Tax for New Vehicles

Period		Cars						Commercials	Trucks
		Gasoline	Ethanol / FFV	Gasoline	Ethanol / FFV	Gasoline	Ethanol / FFV	Light	Chassi
Start:	Decrees	up to 1.0	up to 1.0	1.1 to 2.0	1.1 to 2.0	2.1 or more	2.1 or more		
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.1: 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.2: 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

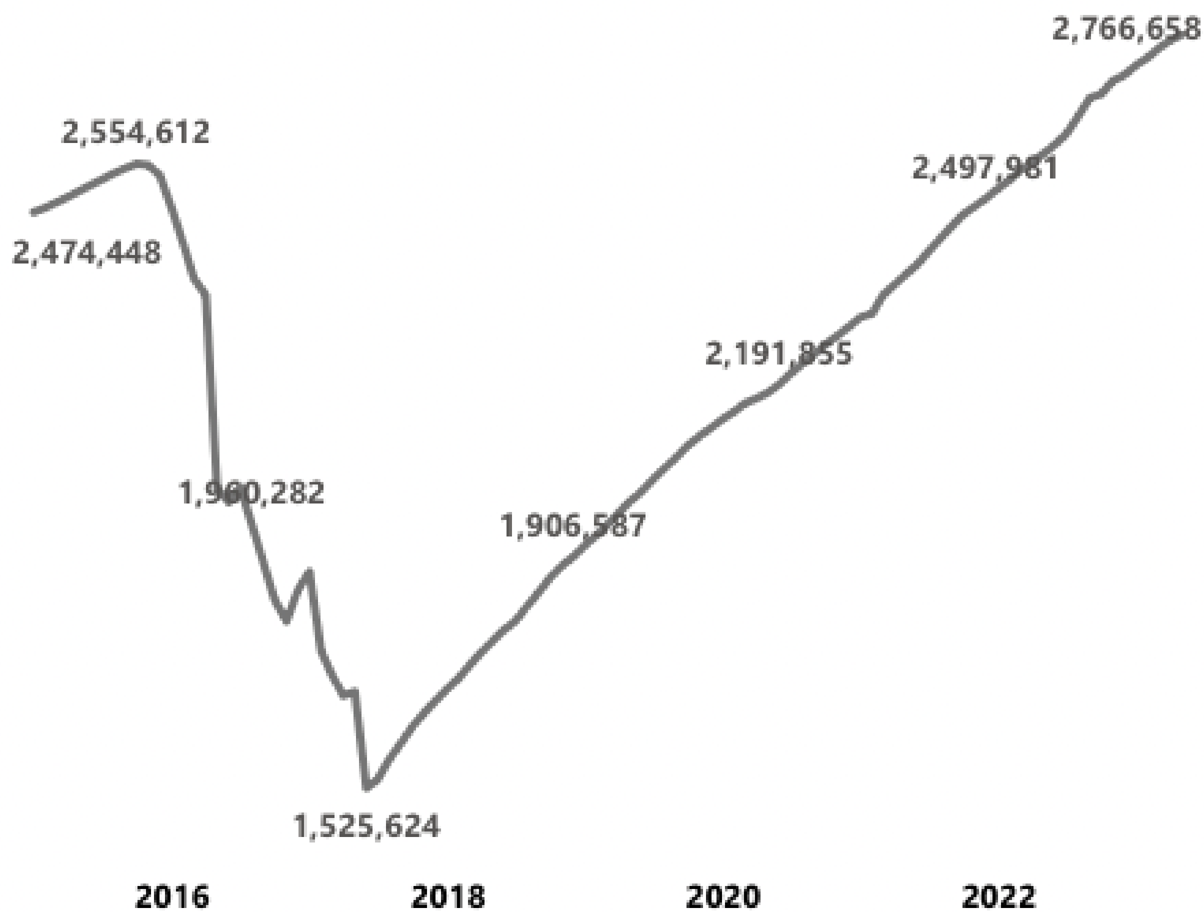

Figure B.1: Mandatory Truck Registration Renewal

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.

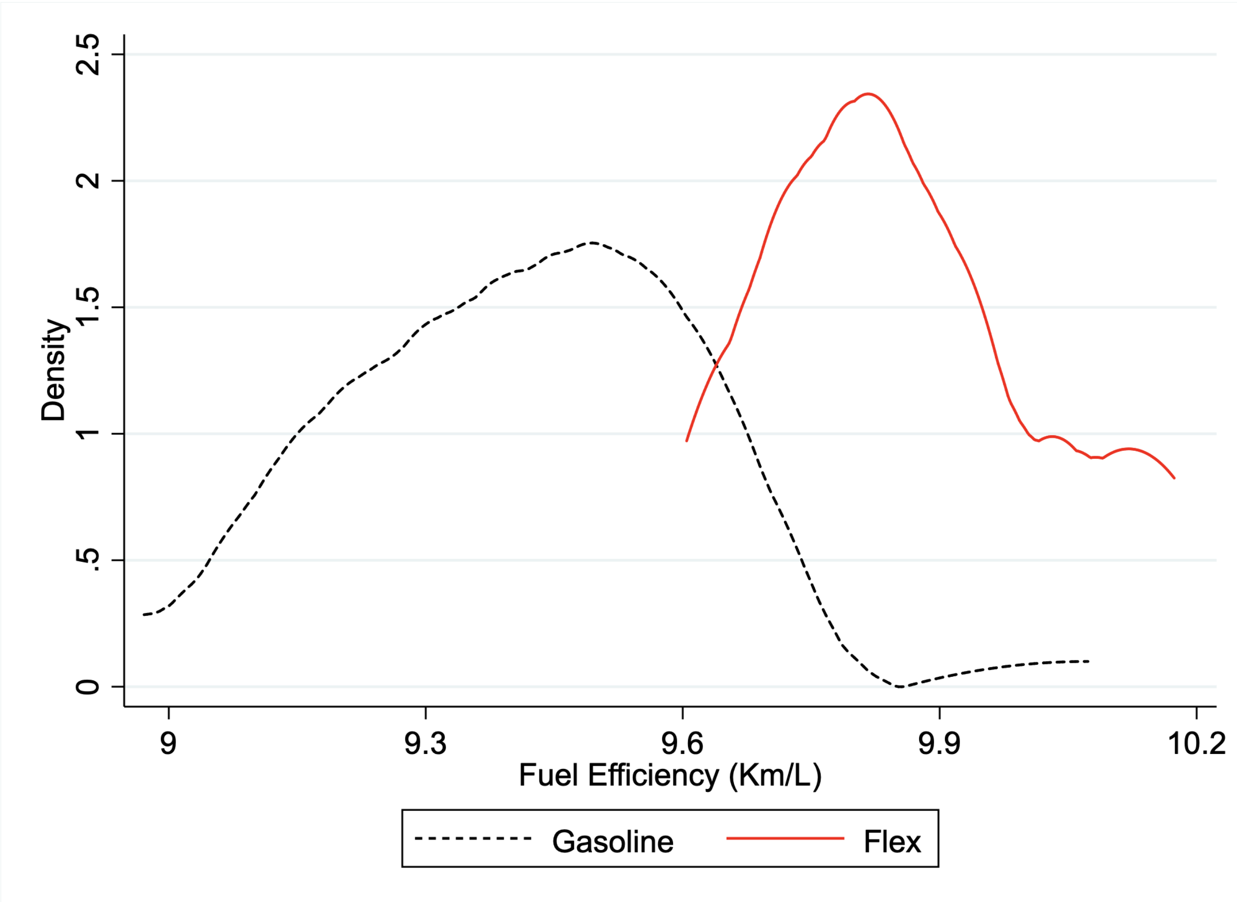

Figure B.2: Fuel Efficiency of Gasoline and Flex Fuel Vehicles - Density

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