Technology Innovation and Climate Change Mitigation: The case of Flex-Fuel cars in 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 the contribution of flex-fuel technology in mitigating climate change by allowing consumers to opt for a cleaner, renewable alternative fuel. I examine the rate of diffusion of the new technology, in terms of turnover of the fleet, and study how these new engines allowed for a closer substitutability between ethanol and gasoline. Finally, I simulate scenarios to understand the full impact of flex-fuel on carbon emissions. I found that, from 2003 to 2020, flex-fuel cars were responsible for the avoidance of 149 billion tons of CO_2, with a potential to increase it to more than 960 billion tons depending on the percentage of ethanol consumed. My results also indicate how temporary price control favoring fossil fuel usage can inadvertently offset most of the results obtained by promoting cleaner technology in the fleet.

Keywords: Fleet Turnover, Fuel Demand, Flex-Fuel Vehicles, 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] Far from being a problem only to the developed world, estimates from the United Nations show that 55% of all GHG emitted in 2020 was produced and emitted by the five largest emerging countries, being the transportation sector responsible for one-third of these emissions (Inger et al. (2022)). In this context, the development of new technologies and the use of alternative and renewable fuel sources that offset greenhouse gas emissions may contribute to mitigating the impacts of climate change.

This paper explores the Brazilian experience with alternative fuels and evaluates the impact of the flex-fuel technology on reducing carbon emissions. I start by investigating consumers' incentives to replace old and used vehicles. To this goal, I leverage insurance data and define turnover rate as the number of vehicles leaving the insurance database, compared to the previous period. This measure allows me to examine how tax policies and other subsidies and incentives accelerated the dissemination of flex-fuel technology in the second half of the 2000s.

Next, I turn to the fuel markets to understand how this new bi-fuel engine changed the level of substitutability of gasoline and ethanol. Using market-level data, I estimate an almost ideal demand system (AIDS) and investigate how fuel price elasticities turn from inelastic to elastic over time. These demand models are used in combination with the turnover estimates, to simulate carbon emission scenarios and investigate the effectiveness of the flex-fuel technology in reducing GHG emissions.

I use the information on Brazilian-insured vehicles to construct a novel database with

[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.

detailed information on vehicle models and insurance characteristics. This database covers the period from 2002 to 2020, with vehicle vintages varying from the 1970s to 2020. This information represents about one-third of the total fleet, with varying degrees of market coverage.[2] Even though the information is restricted to the universe of vehicles with private insurance, the results are suggestive of the impact of tax policies over consumer incentives in general. For the fuel demand model, I use fuel prices and volume data from the National Petroleum Agency (ANP), while the current fleet is estimated using data from the Automobile Manufacturers Association (ANFAVEA) in combination with private insurance information.

The empirical approach used for the turnover model 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 vehicle turnover rates only through their impact on used car prices. Similar to Jacobsen and Van Benthem (2015) when analyzing scrappage, these fixed effects isolate the differential impact of gasoline prices on vehicle models of varying fuel economy and the impact on specific vintages across different periods. My results are robust to different combinations of fixed effects.

The second approach is a structural model based on an almost ideal demand system (AIDS). The identification here relies on a set of cost and distributional variables for the fuel prices and current fleet. I used month-of-year and municipality fixed effects to isolate the governmental intervention impacts on gasoline prices, as well as sugarcane crop quality effects on ethanol.

I highlight three main findings. First, I estimate the turnover elasticity of the insured fleet

[2]According to estimates from the Union of Auto Parts (Sindipeças), estimates of the full actual fleet are about three times the amount of privately insured vehicles (38.1 million cars as of 2020). The problem with using Brazilian official records is that they only accumulate registration over the years, never excluding vehicles that were scrapped or incurred in total loss accidents, resulting in a significant overestimation of the fleet.

in Brazil to be -0.43. The turnover rate comprises both scrappage and replacement of used vehicles. The effect found is significantly smaller than scrappage elasticity for the US market using more conventional settings (Jacobsen and Van Benthem (2015)). Notwithstanding, the smaller estimates are consistent with the environment found in a typical emerging country, such as low average income, worse income distribution, credit restrictions, and anti-scrapping incentives. When investigating heterogeneous effects, I find no significant difference for gender, but results suggest some variability for younger versus older drivers (-0.36×-0.17), and for personal versus firm use, especially for older vehicles (-0.47×-0.62). The results indicate that tax reduction policies were responsible for the replacement of an average of 185,000 cars per year from the fleet.

Second, I estimate an almost ideal demand system to assess the demand for gasoline and ethanol using data from 2002 to 2020. I found a strong and elastic price sensitivity of -2.18 for gasoline prices and -3.67 for ethanol. Using subperiods of the sample, I show how price elasticities change from inelastic (-0.50 for gasoline and -0.47 for ethanol) to elastic as the flex-fuel technology is disseminated in the fleet. These results seem to confirm the substantial increase in the substitutability of both fuels once the decision of which fuel to buy moves from the time of purchasing a new vehicle to the time of pumping fuel at the gas station.

I use information from the turnover and estimates of average scrappage rates from Mattos and Correia (1996) to construct an estimation of the current fleet in use. Using this estimated fleet and the fuel demand system, I simulate counterfactual scenarios studying the impact of the new technology, as well as the adverse effects of the gasoline price ceiling policy implemented by Dilma Rousseff's government. My simulations show that, from 2003 to 2020, flex-fuel vehicles avoided the emissions of 149 billion tons of CO_2, roughly 28% of the emission effectively done. Moreover, the potential for carbon dioxide avoidance is significant in the scenario where flex-fuel vehicles use only ethanol. I also investigated the negative impact of the price ceiling policy and found that promoting gasoline from 2011 to 2014 contributed to 137 billion tons of CO_2 released into the atmosphere, almost completely offsetting the avoidance of ethanol use up to 2020.

This work contributes to different pieces of literature. First, it adds to the literature investigating scrappage and vehicle replacement, especially in developing countries. While most of the studies focus on a measure of scrappage (Bento, Roth and Zuo (2018), Jacobsen and Van Benthem (2015), Baltas, Xepapadeas et al. (2001)), 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 work extends it by including the replacement of used vehicles and by analyzing data from an emerging country.

In the same context, my work contributes to the study of the impacts of fuel prices on used car valuation (Busse, Knittel and Zettelmeyer (2013), Leard, Linn and McConnell (2017)) and allows me to extend the analysis to study the impact of sales tax incentives and technological changes on turnover 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.

I also contribute to the literature on aggregate demand models. The structural model is built upon the original work of Deaton and Muellbauer (1980), and my focus relies on investigating the substitutability of gasoline and ethanol post-introduction of flex-fuel vehicles. the literature on almost ideal demand systems is vast and includes estimations related to fuel markets (Chambwera and Folmer (2007) and Mehrara and Ahmadi (2011)), residential energy use (Guta (2012), Filippini (1995), Murjani (2017), Ngui et al. (2011)), among other fields. In particular, I show how a new engine technology that increased the substitutability of gasoline and ethanol made consumers more responsive to price changes.

Finally, I also contribute to the literature on climate change by investigating the impacts of flex-fuel cars in mitigating carbon dioxide emissions. This field comprises different studies, among which I highlight those focusing on diverse fleet technologies reducing emissions (Benvenutti, Uriona-Maldonado and Campos (2019), Pasaoglu, Honselaar and Thiel (2012), Kopfer, Schönberger and Kopfer (2014)). My work relates directly to others investigating mitigation scenarios (Hao, Wang and Ouyang (2011), Alam et al. (2017), Palencia, Furubayashi and Nakata (2012)). In particular, I estimate that flex-fuel technology contributed to reducing CO_2 emissions by approximately 28% between 2003 and 2020. However, I also show how policies promoting fossil fuel usage can easily revert the benefits of this bi-fuel technology.

This paper proceeds as follows. Section 2 describes the evolution of transportation in Brazil, from the introduction of sugarcane-based ethanol-driven vehicles to the development and adoption of flex-fuel vehicles. In section 3 I describe the data used in this paper. Section 4 presents my empirical strategy while section 5 reports the results, and discusses heterogeneous effects and robustness checks. Next, I describe and discuss the simulation exercises and counterfactual scenarios used in this study, concluding in section 7.

2 Background

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

Brazilian automobile and fuel markets have undergone a series of transformations in the past 50 years. These processes would not have been possible without a combination of factors, including international fuel price shocks, appropriate geographic conditions, intense industry research, and heavy subsidies to industry, research, and development.

The first petroleum shock in 1973 was the necessary trigger to motivate the Brazilian government to create the ProAlcohol program and start phasing out gasoline in favor of ethanol, reducing the country's dependency on imported oil. The use of ethanol as fuel was not a new idea. A blend of 10% in volume of anhydrous ethanol has been mixed with gasoline since the 1930s. The revolutionary aspect of Proalcohol and other policies in this period was to create an environment of incentives to favor the production of ethanol, and later on, of ethanol-driven vehicles[3].

The geographic location of Brazil and the abundance of lands favored the development of ethanol from sugarcane. The synergy between ethanol and sugar markets, and the easiness for the distilleries to switch production between one product and another also contributed to the cultivation of this crop (Moreira (2006))[4].

In addition, the central government provided a series of incentives and subsidies for activities related to the use and production of ethanol. On the production side, there were guarantees of purchase at a regulated price of ethanol, an increase in the percentage of the gasoline blend, quotas on sugar exports, loans for new distilleries, and heavy investments in research to develop better and more efficient sugarcane crops (Moreira (2006), Rask (1995)). The perspective of the continuation of these incentives and subsidies led manufacturers to start the development and production of an Otto-cycle engine that could run on 100% (hydrous) ethanol. This resulted in the first ethanol-driven vehicle, which was promoted by the Brazilian government through lower taxes and lower license fees.

Maintaining the ProAlcohol program, investments in infrastructure, and all subsidies was expensive, and with the economy facing hyperinflation in the late 1980s and early 1990s, the government had no other option than to reduce gradually these expenses. This situation

[3]Among the incentives created, there were (i) quotas for sugar exports, limiting competition to ethanol production; (ii) regulated price and guaranteed purchase of the product by Petrobras; (iii) credit availability (through Bank of Brazil (BB)) to build new distilleries and invest in infrastructure; (iv) and investment in research (Embrapa) to reduce costs and improve production (Nass, Pereira and Ellis (2007), Cortez et al. (2016))

[4]In addition, other synergies exist, such as the use of the sugarcane residues as biomass to produce electricity, and the amount of direct and indirect employment these activities require.

reversed the benefits of owning a car based only on ethanol, and the market started to switch back to gasoline vehicles. By the beginning of 2000, hydrous ethanol (E-100) represented a declining and small fraction of fuel in the market. Only anhydrous ethanol remained consistent in the blend with gasoline, being transformed later into an instrument of policy to mitigate gasoline price fluctuations.

Estimates indicate that in this period of thirty years between 1975 (ProAlcohol creation) and 2005 (beginning of the flex-fuel era), about 280 billion liters (1.7 billion barrels) of gasoline has been displaced by ethanol, saving over US$65 billion in costs of imported oil (Moreira (2006)). In terms of greenhouse gas emissions, it is estimated a tonne of sugarcane used as ethanol fuel can reduce 147.4 kilograms of carbon dioxide equivalent in comparison with the same gasoline energy content (Alckmin-Governor and Goldemberg-Secretary (2004))[5].

It was only in 2003 that the first flexible-fuel vehicle was finally introduced in Brazilian markets. The pioneer was Volkswagen, followed by GMC and Fiat in the same year. Ford released its flex-fuel vehicle in 2004. The development of this particular type of vehicle occurred simultaneously among those firms in the preceding years, and its manufacturing was possible due to another cycle of increased international oil prices, which made hydrous ethanol viable again. In 2003, the Brazilian automobile market was highly concentrated, and the participation of these four manufacturers in the registration of new vehicles was around 83.7%[6].

2.2 Flex-Fuel Vehicle: What is it, and Why is it Relevant?

Flex-fuel vehicles (FFV) are vehicles whose engine was designed to efficiently run on either gasoline or ethanol or any mix of both fuels[7]. The most relevant aspect of this type

[5]This value represents substitution for hydrous ethanol. Substitution for anhydrous ethanol would represent a net avoidance of 220.5 kilograms per ton of cane used.

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

[7]Contrary to other technologies that have different tanks for different fuels (like the natural gas adaption of gasoline-driven vehicles), the flex-fuel technology allows for any mix of gasoline and ethanol in the same tank. This generates the benefit of saving space and reducing weight (no second tank is necessary), but

of vehicle is that consumers' decisions on which fuel to use shift from the time of purchasing a new car to the time of pumping fuel. In other words, consumers were not locked in to use only one type of fuel when they purchased a car. Instead, they could now switch from gasoline to ethanol at any time, depending on conditions such as performance, personal preferences, and relative prices.

An advantage of flex-fuel vehicles over the previous ethanol-driven vehicles is the lower dependence on ethanol supply, which minimizes problems related to the shortage of fuel. One of the reasons for the decline of ethanol-driven vehicles during the beginning of the 1990s was the increase in international sugar prices, which attracted most of the production to sugar and away from ethanol. During the 1980s, the government could contain these movements by guaranteeing a minimal purchase price for ethanol and limiting sugar exports but, as mentioned, these subsidies were not sustainable for large periods.

Besides eliminating the risk of shortage of fuel, this new technology also brought some gains in fuel economy for traditional gasoline consumers (see figures 9.4 and 9.7). The first models released were based on the most popular vehicles in the market at that moment, and they were designed to show efficiency and gain public acceptance. Over time, each new vintage of flex-fuel continued to improve in both efficiency and technology, differing more and more from mono-fuel vehicles.

Flex-fuel vehicles also affected fuel markets and how consumers perceive fuel prices. Before the new technology, consumers had to decide which fuel they would buy by the time of purchasing a new vehicle. Once this decision was made, they would be locked in to always buy one type of fuel, no matter its price. After the advent of flex-fuel vehicles, consumers could now evaluate which fuel has better cost-benefit, and switch their decision every time they would pump on fuel. As a result, FFVs induced a higher market substitutability between gasoline and ethanol.

Consumers had to adapt to this new reality when deciding which fuel to buy. From the

brings some challenges due to different combustion patterns and deterioration of the parts due to the higher water content in the hydrous ethanol.

standpoint of a consumer, and considering only price in their cost-benefit analysis, if the price ratio of ethanol to gasoline is lower than 0.7 (or 70%), then ethanol would present a better economy for the automobile. This is due to the lower energy content that ethanol has. This number varies slightly according to other factors, such as the amount of anhydrous ethanol in the gasoline blend, the vehicle fuel economy, and driver skills or overall vehicle performance.

Therefore, in practice, the switch from gasoline to ethanol would require consumers to pump more often to run the same amount of distance. And it adds the mental requirement of calculating the price ratio to decide which fuel is more cost-effective. An experiment made by Salvo and Huse (2013) shows that consumers would require a larger discount to move away from gasoline and that in many situations, they would choose gasoline even if the price ratio was below 70%. A potential critique of their work is that their experiment was made between 2010 and 2011 when the flex-fuel fleet was about to reach 50% of the actual fleet (i.e., technology was not so well spread yet and consumers were still learning about it). In addition, since 2007, and more often after 2010, many cities or states imposed laws mandating gas stations to display at their pumps the current fuel price ratio and discriminate which was more cost-effective. Whether this law exerted some effects on consumers or not, was never fully investigated.

2.3 Evolution of Automobile and Fuel Markets

At the end of the 1970s, and after both petroleum shocks, manufacturers found in Brazil the perfect conditions to develop an Otto-cycle ethanol-based vehicle. Because of the subsidies and consequent abundance of ethanol in the market, alongside the high gasoline prices, consumer acceptance was high and the sales of these new ethanol-driven vehicles reached the mark of, on average, 92% of all registrations of new cars between 1983 and 1988. These numbers reflect the enormous success and acceptance that ethanol-driven vehicles had in Brazil.

In contrast to the mid-1980s, the second half of the 1990s saw the popularity of ethanol-driven vehicles fall to 0.5% of the new registrations, reinforcing the importance that the subsidies and market protection (exports, prices, guaranteed purchase) had to support the adoption and use of this technology. Without the perspective of continuous subsidies, the ethanol market would be subject to sugar market fluctuations and would not be a sustainable investment for firms or a good option for consumers. Figure 9.3 shows how ethanol-driven vehicles expanded in the 1980s and practically disappeared after 1995.

As a consequence of consumers migrating back to gasoline-driven vehicles, by the beginning of the 2000s, ethanol sales reached very low levels, representing less than one-fifth of gasoline consumption. After 2003, with the advent of flex-fuel technology, consumers naturally resumed consuming ethanol as seen in Figure 9.1.

The period between 2011 and 2014 represents a period where the federal government favored the consumption of gasoline, by imposing a price ceiling on gasoline. Since ethanol price was not controlled, the price ratio increased, favoring the consumption of gasoline, and reducing ethanol sales. These movements between one fuel consumption and another are now possible due to the increased number of flex fuels in the fleet.

By 2003, the Brazilian automobile market was highly concentrated, having above 83% of the car market among the four big manufacturers (Volkswagen, GMC, Fiat, and Ford). Even within these four manufacturers, there was a significant concentration on a few popular vehicle models (Gol, Corsa, Palio, Fiesta). The strategy adopted by them for the introduction of the flex fuel was to focus on these major vehicle models that had higher acceptance in the market.

The first flex-fuel vehicle was released in May 2003 by Volkswagen, followed by GMC in June and Fiat in October of the same year. Ford released its first flex-fuel model in 2004.[8] Immediately after releasing them, Volkswagen and Fiat compromised to gradually switch their entire production to flex-fuel technology by December 2005. GMC and Ford followed

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

the same strategy, which dictated the strategy for any other entrant or potential competitor in the coming years.

Other manufacturers operating in Brazil by 2003 had different market strategies, either focusing on imports of luxury cars (e.g.: BMW, Mercedes, Audi) or having the majority of their production dedicated to pickups and commercial vehicles (e.g.: Renault). Gradually, after 2006, some of these manufacturers as well as new entrants started to offer competing options in the value and low-price passenger car segments. Many of these were forced to adapt immediately to flex-fuel technology to obtain competitiveness in Brazilian markets. According to ANFAVEA's report, by 2010, approximately 95% of all new car sales were using a flex-fuel technology and this type of vehicle became the majority of the fleet in use by 2011.

3 Data

This paper uses two main sources of information. The first is the vehicle's private insurance database (AUTOSEG) from the Superintendence of Private Insurance (SUSEP), a Brazilian federal agency that regulates and monitors all markets related to private insurance, from capital markets and private social security to housing and vehicle insurance segments. The second source of information is the Brazilian National Petroleum Agency (ANP), which regulates and monitors the markets in Brazil, providing statistics from different segments, ranging from refinery and production volumes and prices to downstream market price surveys and distribution.

Information from the private insurance agency comes in an individual-level, anonymous format, comprising all the contracts and their respective changes. Local private insurance firms are mandated to report twice a year information on all vehicle insurance contracts dealt with in the past three semesters. This dataset contains information on the type of contract, insured amount (premium), vehicle model, and version, including its respective vintage. It also offers a few demographic characteristics from the insurer, such as gender, age, and if the purpose of the insurance is for personal usage or work.

This insurance information will be used for two main purposes: to calculate the turnover rate of the fleet since 2002 and to estimate the current fleet in the streets. Information on scrap rates is relatively hard to obtain, even for some developed countries[9], and usually depends on having a good and precise estimate of the current fleet by vehicle type and model, and not only the accumulated fleet. Most developing countries, Brazil included, do not have the latter, much less the former. In the case of Brazil, the number provided by official agencies, DENATRAN and SENATRAN, shows the cumulative vehicles registered since their first purchase at a retail store. It does not account for depreciation or scrappage of vehicles and, therefore, tends to overestimate the total number of vehicles currently in activity.[10]

Information provided by ANP refers to fuel volumes consumed at a monthly and municipality level, and prices for both producer and retail stores (gas stations). The producer price comes from Petrobras, a state-owned firm responsible for the extraction and refinery of over 90% of the fossil fuels consumed in Brazil. This data comes in two formats, including or not federal taxes, and is available at a monthly level and to all different states to which fuels are delivered (approximately 40 different municipalities). These locations represent the state distributors where the original gasoline, also known in Brazil as "gasoline type A", will be blended with some additives and a regulated percentage of anhydrous ethanol. It is this blended gasoline (or "gasoline type C") that is commercialized at any gas station in Brazil. For the proposed work, the refinery fuel prices are averaged into five regions and will be used as cost instruments for the fuel model.

The other fuel prices available, the retail prices, come from a survey of a representative

[9] See for instance, information used by Jacobsen and Van Benthem (2015), which comes from a private firm and is not openly available for the general population.

[10] A recent mandatory renewal of truck registration between 2016 and 2018 showed a difference leading to a previous overestimation of more than 67%, dropping the estimated fleet of trucks from 2.5 million to 1.5 million.

set of municipalities. This survey has been implemented and supervised by ANP since 2001, on a weekly basis, and the municipalities included comprise close to 70% of the total fuel consumed in Brazil in a given year. The information available comprehends gasoline and ethanol prices, natural gas (whenever available), and diesel prices. After 2013, this survey discriminates between high-sulfur content diesel and low-sulfur content diesel.

3.1 Data Description and Summary Statistics

Between 2002 and 2020, the insurance database comprises 278 million vehicle contracts, of which 70% are for personal use and 30% for professional use. Table A.1 summarizes some of the most relevant characteristics.

The insurance database was aggregated by year for the turnover study, considering the different vehicle models and vintages. An additional aggregation was necessary for those vehicle models that were not representative enough in the database, reducing the total number of unique vehicle models from 424 to 177, distributed among 88 makers.

One key characteristic of Brazil's vehicle insurance market is the fact that vehicle owners are mandated to enroll in federal vehicle insurance (DPVAT), but not private insurance. The federal insurance covers small medical and accident assistance costs but does not cover physical and property damages. Detailed data from this federal insurance is not publicly available. Since private insurance is not mandatory, not all cars in Brazil will have insurance that covers costs in case of accidents or theft, and the market coverage of the private insurance decreases as vehicles age.

The Association of Manufacturers, ANFAVEA, reports the number of vehicle sales annually, discriminating by fuel type and category (see figure 9.3). By using estimations of a survival curve, developed by Mattos and Correia (1996), I can recompose the current fleet by age. Comparing this fleet estimation to the number of privately insured vehicles, I can recover the coverage of the insurance market, by vehicle age, as in figure 9.5.

Estimations of the current fleet using sales records are much higher than the number of insured vehicles for all ages, except for new vehicles (age zero in the figure). This information transmits two relevant facts: first, the insurance database is not a good representation of the total fleet because many vehicles become uninsured as they age. This occurs either because these vehicles suffered a total loss and were scrapped or because they were resold to a non-insured agent. Second, sales records from the association of manufacturers may not contain all annual new sales of vehicles (see figure 9.2). This can occur if not all manufacturers are present in the association, if they do not account for imports, or even if some values are misrepresented.

One caveat must be noted concerning the difference between data in the insurance database and the sales records for the first year of usage. Some differences are expected because there could be a gap between the moment of the sale and the moment of buying an insurance contract. For instance, sales from December may only become insured in the following year. Or vehicles that were sold in a given month, but delivered with some months of delay, may be registered in the insurance database also in a different year. [11]

Using historical data from ANFAVEA up to 2002, and data from new purchases from the insurance database, I can recover what would be the current fleet by year and by vehicle age. Comparing this estimated fleet with the actual number of insured vehicles, I obtain the turnover of the insured vehicles. This turnover represents those vehicles that suffered total loss and were scrapped and those vehicles that were sold to a non-insured agent. This can be seen in figure 9.6.

This is an important measure, especially in the moment of the introduction of a new technology. As the total number of sales of new vehicles using the flex-fuel technology becomes the majority, part of the consumers will have access to this technology via the first purchase of a new vehicle, and part of the consumers will have access via the purchase of a used vehicle. In this work, I assume that agents are either risk-averse or non-risk-averse

[11] An example here is the case of the first launch of the Hyundai HB20 in Brazil. Sales were beyond the manufacturer's expectations and many consumers had to wait months to receive the vehicle. Since many of these new releases occur sometime in the second semester, it is quite plausible that a vehicle is marked as sold in one year and insured at the beginning of the coming year.

and that they do not switch risk-aversion preferences. In addition, I assume that risk-averse agents will always buy insurance. Under these conditions, part of the purchase of new flex-fuel vehicles by risk-averse agents ends up being sold to non-risk-averse agents after one or more years of usage, and this movement is captured by this turnover rate.

Some facts that reinforce this reasoning are (i) the fast switching of production by the four major manufacturers to produce 100% flex-fuel vehicles by the end of 2005, (ii) market reports and news stating that, by 2010, over 95% of all new car purchases were flex-fuel vehicles, and (iii) the presence of many vehicle rental firms and other companies that renew their fleet after just a few years of use[12]. Since the four major manufacturers represented over 80% market share by 2003, their decision to switch relatively fast to flex-fuel production may have induced a fast adoption of the technology among consumers.

For the purpose of the turnover rate study, I worked with the insurance database information, in addition to complementary sources. In the insurance database, vehicle data is identified by a tag name with full model description and includes insurance and demographic information such as type of insurance coverage, type and monetary value of claims, main driver's age, zip code, amount insured, and other specific information.

I merged fuel economy information and other vehicle characteristics obtained from a variety of sources.[13] Fuel prices were obtained from a Petrobras price survey based on a representative set of retailers.[14]

[12]rental firms are a relevant market in Brazil. These firms tend to renew their entire fleet at least every two years. In addition, other firms tend to keep newer vehicles in their fleet, promoting this turnover discussed. And lastly, by 2010 when Uber and similar services became available, one of the requirements back then was to use newer and more reliable vehicles, which caused many drivers to purchase either a brand-new vehicle or a second-hand newer car. The insurance database indicates which vehicles were used for work, except for the case of Uber services.

[13]Fuel economy came mostly from specialized vehicle websites, vehicle manufacturer manuals, and governmental agencies (IBAMA). Trucks and light trucks as well as buses and other heavy cargo vehicles are not considered in this work.

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

The database I use represents the full universe of privately insured vehicles. My measure of turnover follows a similar definition used by Jacobsen and Van Benthem (2015) to calculate the US scrap rate. In the case of this work, this measure can be understood as the turnover of the insured fleet, and it is defined as the number of vehicles leaving the insurance database in a given year, 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, maker-model m in year t in the insurance database. Age is measured as the difference between the year of the contract and the vintage, v, of the vehicle model.

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

Table A.1 shows the turnover rates for the insured fleet. Two main aspects are relevant here. First, these rates are significantly higher than simply scrap rates shown for other markets, such as the US (see the work of Jacobsen and Van Benthem (2015) and Bento, Roth and Zuo (2018)). Because they include reselling to non-insured agents, this pattern is expected. Second, vehicle turnover rates seem to consistently fall after a vehicle ages 15 years.

Figure 9.8 and table A.1 inform us of the special turnover rate pattern across ages and show us some heterogeneity among manufacturers. This decaying pattern after a vehicle ages 15 years can be associated with some anti-scrapping incentives, such as ownership tax exemption for older vehicles. Each Brazilian state has a different threshold from which older

higher maintenance costs.

vehicles are exempt from ownership taxes. The average cutoff is around 15 years, and the format of the turnover rates perfectly captures this information by showing smaller rates for older vehicles.

For the fuel market models, the methodology applied in this work requires the use of instruments. I have created three different sets of instruments, tested in this work: gasoline price instruments, ethanol price instruments, and fleet instruments.

There are two sets of instruments for gasoline prices. I refer to the first as the "Triple Policy" instrument. This instrument refers to the Petrobras price (producer price) added to federal taxes, and adjusted by the proportion of anhydrous ethanol in the final gasoline blend. Each of these factors (Petrobras price, federal taxes, and percentage of anhydrous ethanol in the final blend) is controlled by the federal government and has been used in the past 20 years to reduce fuel price oscillations or literally to control final prices.[15] Hence, the name triple policy. The second instrument was named "double policy‘‘ and includes only the Petrobras price added to federal taxes. Both instruments are an important measure of cost for the production of the final gasoline blend.

The ethanol instruments used in this work refer to export sugar prices at the São Paulo port and a measure of sugar quality. Since ethanol in Brazil is produced out of sugarcane, and this crop can be also used to produce sugar, it is natural that sugar prices influence the amount of sugarcane destined for ethanol production, which affects its price. The second instrument, sugar quality, refers to an estimation of the potential value of the crop to be transformed into either sugar or ethanol. Every year, each of the regions producing sugarcane estimates a quality factor of the crop, that depends on the quality of the sugarcane and market conditions. This factor is weighted by the respective crop size and used as an instrument. The sugar quality varies according to two yearly crops and three regional sugar quality factors.

Finally, as an instrument for the fleet, I use two different sets of instruments. The first is

[15]During the period of 2011 to 2014, the president Dilma Rousseff used her influence over Petrobras to set a price ceiling on gasoline and isolate Brazilian economy from fluctuations of the international oil prices.

the number of vehicle versions available in the state at a given quarter and by fuel type. As ethanol and gasoline mono-fuel vehicles phase out of the market, producers will invest less in releasing new vehicle versions, and hence the consumer will have a different choice set of cars to buy. For the flex-fuel fleet in particular, I also test a second type of instrument which refers to a one-year lag of the price ratio of ethanol to gasoline. This measure is relevant for flex-fuel since it represents the decision factor for consumers to choose the best cost-benefit fuel when refilling their vehicles.

4 Methodology

4.1 Technology Diffusion of Flex-Fuel Vehicles

Like any traditional durable good, automobiles are purchased with the expectation of being consumed (or used) over some extent of time. This amount of time depends on several factors, including the intensity of usage, the price of a new product, the costs associated with regular usage, the features and characteristics of the product owned, and those of potential replacements.

When it comes to new technologies for durable goods, a series of factors could influence how fast or slow consumers will buy, accept, and feel comfortable using the technology. Such factors may include (i) aspects of the supply side (how many suppliers exist and their reputation and their products' credibility in the market); (ii) population knowledge about the new technology and how to take advantage of it; (iii) and the presence of alternative products in the market.

For automobiles, an extra factor could be represented by a second-hand vehicle with the new technology. This product has the advantage of offering the same features as a new vehicle but at a lower cost. This option offers the experience of trying the new technology without incurring a high cost for a brand-new vehicle.

In the Brazilian automobile market, as highlighted previously, the main suppliers opted for the strategy of replacing their entire production with flex-fuel between the end of 2005 and the end of 2006. Not only did they have a good reputation in the market and their vehicles were well accepted, but their strict dominance of the car market seemed to impose a faster acceptance rate from consumers' side, since no other viable choices were available.

To facilitate the transition, the four manufacturers established their flex-fuel vehicles to have the same average price as their gasoline-driven vehicles. In addition, there were campaigns explaining the difference in the technology and how to decide when ethanol had a higher cost-benefit. The government also applies the same tax cutoff as ethanol vehicles, and after 2007 implemented extra tax benefits to help promote the purchase of these cleaner vehicles.

In the next subsection, I will detail the analysis of the spread of the flex-fuel technology, and highlight the role the government had in promoting it.

4.2 Scrappage and Replacement of the Fleet

This work will analyze the diffusion of flex-fuel technology from the point of view of product replacement. Automobiles are products that usually span a long lifetime period. For the United States, work such as Jacobsen and Van Benthem (2015) and Bento, Roth and Zuo (2018) indicate that most of the fleet is deteriorated and scrapped in the initial 20 years of use. Still, factors related to its utilization can double that span depending on some conditions.

As mentioned, the private insurance database is not ideal for the calculation of the price elasticity of scrappage (henceforth, scrap elasticity). I will refer to the ratio developed at equation 1 as the turnover of the fleet, in reference to the fact that this measure captures not only the actual scrappage (in the form of total loss accidents, theft, and fire) but also includes a measure of the individuals who left the private insurance database, potentially reselling the vehicle.

The focus of this section is the estimate of the turnover elasticity, since it tells us how fast the new technology spread among consumers, by either replacing old mono-fuel vehicles or simply scrapping them.

4.2.1 The Fleet-Turnover Elasticity Model

As described in previous sections, assuming that risk-averse agents always buy insurance, the change in the number of private insurance databases can be understood as the composition of two facts: real scrappage (when a vehicle suffers a total loss, or theft, or even another critical damage event), and the replacement of the vehicle, with consequent reselling of the used one. Combined, these two effects represent the turnover of the insured fleet.

The method applied to the price elasticity of the turnover of the insured fleet (henceforth, turnover elasticity) is similar to the approach used by Jacobsen and Van Benthem (2015) to estimate the scrappage elasticity for the US market. It is a panel instrument variable approach, and can be represented by equation 2. Here, Y_{amt} represents the turnover 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. I use a cost-by-kilometer variable as an instrument. This measure can be represented by the producer price divided by the respective vehicle's fuel economy.

$$ln(Y_{amt}) = \gamma_1 ln(\hat{P})_{amt} + \alpha_{am} + \alpha_{at} + \epsilon_{amt} \tag{2}$$

$$ln(P_{amt}) = \Sigma_{m=1}^{M} \beta_m Z_{mt} + \alpha_{am} + \alpha_{at} + \mu_{amt} \tag{3}$$

4.2.2 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 turnover rates. Understanding the relationship between fuel prices and used car valuation is relevant itself, especially for countries where fuel price controls are so widely used as is the case for Brazil.

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

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

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

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

The regression to be estimated is then represented by equation 3. As mentioned, fuel prices, represented by the term Z_{mt}, are weighted by fuel economy. I use dummy interactions at the make level to add flexibility to the model and estimate an average impact at the manufacturer level. The results can be seen in the figure 9.12. I didn't impose any specific restriction on the parameters, so negative or positive impacts depend on the average level of the manufacturer left out (baseline options). The relevant aspect is the magnitude of the impacts.

I also follow Busse, Knittel and Zettelmeyer (2013) and Jacobsen and Van Benthem (2015) and estimate a used car price model based on the quartile of fuel economy. Table A.2 presents such results. For each \$1 Real (1 BRL) increase in fuel prices, used vehicles in the most efficient quartile increase their valuation in \$1,190 Reais compared to the less efficient quartile. This effect is significant, in line with the literature, and remains relevant for both newer and older vehicles (columns 3 and 4).

To complement this analysis and link to the study of turnover rates, in figure 9.12 I show estimates from the reduced form, investigating fuel price impacts on turnover rates. Again, I assume that controlling for the model-by-age and age-by-year fixed effects, the fuel impact captured in the reduced form comes through, and only through, its impact on car prices.

4.2.3 Identification

For the identification of the turnover 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 turnover rates only through used car prices.

For the relevance assumption, the study on the impact of fuel prices on section 4.2.2 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 9.12).

For the exclusion restriction, the key element resides in the fixed effects used in the model. For the economy-weighted fuel prices (cost-by-kilometer instrument) to be a good instrument, any unobservable confound must be partially out, so the variation remaining explains turnover rates only through the effects of used car prices. To control for these unobservables, the set of model-by-age and age-by-year fixed effects play a key role: they absorb the impact of factors affecting the physical turnover 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 turnover rates via used car prices according to each specific model efficiency.

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

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

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

4.3 Demand for Gasoline and Ethanol

In this section, I describe the structural methodology employed for the estimation of demand for gasoline and ethanol. Before proceeding, though it is necessary to highlight some caveats. First, for the fuel demand, and consequently, for the greenhouse gas emission simulations, I will focus only on automobiles, excluding cargo and other utility vehicles such as vans, pickups, and mini-buses. Second, I will focus on the relationship between gasoline and ethanol, leaving out other fuels such as diesel, natural gas, and electricity.

The reason for the first caveat is that the relationship between diesel and ethanol is not well established. While gasoline and diesel are acceptable substitutes for cargo vehicles, it is not necessarily the same for ethanol and diesel. Flex-fuel pickups may have an advantage over gasoline-driven pickups because of the increased fuel economy, but not necessarily because of the ethanol alternative option. The second caveat refers to the fact that in Brazil it is not allowed diesel-based passenger cars, except for some imports. And finally, electric vehicles are very recent, and within the period of analysis, they comprehend a negligible share of the passenger car markets, as well as diesel-driven cars. Hybrid cars, in this context, are assumed to run on gasoline since they have been in the market for at least ten years, but only after 2020, electricity become a marginally relevant source of vehicle fuel. One last fact is that diesel itself had a series of regulation changes and even a cleaner biodiesel version developed after 2004, which makes the gasoline-diesel (and potential gasoline-diesel-ethanol) relationship a lot more complex.[16]

[16] Alternative specifications could include diesel as a competitor for gasoline, but not for ethanol, or even set diesel as a competitor for the other two fuels. Both scenarios would be relevant if I included light cargo vehicles in the analysis. I might explore these alternative specifications for future work.

The methodology employed in this section follows the almost ideal demand system, developed by Deaton and Muellbauer (1980). To start describing this model, the first step is to define the individual expenditure function, as in equation 4, where the functions $a(p)$ and $b(p)$ follow a second-order approximation as represented in 5 and 6. I will suppress individual and time for simplicity of notation.

$$log(c_i(p, u_i)) = (1 - u) \times log(a(p)) + u \times log(b(p)) \tag{4}$$

$$log(a(p)) = a_0 + \sum_{k \in (g,e)} a_k log(p_k) + \frac{1}{2} \sum_k \sum_k \gamma_{k,j} log(p_k) log(p_j) \tag{5}$$

$$log(b(p)) = log(a(p)) + \beta_0 exp\left(\sum_{k \in (g,e)} beta_k log(p_k) \right) \tag{6}$$

Substituting the functions 5 and 6 in the equation 4, I obtain the AIDS cost function 7. To illustrate the model for gasoline and ethanol, I will use from now on the appropriate subscripts (g for gasoline, e for ethanol). Next, differentiating equation 7 with respect to the logarithm of the gasoline price, and accounting for Shephard's lemma on the left-hand side, we arrive at the expenditure-share equation 8.

AIDS cost function:

$$\begin{aligned} log(c_i(p, u_i)) = a_0 + \sum_{k \in (g,e)} a_k log(p_k) + \frac{1}{2} \sum_{k \in (g,e)} \sum_{j \in (g,e)} \gamma_{k,j} log(p_k) log(p_j) + \\ + (1 - u)\beta_0 exp\left(\sum_{k \in (g,e)} beta_k log(p_k) \right) \end{aligned} \tag{7}$$

Expenditure-share function (simplified version):[17]

$$\frac{p_g \times q_g}{c(p, u)} = w_g = a_g + \gamma^*_{ge} log(p_e) + \gamma_{gg} log(p_g) + u\beta_0 \beta_g exp\left(\beta_g log(p_g) + \beta_e log(p_e)\right) \tag{8}$$

For a utility-maximizing consumer, the total expenditure w should equate to $c(u, p)$. By

[17] For this version, I define $\gamma^*_{ge} = \frac{\gamma_{ge} + \gamma_{eg}}{2}$.

defining a price index P as in 9, I can invert equation 8 and solve it for the utility as a function of prices and demand for fuel.

$$P = a_0 + \sum_{k \in (g,e)} a_k log(p_k) + \frac{1}{2} \sum_{k \in (g,e)} \sum_{j \in (g,e)} \gamma_{k,j} log(p_k) log(p_j) \tag{9}$$

$$log(x) = log(P) + u\beta_0 exp\left(\beta_g log(p_g) + \beta_e log(p_e)\right) \tag{10}$$

$$u = log\left(\frac{x}{P}\right) \times \frac{1}{\beta_0 exp\left(\beta_g log(p_g) + \beta_e log(p_e)\right)} \tag{11}$$

Finally, substituting the utility into equation 8, I can obtain the expression for the share of expenditure as in 12.

$$w_g = a_g + \gamma^*_{ge} log(p_e) + \gamma_{gg} log(p_g) + \beta_g log\left(\frac{w}{P}\right) + \xi_g \tag{12}$$

The restrictions for this model to become a closed system require that $\sum_i a_i = 1$, $\sum_i \gamma_{ij} = \sum_i \beta_i = 0$ and $\sum_j \gamma_{ij=0}$. This set of equalities guarantees that the system is homogeneous of degree zero with respect to prices. In addition, Slutksy symmetry requires that $\gamma_{ij} = \gamma_{ji}$.

Lastly, this almost ideal demand system can be aggregated to the industry level, defined as $Q = \sum_i q_i$. This aggregation leads to the superior stage of the model, represented by equation 13. Based on the aggregated stage and the expenditure-share equations, I can derive the price elasticities as indicated in equation 14.

$$log(Q_n) = n + \beta log(I_n) + \gamma log(P_n) + Z_n + \epsilon_{nt} \tag{13}$$

$$\nu_{ij} = \frac{1}{w_i}\left(\gamma_{ij} - \beta_i w_j\right) + \left(1 + \frac{\beta_i}{w_i}\right)\left(1 + \gamma\right) w_j - 1[i = j] \tag{14}$$

Where I represents real income, P is the price index, and Z are additional controls. I estimate this model at the municipality and monthly levels, ranging from 2002 to 2020. In the set of additional controls, Z, I also include month-of-year and municipality fixed effects, controlling for population and three current fleet estimations: gasoline-driven cars (including hybrids), flex-fuel cars, and ethanol-driven cars.

4.4 Identification of the AIDS models

The identification of the AIDS models relies on a set of instruments for prices and fleet. For the gasoline price, I use as an instrument a triple-policy gasoline price. In Brazil, the gasoline available for consumers is a blend of pure gasoline (also known in Brazil as "gasoline type A") and anhydrous ethanol. The percentage of anhydrous ethanol in this blend has changed over time, initially as a manner of decreasing the dependence on imported gasoline and decreasing greenhouse gas emissions. After 2000, however, this policy was used often as an instrument to control gasoline prices and minimize price oscillations.

In addition, most of the Brazilian gasoline is produced by Petrobras, a state-owned refinery and producer. Throughout the past 20 years, Petrobras has not been isolated from political influence, and as a consequence, the producer fuel prices have been set according to the country's political interests. Finally, federal taxes are all paid at the producer level. These taxes have also been used to control gasoline prices since 2000, and more often between 2011 and 2014. These three instruments – gasoline refinery price, percentage of anhydrous ethanol in the final blend, and federal taxes – have been combined, resulting in the final Petrobras price, a measure of costs used to predict the final price for consumers.[18]

For ethanol prices, the instrument used was a measure of the sugar (or crop) quality. This measure is estimated for each crop and takes into account the potential market value considering both alternative usages of the sugarcane crops: the production of sugar for the international market and the production of ethanol for the domestic market. There are three measures of sugar quality, one for the crops in the south and southeast regions, and two for

[18] An alternative instrument tested was the Petrobras price without considering the percentage of ethanol in the blend, i.e., the gasoline type A price and federal taxes.

the north and northeast regions.[19] Since sugar and ethanol are both produced, in Brazil, from sugarcane, the use of sugar prices, or potential sugar quality, can be seen as a factor that influences costs in the production of ethanol.[20]

For the fleet, I test two types of instruments. The expenditure-share models use each (i) gasoline-driven car fleet, (ii) ethanol-driven car fleet, and (iii) flex-fuel fleet. First, I use the total number of vehicle model versions in the local market. I use the private insurance database to identify the number of unique vehicle versions effectively purchased and consider these chosen versions as the market availability. As the number of ethanol vehicles decreases, the total fleet of ethanol-based vehicles decreases as well. A similar process happens to gasoline-based vehicles, as they start to be replaced by flex-fuel vehicles. For the flex-fuel fleet, the process is reversed: as the technology is adopted by all manufacturers and the production of mono-fuel is replaced by the bi-fuel engine, more versions become available, increasing consumers' choice set of products. The idea is that changes in the consumers's choice set can predict current and future fleet size.

For the flex-fuel vehicle, I also test an additional instrument: a one-year lag of the fuel price ratio (ratio ethanol-gasoline). Ethanol and gasoline have different fuel efficiencies, and they become equally cost-efficient when the price ratio equals 0.7. This information was widely disseminated since the 2000s with the advent of flex-fuel. Some municipalities and states even established regulations according to which gas stations should indicate the price ratio and corresponding fuel that is more cost-beneficial to consumers.

Finally, the set of month-of-year and municipality fixed effects are used to control for any unobservables that may affect consumers' decisions on fuel or vehicle purchases, and isolate the effect of the described instruments.

[19] As an alternative instrument, I also test the export price of sugar in São Paulo ports.

[20] In fact, this measure represents an opportunity cost of farmers, that can produce sugar instead of ethanol if it turns out to be more profitable.

5 Results

In this section, I discuss the main results obtained and the policy implications they bring. I start with table A.3 that presents my main estimates for the turnover elasticity, (γ_1), using equation 2. Panel A shows OLS results while panel B uses instrumental variables to account for potential bias. The third panel focuses on all vehicles, which includes pickups, vans, and other light cargo vehicles (commercial vehicles). In this paper, I am not working with trucks, buses, or motorbikes. Appropriate analysis for those categories would require analysis beyond the scope of this work.

There is an important caveat regarding vehicle prices. The variable used here is the amount insured (or the total insurable value), which is based on and 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. [21]

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

5.1 IPI Sales Tax Reductions

As discussed, IPI sales tax affects used vehicle prices only indirectly, by making them less attractive compared to newer, more efficient vehicles. In column three of table A.3 I present

[21] The number of luxury vehicles by vehicle model is not substantial, which brings noise to the regressions. Since, altogether, they represent only a small fraction of the fleet, this restriction may not affect significantly the elasticities.

an IPI model. In this version, I interact vehicle prices with a dummy for years with reduced IPI sales tax to identify any differential turnover elasticity when tax reduction policies are in effect.[22] Models 3 and 4 use the same procedure but split the analysis into newer vehicles (aging up to 10 years) and older vehicles (above 10 years).

Policies aimed at promoting new car sales by reducing taxation on brand-new vehicles seem to be ineffective for cars aged up to 10 years (model 3, column 4). However, the same is not true for cars older than 10 years. The last column of table A.3 shows a significant interaction of the IPI dummy with the turnover elasticity. Combined, the effect is of the same magnitude as the impact for the overall impact (model 2) and for vehicles up to 10 years (model 3). This result seems to suggest that tax reduction policies indeed incentivize the replacement of older, more pollutant vehicles.

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

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

This last result is particularly relevant for policymakers, who can use tax reduction on

[22] The dummy interaction was built to be one for the years 2009 and 2012 to 2014. I left 2008 out because IPI reduction started only on December 16, so its impact was reduced in that year. I am also not taking into account that 2013 and 2014 were years where the reduction was smaller than in 2008 and 2012. My criteria here is any period where IPI is below the usual tax standard. For a full description of the IPI tax reductions, the period they last, and other details, see table A.2

new vehicles as a mechanism to reduce the amount of less efficient vehicles from the current fleet and, consequently, improve local air pollution.

5.2 Flex Fuel Vehicles

Table A.4 shows the IV results for flex fuel vehicles (FFV). Two effects occur simultaneously here: the complete switch of domestic production of major manufacturers to flex-fuel vehicles (2005, 2006) and the first IPI sales tax reduction policy (2009). The second sales tax reduction (2012 to 2014) occurred in a period where the majority of the current fleet is estimated to be using the flex-fuel technology. Given this configuration, it is a challenge to disentangle one impact from the other. Therefore, the analysis here will contemplate both effects of FFV and IPI sales tax reduction combined.

The analysis used here is similar to the IPI sales tax reduction where I interact a dummy with vehicle prices. The idea is to study the salience effect of flex-fuel, once it is impossible to compare it to a control group as in a difference in difference approach.[23] I use dummy interactions for three different periods, to account for the proportion of flex-fuel vehicles in the current fleet.

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

Next, I set 2007 to 2010 as the "diffusion" period. The IPI sales tax reduction (December 2008 to December 2009), associated with faster economic growth in the second half of the 2000s, boosted the sales of FFV vehicles and by 2010, 95% of all new car sales were FFV, practically leaving only imported cars as gasoline-only engines. According to the Union of Auto Parts, in 2011 the market share of FFV cars and gasoline cars was similar in the fleet,

[23] The introduction and diffusion of flex-fuel technology affects both mono-fuel markets by reducing the number of vehicle versions available in the market. Since diesel cars are not allowed to be produced in Brazil and other technologies were incipient or not available (electric, natural gas), a control group to compare the effects of flex-fuel is not possible.

so I called the next period (2011 to 2015) as “majority”. The last period of analysis, entitled “maturity”, regards 2016 to 2020, and refers to a period where no IPI sales tax reduction has been implemented and FFV technology has become the standard in the fleet (above 80% of the current fleet).

Column 2 from table A.4 shows the turnover elasticity for cars for the baseline period to be -0.42. When the diffusion period starts, this elasticity is strengthened by -0.165, summing up to -0.585. The elasticity for the majority period is reinforced by -0.163, resulting in -0.583. Finally, in the last period, maturity, the interaction with price is not statistically significant (-0.002), and the resulting elasticity would return to -0.42.

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

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 sales tax reduction contributed to the further dissemination of flex fuel engine cars by reducing the price of new vehicles and inducing scrappage and turnover of old and used cars. And third, once the tax stimulus ended and the new technology became the standard in the fleet, the turnover elasticity returned to the level of the baseline period, before the dissemination of the new technology.

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

5.3 Turnover Impacts by Car Age

Next, I split the sample into different car age brackets to evaluate how the turnover effect varies as vehicles get older. There are four main brackets: cars aged 1 to 5 years-old, 6 to 9, 10 to 14, and above 15 years. Table A.5 shows the results for the OLS and the IV models.

The models suggest here that cars aging up to 5 years or more than 15 years are less sensitive to car price changes than models aging 6 to 14 years. In practice, this result makes sense since the usual credit for new cars represents loans to be paid in up to 5 years, so it might be unlikely that an individual who took some vehicle credit would switch cars before the loan is completely paid. Cars aged more than 15 years are exempt from ownership taxes, so individuals with older cars tend to hold on to them for longer, except when the price of brand-new cars is exceptionally lower (case of IPI sales tax reduction discussed before). It is important to highlight that these results here are only suggestive since most standard errors are relatively higher, and I can't rule out that coefficients from each age bracket are statistically different from each other.

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

In practice, the last model (cars aged 15 or more) indicates that owners of older vehicles were already less sensitive to car price changes. Given the lack of a policy to enforce the scrappage of such vehicles, if an older vehicle, exempt from ownership tax, falls outside the emission level brackets, its owner would still have an incentive to keep the vehicle, provided that maintenance costs are not impeditive. This occurs because of the lack of a scrappage program, guaranteeing a minimum reward for scrapping, and because of the low average income and restricted access to credit, which difficult old vehicle replacements for a newer version.

5.4 Ethanol and Gasoline Markets

The first advantage of buying a flex-fuel vehicle becomes evident when pumping for fuel.[24] Consumers now can effectively choose between gasoline and ethanol, depending on price conditions or personal preferences. Therefore, a model establishing the new relationship between both fuels after the advent of the new technology and the replacement of the old mono-fuel vehicles is essential.

The fuel model developed in this work is a structural model system, wherein the upper stage estimates the total fuel quantity, while the lower stages estimate expenditure market shares. This system can be summarized as follows.

$$log(Q_{nt}) = a_n + \beta log(I_{nt}) + \gamma log(P_{nt}) + Z_{nt} + \epsilon_{nt} \tag{15}$$

$$w_{gnt} = a_g + \gamma^*_{ge} log(p_{ent}) + \gamma_{gg} log(p_{gnt}) + \beta_g log\left(\frac{w_{nt}}{P_{nt}}\right) + Z_{nt} + \xi_g \tag{16}$$

Table A.9 reports gasoline and ethanol models' own and cross-price elasticities. The first model presents OLS results for the period of 2002 to 2020. Own price elasticities are all elastic, while the cross-elasticity in the gasoline model remains inelastic. From model 2 to model 5 I test different sets of price instruments, varying between double or triple policy for gasoline prices and sugar price or sugar quality for ethanol. The gasoline price elasticity in

[24]On average, flex-fuel vehicles are also more efficient than gasoline vehicles, presenting better fuel economy as can be seen in figures 9.7 and 9.4.

the gasoline model is quite stable, varying from -2.05 to -2.21. For the ethanol model, its own-price elasticity is stronger, ranging from -3.06 to -3.88.

All cross-price elasticities in the gasoline model are inelastic, indicating that ethanol prices are relevant, but a small factor to decide on consumption of gasoline. In the ethanol price, however, the cross-price elasticity is significantly higher, becoming elastic and ranging between 1.02 to 1.76. This result indicates that gasoline prices affect in a significant way the decision to consume ethanol.

While elastic fuel prices may sound unusual, this is not the case for markets where a viable alternative fuel is present. Studying multifuel vehicles for the Swedish market, Huse (2018) found that ethanol's own-price elasticity as well as its cross-price elasticity become highly elastic as a result of consumers being able to easily switch between ethanol and petrol. From studies using Brazilian data, Cardoso et al. (2019) and Uchôa, Jesus and Cardoso (2020) found gasoline own-price elasticities to vary between -1.5 to -2.2 under different instruments and periods. A review done by them of the literature shows that most estimates after the introduction of flex-fuel present elastic price effects.

Table A.10 re-estimates model 2 splitting it into sub-periods. The first period, from 2002 to 2004, represents the moment when flex-fuel technology was still incipient and its market share in the current fleet was negligible. Own-price elasticities are inelastic ($\eta_{gg} = -0.47$ and $\eta_{ee} = -0.50$), and cross-elasticities are not statistically significant, with impacts close to zero ($\eta_{ge} = 0.009$ and $\eta_{eg} = 0.0139$). This brings stronger evidence that prices were inelastic before the introduction of flex-fuel vehicles.

The first model in table A.10 also reinforces the idea of low substitutability between gasoline and ethanol for mono-fuel vehicles. Before the flex-fuel technology, each individual would be locked into a given technology and to a given fuel, not having the option to switch when pumping fuel. This limits the influence of gasoline prices on ethanol sales and the influence of ethanol prices on gasoline sales.

The second period, from 2002 to 2010, includes the moment of technology diffusion up to the moment where it represents 95% of all new car sales. Price elasticities switch from inelastic to elastic, and the market share of flex-fuel in the current fleet reaches close to 50%. This increase in elasticities is possible only through the diffusion of dual-fuel technology, which substantially increases the substitutability of fuel by allowing consumers to decide at the pump which fuel to buy.

The last two models extend the subperiods to 2014 and 2020. Model 3 incorporates the second Dilma government, when she imposed a price ceiling on gasoline, making it a more cost-attractive option than ethanol. Despite this ethanol disadvantage, price elasticities became even more elastic due to a higher spread of the flex-fuel technology. As expected, due to the gasoline price ceiling, ethanol consumption fell substantially (see figure 9.1. Notwithstanding, ethanol sales remained at a higher level compared to the period pre-flex technology. This may suggest that some individuals may choose ethanol despite small price disadvantages. More studies on this aspect may be necessary in the future.

Finally, table A.11 shows alternative models where the instrument for the flex fleet is replaced by the 12-month lag of the price ratio. Since the beginning of the flex technology, the information on the price ratio calculation to identify which fuel had better cost-benefit was widely spread across media and campaigns. In these models, I am using a lag of the price ratio to indicate the thought process consumers would go through before pumping fuel. The 12-month lag serves two purposes: to avoid endogeneity with current prices and to indicate that consumers might not do this mental calculation often, but instead, provided that price changes are relatively small, they tend to rely upon previous calculations rather than recalculating the ratio.

Switching flex-fuel instruments had small changes to own-price elasticities for the gasoline model. For the ethanol model, noticeable changes occurred for the cross-price elasticities, where the gasoline effect on ethanol sales became much more elastic, ranging from -4.06 to -4.66. A potential reason for this change could be the year 2002, which is included in the models in table A.9 but not in the models in table A.11 due to the 12-month lag instrument.

Since detailed data available on periods without flex-fuel is limited, the higher elasticities may simply indicate fewer periods of only mono-fuel technology.

6 Simulations and Counterfactuals

In this section, I present a counterfactual exercise to estimate the amount of pollution avoided by the flex-fuel technology. To this goal, I first establish the expected amount of pollution effectively released by cars, describing the pollutants available and the necessary variables and steps, and then I draw alternative scenarios to simulate situations of interest.

There are different methodologies to compute the amount of pollution emitted, depending on data availability. One such method follows equation 17 and multiplies the number of kilometers traveled by a vehicle (VKT) by a measure of pollution emitted by distance (emission factor), obtaining the total amount of pollution per year. The number of kilometers traveled can be obtained by multiplying the number of vehicles in the fleet by their respective average usage (variable *intensity of use* in equation 18). Alternatively, the researcher can obtain the number of kilometers traveled by multiplying the total volume of fuel consumed by the vehicle's fuel economy (equation 19). The average intensity of use of a vehicle is calculated as equation 20.

$$\begin{gathered} KmTraveled \times EmissionFactor = Pollution \\ (Km/year) \times (g/Km) = (g/year) \end{gathered} \tag{17}$$

$$KmTraveled = Fleet \times IntensityOfUse \tag{18}$$

$$KmTraveled = \sum_{g,e,d} (FuelVolume \times FuelEconomy) \tag{19}$$

$$IntensityOfUse_g = \frac{\sum_i (FuelEconomy_{i,g} \times FuelVolume_{i,g})}{Fleet_g} \tag{20}$$

Data regarding pollution emission factors is obtained from a series of reports produced by the Brazilian Ministry of Environmental Affairs, MMA, (see MMA (2013)), CETESB (see CETESB (2019)), and their respective updates in the past ten years. CETESB is a regulatory environmental agency from the State of São Paulo, responsible for monitoring all pollution-producing activities and guaranteeing minimum air, ground, and water quality levels for all regions within the state. Since São Paulo state comprises around one-third of the current fleet in Brazil, some metrics obtained by this agency will be used as parameters for other states, in addition to the federal report by the MMA agency.[25]

Data from the intensity of use of vehicles (and consequently, VKT) was estimated by Bruni and Bales (2013) with data before 2012, and making predictions for the fleet and emission evolutions from 2010 to 2020. However, a series of government interventions in fuel markets and adverse economic scenarios after 2011 changed the behavior of consumers, and ultimately the behavior of drivers, requiring such estimates to be updated. This report estimates the following curves (equations 21, 22, and 23) based on observational data obtained from annual vehicle emission inspections.

For gasoline cars:

$$\begin{aligned} IntUse &= 0.6716age^3 - 49.566age^2 + 799.66age + 11266 \\ IntUse &= 6,174 \text{ if the vehicle has over 40 years} \end{aligned} \tag{21}$$

[25]One of the first government reports to provide detailed information on vehicle emissions was the MMA (2011).

For ethanol cars:

$$IntUse = -3.292age^3 + 174.31age^2 - 3083.6age + 31628$$
$$IntUse = 8,275 \text{ if the vehicle has over 28 years} \tag{22}$$

For flex-fuel cars:

$$IntUse = -24.288age^3 + 426.19age^2 - 2360.4age + 19178$$
$$IntUse = 15,000 \text{ if the vehicle has over 8 years} \tag{23}$$

Where $IntUse$ represents the average expected VKT per year.[26] Notice that the estimated value for flex-fuel is a general metric, that doesn't specify which fuel (ethanol or gasoline) is used or in which proportion. These numbers have been used in several reports over the past ten years. It is possible to calculate, based on these VKT estimates, the total amount of pollution based on equation 17. Taking a step back, I used the estimated value for the fleet, data on fuel economy, and based on equation 20 I retrieved the required fuel volume that would accommodate an intensity of use according to the estimations from the CETESB.

Figures 9.13 and 9.14 show the estimated volumes for gasoline and ethanol using equation 20 against the realization of such fuels. I used equation 20 to estimate fuel volumes based on fleet estimates using Susep and Anfavea fleet numbers. For gasoline, Anfavea shows a better fit up to 2017, although it shows some moments of scarcity or excess of fuel. Both series overestimated by a large amount after 2017. Ethanol volume presents considerable overestimation when using either fleet since 2010, with a significant underestimation between 2006 and 2009.

These disparities evidence the challenge of using the VKT based on past estimations

[26] Intensity of use and VKT terms are used interchangeably in this work.

without considering changes in the automobile and fuel markets. For the Brazilian case, among the features that could explain such disparities is the gasoline price ceiling that occurred between 2011 and 2014, which made gasoline more cost-efficient than ethanol during this period. After 2015, the international price parity for fuels introduced by the federal government increased fossil fuel prices considerably, being another potential factor to explain the divergence, especially after 2017.

I corrected this disparity by calibrating the intensity of use to make both estimated volume and effective fuel volumes match. In other words, I supposed the distribution of the VKT would remain the same among vehicles of different technology and different ages, but adjusted the level of the VKT to match the gasoline and ethanol effectively consumed from 2003 to 2020. Even though the original work was based on Anfavea's estimation of the fleet, I used Susep estimates for recent years. I also supposed the estimated VKT for flex-fuels was based on using only gasoline and created the potential kilometers traveled if consumers were pumping only ethanol using the relationship between VKT for gasoline cars and VKT for ethanol cars.

The fleet estimation used information from both the Anfavea and Susep databases. From Anfavea, I obtained vehicle licensing numbers before 2003 by fuel type. From Susep, I obtained information on insurance contracts for new cars, i.e., cars with less than one year of usage.[27] I restricted the insurance database to obtain information from contracts of at least 12 months with no claims that could induce an anticipated end of the contract. Using this method, I eliminated any duplicated observation, retaining almost 59 million new cars from 2002 to 2003. The current fleet curves used for these estimations took into consideration the survival rate curve estimated by Mattos and Correia (1996), adjusted by turnover estimations during the IPI sales tax reduction years.

Pollution information was obtained from a set of official reports and their respective

[27] Anfavea is the most reliable source for vehicle licensing, and it is widely used for fleet estimation. However, some studies claim these numbers may underestimate the current fleet-level because not all vehicles keep an active license. In addition, Anfavea reports information from associated manufacturers, and, since 2006, many new producers entered the Brazilian market, which can induce disparities with Anfavea's estimates.

updates (see MMA (2011), MMA (2013), CETESB (2019)). This work focuses on three different pollutants: carbon dioxide (CO_2), methane (CH_4), and oxide nitrous (N_2O). The complete table with pollutant levels by vehicle vintage and fuel type can be seen in CETESB (2011).

The counterfactual volume and market shares for gasoline and ethanol were obtained using the fuel demand model (equations 15 and 16). I simulate three types of scenarios: (i) *flex-fuel cases*, decomposing the effect among fuel improvement, pollution emission reduction, and increased usage of ethanol, (ii) *all-in scenarios*, supposing flex-fuel consumers would buy only gasoline or only ethanol, and (iii) *price scenarios*, investigating the potential negative effects of the gasoline price ceiling. A summary of each simulation is described below.

Same Emission Factors: supposes the level of pollutant per kilometer traveled by flex-fuel vehicles is kept constant and equal to the gasoline-driven cars. In other words, no catalytic converters or any new flex-fuel-specific technology is considered.

Same Fuel Economy: supposes flex-fuel vehicles do not present fuel economy improvements, keeping the same level of fuel economy as gasoline-driven cars.

No Flex-Fuel, Same Stats: supposes no flex-fuel has ever been released. In this scenario, the full flex-fuel fleet is supposed to be gasoline-driven cars, retaining their fuel economy and pollution emission levels.

All-in Gasoline: supposes flex-fuel vehicle owners use only gasoline and no ethanol. For this scenario, I used the baseline VKT estimated by flex-fuel vehicles using ethanol and converted it to additional gasoline volume.

All-in Ethanol: supposes flex-fuel vehicle owners use only ethanol and no gasoline. For this scenario, I used the baseline VKT estimated by flex-fuel vehicles using gasoline and converted it to additional ethanol volume.

Constant Federal Taxes: supposes no federal tax reduction, keeping CIDE tax constant at the levels pre-2011 intervention.[28]

US Prices: supposes Brazilian prices follow US price changes.[29]

US Prices + Constant Taxes: : combine both price scenarios.

All simulated scenarios are expanded to represent Brazil's total number of municipalities and obtain an estimate of total pollution emitted at the national level. This adjustment is made by multiplying the estimated volume by the actual consumption and dividing it by the baseline volume, to account for some overestimation of the AIDS models. The external validity of the model relies on the fact that the 691 municipalities come from the ANP price survey set, which is chosen to be a representative sample for each state. In addition, these municipalities comprise around 70% of the total fuel consumed in Brazil in any given year.

Table A.14 shows the results for each of the simulated flex-fuel scenarios at the national level. The top three rows show the amount of pollution effectively emitted by passenger cars between 2003 and 2020, and the split due to gasoline or ethanol usage. Next, we can see the estimative from the baseline AIDS model. On average, the model overestimates the total volume by about 3.6%, which is consequently reflected in the pollution estimates. All subsequent simulations will be compared to these baseline estimates. I will focus the description of the results on CO_2 emissions, but interesting aspects can also be inferred from CH_4 and N_2O emissions. In terms of magnitude, though, while the former represents approximately 95% of all greenhouse gas emissions, the last two represent 3% to 5% of emissions.

[28] Federal taxes have been used since the beginning of the 2000s as gasoline price instruments to minimize price fluctuations (see figure 9.10). This scenario I constructed keeps any tax policy done before 2011, and suppose the reduction after 2011 (during the explicit price control policy) does not occur. This assumption keeps the federal tax CIDE constant after 2011. CIDE is a federal tax related to infrastructure investments and other environmental projects linked to transportation and petroleum usage. It has been mostly used to regulate fuel markets, promote cleaner technologies, and minimize fuel price oscillations.

[29] Pre-2011 intervention, Brazilian prices used to follow US prices, on average. Petrobras' price policies were used to minimize oil price oscillations while keeping domestic oil prices close to the average US price trend (see figure 9.9).

The first flex-fuel decomposition scenario refers to a situation with no changes in the emission factor for this technology. It is important to highlight that the emission factors, measured in grams per kilometer traveled, can change mainly due to two aspects: an improvement in the fuel economy, which will reduce the amount of fuel burnt by kilometer, and the development of better catalytic filters and other technology that mitigate pollution emissions. Fuel economy improvements can have an additional impact, a potential rebound effect, inducing individuals to drive more. I cannot disentangle both fuel economy effects with the pollution emission factors available. Therefore, the first flex-fuel scenario supposes there are fuel economy enhancements, but that individuals adjust their VKT to compensate for the reduced emissions.

The second flex-fuel scenario represents the situation where no fuel economy improvements have been made. In particular, this scenario can be thought of as no fuel economy enhancement that induces changes in the VKT. Both scenarios show a significant increase in pollution emitted by ethanol, but almost no changes in the total CO_2 emissions (-0.8% and -1.3% respectively). This occurs because the average emission factors by gasoline have not changed much from mono to bi-fuel technology, but it has diminished significantly on flex-fuel using ethanol.

The last flex-fuel scenario refers to the hypothetical case in which flex-fuel vehicles were not invented, and the entire FFV fleet was running on gasoline. The first relevant difference in this scenario is the volume consumed by ethanol, which falls 54% compared to the baseline, increasing gasoline consumption by 14.8%. Emission factors and fuel economy are kept the same as gasoline vehicles. The total amount of CO_2 emitted is reduced by 2.9%.

Table A.15 shows scenarios in which drivers consume only gasoline or ethanol. In the first case, the total amount of ethanol consumed falls over 80% and is restricted to the declining fleet of ethanol-driven vehicles.[30] The total amount of CO_2 is predicted to increase by 28.4%. If, instead, all consumption from flex-fuel vehicles is directed to ethanol, the increase in CO_2

[30]Production of new ethanol-driven vehicles stopped by 2006. Sales after this period comprise stored production from previous years.

emission is around 25%, with a substantial decrease of the emission by gasoline-driven cars (-49.2%). Ethanol emits approximately 25% less CO_2 than gasoline, but the volume necessary to keep the same VKT increases ethanol consumption by approximately 40%.

Finally, table A.16 shows alternative price scenarios. These are potential counterfactuals for the price ceiling policy implemented in Dilma Rousseff's government between 2011 and 2014. The first of these scenarios supposes that federal taxes are kept constant at the level of January 2011. The second scenario supposes gasoline prices follow the same variation as US gasoline prices. The third scenario combines both constant federal taxes and US price variations. The impact of the price scenarios is significant. In the first, we observe a 13.5% increase in ethanol usage, while the scenario using US price variations increases ethanol consumption by 33%. Overall CO_2 emissions fall only marginally (-0.3% with constant taxes and -1.3% with US price variation).

Focusing only on the local pollution emissions, switching from gasoline to ethanol provides only a marginal reduction in carbon emissions. In addition, ethanol combustion creates more aldehydes, which under specific weather conditions, usually found in large centers such as São Paulo and Rio de Janeiro, can be transformed into ozone pollution.

The advantage of using ethanol as a fuel source relies upon its almost neutral CO_2 impact when we consider the carbon absorption from the sugarcane crops (Pinguelli-Rosa and Kahn-Ribeiro (1998)). Dias De Oliveira, Vaughan and Rykiel (2005) and Pinguelli-Rosa and Kahn-Ribeiro (1998) highlight the relevance of the source of the sugarcane crops. In the case new plantations arise from deforestation or induce fire to clean the soil, the net result may become negative. Sugarcane crops in regions of natural pasture may lead to zero neutral effects. Modern agriculture techniques and advancements in plantation may reduce the negative effects associated with production, distribution, and water and land use. Since the majority of Brazilian sugarcane comes from the south-southeast regions, using natural pastures and used lands (not new deforestation), I will consider, for this work, a zero net effect, with crops reabsorbing all carbon emitted from the combustion of ethanol.[31]

Taking into account the neutral effects of ethanol, we can summarize the net effect for each scenario as in table A.17. The first column summarizes the total CO_2 equivalent emissions considering all sources studies (carbon dioxide, methane, and nitrogen dioxide). The improvement of fuel economy and emission factors have a similar CO_2 reduction, of approximately 10%. The introduction of flex-fuel vehicles avoided the emission of 149.3 billion tons of carbon dioxide, or 28% of the baseline scenario. Having all flex-fuel vehicles consuming only gasoline would represent an increase of 228.5 billion tons of CO_2, or 63% increase. Consuming only ethanol, on the other hand, would avoid the emission of 961 billion tons, or 172% of the emissions in the baseline.

Price instruments have limited effect compared to the flex-fuel technology. Considering the combined US price variation and constant federal taxes, the price ceiling policy has been responsible for the additional emission of approximately 137 billion of CO_2 or 34% of the baseline scenario. One interesting aspect here is the fact that the four years with the price ceiling policy were almost enough to offset the full impact flex-fuel vehicles had, from 2003 to 2020, in reducing emissions (137 billion vs 149 billion). This result shows how important price policies are with respect to countering greenhouse gas emissions. Policies that drive consumers away from cleaner energy sources can have adverse consequences, offsetting years of environmental policies. Especially when discussing fossil fuels, consumers are very responsive to price incentives and will easily switch back to more pollutant sources if they present better cost-benefits.

7 Conclusion

This paper examines the introduction of flex-fuel technology in Brazil and investigates the potential carbon dioxide emissions avoided under some scenarios. Regarding the release of

[31]for a precise comparison, it would be necessary to account for emissions on extraction, production, and distribution of fossil fuels as well. This could be a topic for further investigations in future work.

the new technology, I focus on measuring the diffusion of flex-fuel vehicles and estimating the price sensitivity of the turnover of the fleet. This measure captures not only the scrappage of old vehicles but also early replacement, which accelerates the spread of the new technology among consumers.

I found that turnover effects for the Brazilian automobile market are significantly weaker than scrappage effects for developed countries. This result highlights how much less sensitive consumers in emerging countries are to car price changes. For every one percent reduction in used car prices, the turnover rate increases by 0.40, on average. This reflects the limited access to credit and high levels of income inequality. Such results may help guide policy-makers in designing more appropriate mechanisms aimed at the scrappage of old and more pollutant vehicles or at incentivizing newer technology and cleaner cars.

Next, I estimate a structural fuel demand model based on an almost ideal demand system. I show how the price elasticity of gasoline and ethanol changed from inelastic (-0.47 and -0.50, respectively) to elastic (-2.18 and -3.67) after the introduction of flex-fuel technology. This change occurred due to the increased degree of substitutability of both fuels, since consumers do not need, anymore, to lock into a determined fuel type by the time of purchase of a vehicle, but instead can choose either fuel when pumping. This result highlights some important aspects of multi-fuel vehicles: competing energy sources increase the set of consumer choices, potentially increasing their welfare, and minimizing risks associated with a shortage of supply of any specific fuel.

These demand models were used to simulate a series of scenarios comprising flex-fuel aspects, fuel choices by consumers, and alternative gasoline price policies. Regarding flex-fuel simulations, I show how fuel economy and emission factor improvements were responsible for approximately 10% of the decrease of CO_2 emissions. The overall impact of flex-fuels, i.e., the substitution of part of the gasoline for ethanol avoided 149 billion tons of CO_2 or 28% of the predicted level of emissions. The scenario with all flex-fuel vehicles consuming ethanol would promote a reduction of 961 billion tons of CO_2, while alternative price scenarios replacing the gasoline price ceiling policy would avoid approximately 137 billion tons of CO_2.

It is essential to highlight that those results rely on the fact that sugarcane crops offset nearly all ethanol combustion. It does not take into account emissions related to preparing the soil and harvesting, producing, and distributing ethanol. As largely discussed in the literature, these aspects can be relevant in determining the extent of greenhouse gas emission neutrality of ethanol. When crops replace natural pastures and abandoned lands, the overall impact is neutral and ethanol is a viable renewable alternative. If the land used comes from deforestation or accompanied by fire to clean up the terrain, absorption of carbon dioxide by the sugarcane crops may not offset all environmental degradation. .

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8 Tables

Table A.1: Descriptive Statistics - Insurance Database

	Mean	**SD**
Vehicle contracts	14,677,404	4,779,277
Personal usage	10,333,218	2,833,053
Work usage	4,344,185	2,363,213
Average total loss per year	86,452	20,389
Vehicles by fuel-type:		
Gasoline	5,068,637	2,273,015
Ethanol	45,157	50,315
Diesel	532,665	348,365
Flex-fuel	9,528,887	6,004,859
Electric	154	138
Hybrid	6,082	10,008
Vehicles by type:		
Passenger cars	13,140,203	4,190,694
Pickups	1,255,397	556,786
Other light commercials	281,804	85,290
Average driver age	12,527,663	3,534,986
Females	5,263,271	1,735,469
Males	6,909,811	1,970,456
No gender identified	2,504,322	1,227,785
Number of vehicle versions	3,312	1,269
Number of makers	71	11

Notes: Values represent summary statistics for all unique privately insured contracts over the period 2002-2020. Other light commercial vehicles include vans, small cargo vehicles, and micro-buses. The first time a hybrid car was ever insured in Brazil happened in 2010, while the first electric happened in 2014. Total loss accounts for vehicles that went through accidents with no possibility of repair (total loss accidents), thefts, or fire.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1: Turnover Rates and Used Car Prices by Age

	All Vehicles			All Vehicles			All Vehicles	
Age (years)	Turnover Rate (percent)	Car Price ($ Reais)	Age (years)	Turnover Rate (percent)	Car Price ($ Reais)	Age (years)	Turnover 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 turnover rates and vehicle prices. Trucks, buses, and motorbikes are not included in the analysis.

Table A.2: Effect of Fuel Prices on Used Car Prices

	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 A.3: Used Vehicle Price Elasticity of Turnover

	Model 1 Main	Model 2 IPI tax	Model 3 up to 10 years	Model 4 above 10 years
Panel A: OLS models for cars				
Turnover Elasticity	-0.1116***	-0.0973***	-0.0573*	-0.1465***
	(0.0202)	(0.0210)	(0.0313)	(0.0261)
Turnover 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				
Turnover Elasticity	-0.4337***	-0.4035***	-0.3933***	-0.3014***
	(0.0678)	(0.0655)	(0.0802)	(0.0753)
Turnover 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				
Turnover Elasticity	-0.5493***	-0.4911***	-0.4657***	-0.3378***
	(0.0520)	(0.0510)	(0.0593)	(0.0698)
Turnover 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 turnover rates. Turnover elasticity represents the elasticity of turnover used in car prices. The instrument 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 interacted with prices to estimate any salience effect from the tax policy. In the 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 A.4: Used Vehicle Price Elasticity of Turnover

	Full Sample		Excluding 2009, 2012-2014	
	Cars	All Vehicles	Cars	All Vehicles
Introduction (2003 to 2006)				
Turnover Elasticity	-0.4205***	-0.4013***	-0.4345***	-0.4609***
	(0.0661)	(0.0555)	(0.0713)	(0.0611)
Diffusion (2007 to 2010)				
Turnover 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)				
Turnover 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)				
Turnover 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 turnover rates. Turnover elasticity represents the elasticity of turnover used in car prices. The instrument 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) 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 2009 and 2012 to 2014, which represent years when the federal government implemented reduced sales taxes for new vehicles. Besides cars, regressions from the columns "all vehicles" also include pickups, vans, minibusses, 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 A.5: Used Vehicle Price Elasticity of Turnover

	All ages	Age 1-5	Age 6-9	Age 10-14	Age 15+
Panel A: OLS, Cars					
Turnover 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					
Turnover 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					
Turnover 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 turnover rates by age group. The turnover elasticity represents the used car price elasticity of turnover. The instrument used for car prices is fuel prices weighted by vehicle efficiency. In the third panel, regressions also include pickups, vans, minibusses, 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 A.6: Used Vehicle Price Elasticity of Turnover by Usage

Panel A: Turnover 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: Turnover 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 turnover rates. Turnover elasticity represents the elasticity of turnover used in car prices. The instrument used for car prices is fuel prices weighted by vehicle efficiency. The first panel represents vehicles registered for firm use. The second panel is registered for personal use. These regressions include all vehicles, i.e., cars pickups, vans, minibusses, 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 A.7: Used Vehicle Price Elasticity of Turnover by Gender

	Model 1 Male	Model 2 Female
Panel A: OLS models for cars		
Turnover Elasticity	-0.0488*	-0.0586**
	(0.0268)	(0.0222)
N	23,871	28,144
Panel B: IV models for cars		
Turnover 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		
Turnover 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 turnover rates by gender. Turnover elasticity represents the elasticity of turnover used in the car prices. The instrument used for car prices is fuel prices weighted by vehicle efficiency. Third-panel regressions also include pickups, vans, minibusses, 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 A.8: Used Vehicle Price Elasticity of Turnover for Cars

	Model 1	Model 2	Model 3	Model 4
	18 to 24	25 to 44	45 to 64	64 or more
Panel A: Turnover Elasticity - Cars				
Turnover 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: Turnover Elasticity - Cars				
Turnover Elasticity	-0.3572***	-0.3601***	-0.1706*	-0.1426
	(0.1293)	(0.0878)	(0.0975)	(0.1453)
Turnover 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
Turnover 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
Turnover Rate (percent)	24.8	26.6	21.2	14.7

Notes: The dependent variable is vehicle turnover rates by driver age group. Turnover elasticity represents the elasticity of turnover used in car prices. The instrument 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 A.9: Fuel Consumption Models

	Model 1	Model 2	Model 3	Model 4	Model 5
		Triple Policy +	Triple Policy +	Double Policy +	Double Policy +
	OLS	Sugar Quality	Sugar Price	Sugar Quality	Sugar Price
Gasoline Equation					
Gasoline Price	-1.4695***	-2.1778**	-2.022**	-2.2172***	-2.0598***
	(0.007)	(0.0105)	(0.0101)	(0.0104)	(0.0098)
Ethanol Price	0.3281***	0.3649***	0.2527***	0.4086***	0.2957***
	(0.0029)	(0.0066)	(0.006)	(0.0067)	(0.0058)
F-Stat		317.65	365.21	255.08	288.73
Ethanol Equation					
Gasoline Price	1.7392**	1.5231**	1.0298**	1.7635**	1.2761**
	(0.0143)	(0.0315)	(0.0292)	(0.032)	(0.0279)
Ethanol Price	-2.7321**	-3.6743**	-3.0663**	-3.8801**	-3.2651***
	(0.0128)	(0.0313)	(0.0285)	(0.0319)	(0.0271)
F-Stat		29.85	36.84	25.14	35.14
N	109,957	106,577	106,577	106,577	106,577

Notes: These elasticities come from the almost ideal demand system, represented by equations 15 and 16. The elasticities take the form of 14. The instrument for gasoline prices accounts for producer prices (Petrobras) added to federal taxes. This price can be adjusted by the percentage of anhydrous ethanol in the final blend (triple policy) or not (double policy). The instrument for ethanol refers to either export sugar prices or the crop-adjusted sugar quality. Instruments for fleet refer to the number of vehicle versions available by fuel type. The F statistic at the bottom refers to the statistic from the first stage of gasoline price.

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

Table A.10: Fuel Consumption Models by Sub-Period

	Model 1 2002 to 2004	Model 2 2002 to 2010	Model 3 2002 to 2014	Model 4 2002 to 2020
Gasoline Equation				
Gasoline Price	-0.4705***	-1.2547***	-1.9754***	-2.1778***
	(0.0191)	(0.0135)	(0.0125)	(0.0105)
Ethanol Price	0.009	0.1824***	0.2816***	0.3649***
	(0.0061)	(0.0058)	(0.0062)	(0.0066)
F-Stat	192.02	359.29	288.01	290.6
N	9,676	48,670	75,155	107,038
Ethanol Equation				
Gasoline Price	0.0139	1.0494***	1.3374***	1.5231***
	(0.0322)	(0.0299)	(0.0318)	(0.0315)
Ethanol Price	-0.5057***	-1.9395***	-3.0981***	-3.6743***
	(0.0256)	(0.027)	(0.0287)	(0.0313)
F-Stat	132.93	49.50	37.03	42.23
N	9,673	48,459	74,704	106,577

Notes: These elasticities come from the almost ideal demand system, represented by equations 15 and 16. The elasticities take the form of 14. The baseline model used for this exercise was model 2 from table A.9. The instrument for gasoline prices accounts for producer prices (Petrobras) added to federal taxes, adjusted by the percentage of anhydrous ethanol in the final blend (triple policy). The instrument for ethanol refers to either export sugar prices or the crop-adjusted sugar quality. Instruments for fleet refer to the number of vehicle versions available by fuel type. The F statistic at the bottom refers to the statistic from the first stage of gasoline price.

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

Table A.11: Fuel Consumption Models - Robustness Check

	Model 1 OLS	Model 2 Triple Policy + Sugar Quality	Model 3 Triple Policy + Sugar Price	Model 4 Double Policy + Sugar Quality	Model 5 Double Policy + Sugar Price
Gasoline Equation					
Gasoline Price	-1.4695***	-2.3219***	-2.1801***	-2.3381***	-2.1813***
	(0.007)	(0.01)	(0.0094)	(0.0099)	(0.0092)
Ethanol Price	0.3281***	0.5473***	0.4497***	0.5754***	0.4657***
	(0.0029)	(0.0058)	(0.005)	(0.006)	(0.0049)
F-Stat		290.6	322.14	219.8	249.69
Ethanol Equation					
Gasoline Price	1.7392**	2.3673**	1.9663**	2.5244**	2.0699**
	(0.0143)	(0.0284)	(0.0249)	(0.0288)	(0.0245)
Ethanol Price	-2.7321**	-4.5445**	-4.003**	-4.6666**	-4.0615**
	(0.0128)	(0.0275)	(0.0233)	(0.0281)	(0.0229)
F-Stat		42.32	68.90	36.72	62.69
N	109,957	106,581	106,581	106,581	106,581

Notes: These elasticities come from the almost ideal demand system, represented by equations 15 and 16. The elasticities take the form of 14. The instrument for gasoline prices accounts for producer prices (Petrobras) added to federal taxes. This price can be adjusted by the percentage of anhydrous ethanol in the final blend (triple policy) or not (double policy). The instrument for ethanol refers to either export sugar prices or the crop-adjusted sugar quality. Instruments for fleet refer to the number of vehicle versions available by fuel type. For the flex-fuel fleet, the number of vehicle versions was replaced by the 12-month lag of the log of the price ratio. The F statistic at the bottom refers to the statistic from the first stage of gasoline price.

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

Table A.12: Used Vehicle Price Elasticity of Turnover

	Model 1 up to \$400k	Model 2 No Luxury	Model 3 Fuel Increase	Model 4 Excluding 2011-2014
Panel A: IV models for cars				
Turnover 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				
Turnover 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 turnover rates. The turnover elasticity represents the used car price elasticity of turnover. The instrument used for car prices is fuel prices weighted by vehicle efficiency. Second-panel regressions also include pickups, vans, minibusses, 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 A.13: Used Vehicle Price Elasticity of Turnover

Panel A: IV Models						
	Main	Model 2	Model 3	Model 4	Model 5	Model 6
Turnover 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 turnover rates by age group. The turnover elasticity represents the used car price elasticity of turnover. The instrument 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.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.14: Pollution Emissions: Actual Emissions and Flex-Fuel Scenarios

Period: 2003 to 2020 *Pollutants in 1,000 tons*	Carbon Dioxide CO_2	Methane CH_4	Nitrogen Dioxide N_2O	Fuel Volume (Million L)
Pollution Effectively Emitted	1,421,586	8,032	38,194	825,082
with gasoline consumption	1,134,839	5,746	31,289	598,703
with ethanol consumption	286,747	2,286	6,905	226,379
Baseline Scenario (prediction)	1,472,122	8,428	39,428	854,337
(% vs effective)	3.6%	4.9%	3.2%	3.6%
due to gasoline consumption	1,173,791	5,777	32,453	620,088
(% vs effective)	3.4%	0.6%	3.7%	3.6%
due to ethanol consumption	298,330	2,651	6,975	234,249
(% vs effective)	4.0%	16.0%	1.0%	3.5%
Same Emission Factors	1,459,868	8,353	41,484	854,337
(% vs predicted)	-0.8%	-0.9%	5.2%	0.0%
due to gasoline consumption	1,120,857	5,226	34,509	620,088
(% vs predicted)	-4.5%	-9.5%	6.3%	0.0%
due to ethanol consumption	339,012	3,127	6,975	234,249
(% vs predicted)	13.6%	18.0%	0.0%	0.0%
Same Fuel Economy	1,453,144	8,156	37,897	854,337
(% vs predicted)	-1.3%	-3.2%	-3.9%	0.0%
due to gasoline consumption	1,115,302	5,140	31,327	620,088
(% vs predicted)	-5.0%	-11.0%	-3.5%	0.0%
due to ethanol consumption	337,843	3,016	6,571	234,249
(% vs predicted)	13.2%	13.8%	-5.8%	0.0%
No Flex-Fuel, Same Stats	1,429,107	7,386	38,727	819,553
(% vs predicted)	-2.9%	-12.4%	-1.8%	-4.1%
due to gasoline consumption	1,275,103	5,569	35,956	711,861
(% vs predicted)	8.6%	-3.6%	10.8%	14.8%
due to ethanol consumption	154,004	1,817	2,771	107,692
(% vs predicted)	-48.4%	-31.5%	-60.3%	-54.0%

Notes: These scenarios represent a decomposition of the impact of the flex-fuel technology. The first three rows calculate the amount of pollutants effectively emitted by all cars from 2003 to 2020. The baseline scenario represents the fit of the model for the actual emissions. All subsequent scenarios use the fitted scenarios as the base for comparisons. The three flex-fuel scenarios are:

Same Emission Factors: supposes the level of pollutant per kilometer traveled for flex-fuel vehicles is kept constant and equal to the gasoline-driven cars.

Same Fuel Economy: supposes flex-fuel vehicles do not present fuel economy improvements, keeping the same level of fuel economy as gasoline-driven cars.

No Flex-Fuel, Same Stats: supposes no flex-fuel has ever been released. In this scenario, the full flex-fuel fleet is supposed to be gasoline-driven cars, embracing their fuel economy and pollution emission levels.

Table A.15: Pollution Emissions: All-in Scenarios

Period: 2003 to 2020 *Pollutants in 1,000 tons*	Carbon Dioxide CO2	Methane CH4	Nitrogen Dioxide N2O	Fuel Volume (Million L)
Pollution Effectively Emitted	1,421,586	8,032	38,194	825,082
with gasoline consumption	1,134,839	5,746	31,289	598,703
with ethanol consumption	286,747	2,286	6,905	226,379
Baseline Scenario (prediction)	1,472,122	8,428	39,428	854,337
(% vs effective)	3.6%	4.9%	3.2%	3.6%
due to gasoline consumption	1,173,791	5,777	32,453	620,088
(% vs effective)	3.4%	0.6%	3.7%	3.6%
due to ethanol consumption	298,330	2,651	6,975	234,249
(% vs effective)	4.0%	16.0%	1.0%	3.5%
All-in Gasoline	1,889,839	7,813	41,812	1,013,239
(% vs predicted)	28.4%	-7.3%	6.1%	18.6%
due to gasoline consumption	1,527,378	5,108	22,224	973,675
(% vs predicted)	30.1%	-11.6%	-31.5%	57.0%
due to ethanol consumption	57,096	2,705	19,588	39,564
(% vs predicted)	-80.9%	2.0%	180.9%	-83.1%
All-in Ethanol	1,839,409	10,156	37,400	991,724
(% vs predicted)	25.0%	20.5%	-5.1%	16.1%
due to gasoline consumption	596,836	4,703	15,804	310,009
(% vs predicted)	-49.2%	-18.6%	-51.3%	-50.0%
due to ethanol consumption	1,242,573	5,453	21,595	681,715
(% vs predicted)	316.5%	105.7%	209.6%	191.0%

Notes: All-in scenarios refer to the hypothetical cases where all flex-fuel cars would use only gasoline or only ethanol. For these scenarios, the total vehicle kilometers traveled (VKT) by flex-fuel cars were held fixed, and the corresponding fuel volume consumed was converted by the fuel economy into the substitute fuel.

Table A.16: Pollution Emissions: Price Scenarios

Period: 2003 to 2020 *Pollutants in 1,000 tons*	Carbon Dioxide CO2	Methane CH4	Nitrogen Dioxide N2O	Fuel Volume (Million L)
Pollution Effectively Emitted	1,421,586	8,032	38,194	825,082
with gasoline consumption	1,134,839	5,746	31,289	598,703
with ethanol consumption	286,747	2,286	6,905	226,379
Baseline Scenario (prediction)	1,472,122	8,428	39,428	854,337
(% vs effective)	3.6%	4.9%	3.2%	3.6%
due to gasoline consumption	1,173,791	5,777	32,453	620,088
(% vs effective)	3.4%	0.6%	3.7%	3.6%
due to ethanol consumption	298,330	2,651	6,975	234,249
(% vs effective)	4.0%	16.0%	1.0%	3.5%
Constant Federal Taxes	1,467,437	8,487	39,217	859,463
(% vs predicted)	-0.3%	0.7%	-0.5%	0.6%
due to gasoline consumption	1,141,024	5,669	31,526	602,579
(% vs predicted)	-2.8%	-1.9%	-2.9%	-2.8%
due to ethanol consumption	326,413	2,817	7,690	256,884
(% vs predicted)	13.8%	6.3%	10.3%	13.5%
US Gasoline Prices	1,452,505	8,626	38,635	870,149
(% vs predicted)	-1.3%	2.4%	-2.0%	1.9%
due to gasoline consumption	1,057,846	5,423	29,157	557,741
(% vs predicted)	-9.9%	-6.1%	-10.2%	-10.1%
due to ethanol consumption	394,659	3,204	9,479	312,409
(% vs predicted)	32.3%	20.8%	35.9%	33.4%
US Gasoline Prices + Constant Taxes	1,444,201	8,700	38,311	875,823
(% vs predicted)	-1.9%	3.2%	-2.8%	2.5%
due to gasoline consumption	1,012,494	5,286	27,867	533,364
(% vs predicted)	-13.7%	-8.5%	-14.1%	-14.0%
due to ethanol consumption	431,707	3,414	10,444	342,459
(% vs predicted)	44.7%	28.8%	49.7%	46.2%

Notes: This table presents four different gasoline price counterfactual scenarios for the 2011 to 2014 price ceiling policy.

Constant Federal Taxes: supposes no federal tax reduction, keeping CIDE tax constant at the levels pre-2011 intervention.

US Prices: supposes Brazilian prices follow US price changes. Pre-2011 intervention, Brazilian prices were following US prices, on average. Petrobras' price policies were used to minimize oil price oscillations while keeping domestic oil prices close to the average US price trend.

US Prices + Constant Taxes: combines both price scenarios.

Table A.17: Net CO_2 Emissions

Period: 2003 to 2020 *Pollutants in 1,000 tons*	Total CO2 Emitted by Gasoline	Total CO2 Emitted by Ethanol	Net Carbon Emission	% vs Prediction
Pollution Effectively Emitted	1,171,873	295,939	875,935	
Baseline Scenario (prediction)	1,212,022	307,956	904,065	
Same Emission Factors	1,160,592	349,113	811,478	-10%
Same Fuel Economy	1,151,769	347,429	804,339	-11%
No Flex-Fuel, Same Stats	1,316,627	158,593	1,158,035	28%
All-in Gasoline	1,554,710	79,389	1,475,321	63%
All-in Ethanol	617,344	1,269,621	(652,277)	-172%
Constant Taxes	1,178,219	336,921	841,299	-7%
US Gasoline Prices	1,092,425	407,341	685,084	-24%
US Gasoline Prices + Constant Taxes	1,045,647	445,565	600,082	-34%

9 Figures

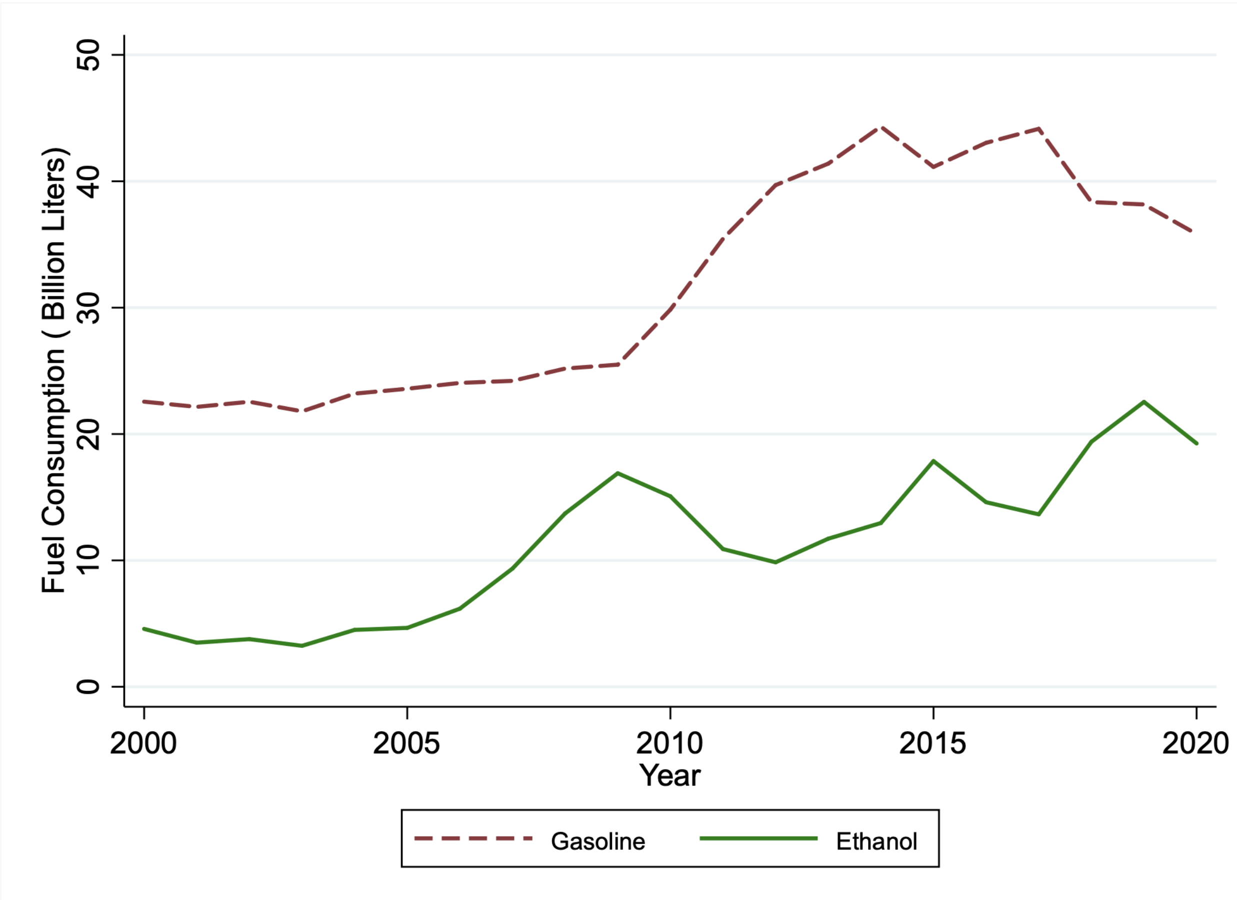

Figure 9.1: Fuel Consumption: Gasoline and Ethanol

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, especially in moments of the gasoline price increase. The graph shows a continuous increase in ethanol consumption up to 2009, the 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.

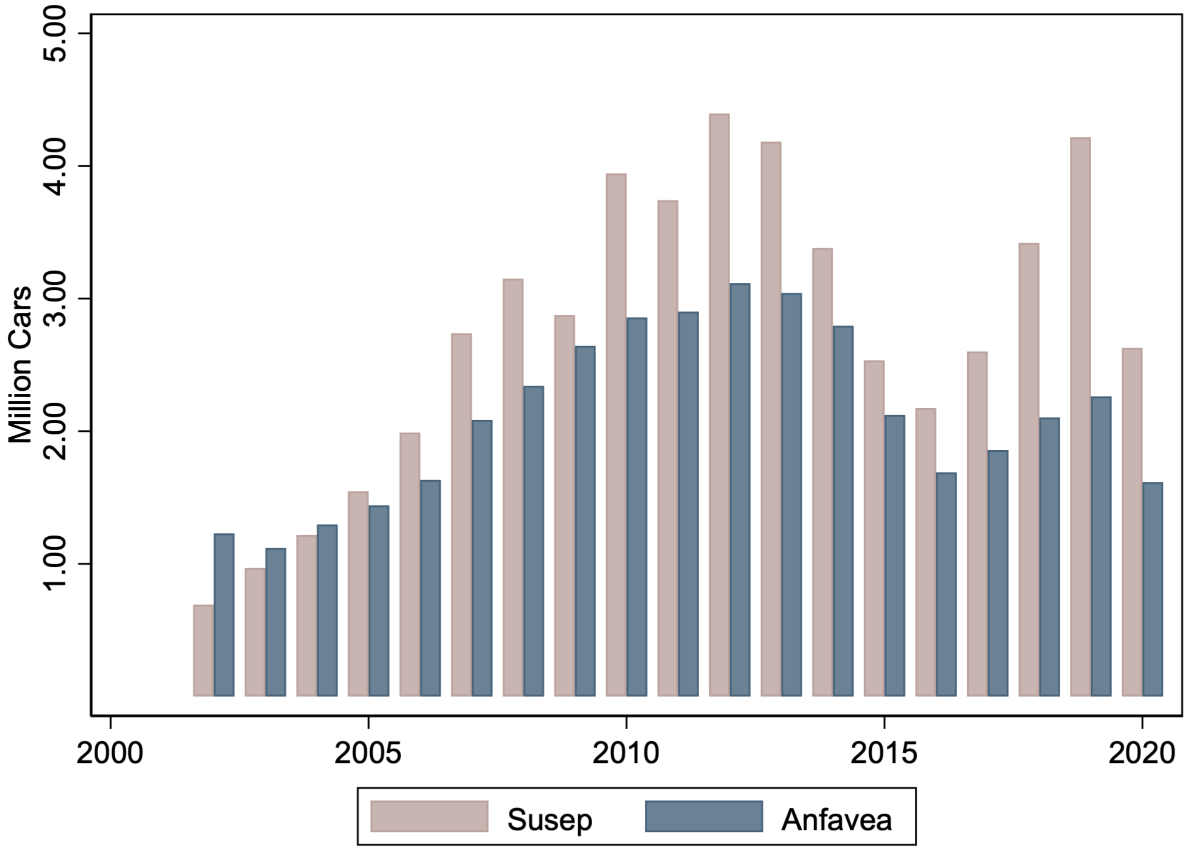

Figure 9.2: Registrations of New Cars: ANFAVEA and SUSEP

Notes: This figure compares the number of new cars in the market for each year between 2003 and 2020. Anfavea numbers come from reports of the members of the Association of Manufacturers, while Susep numbers come from the private insurance database.

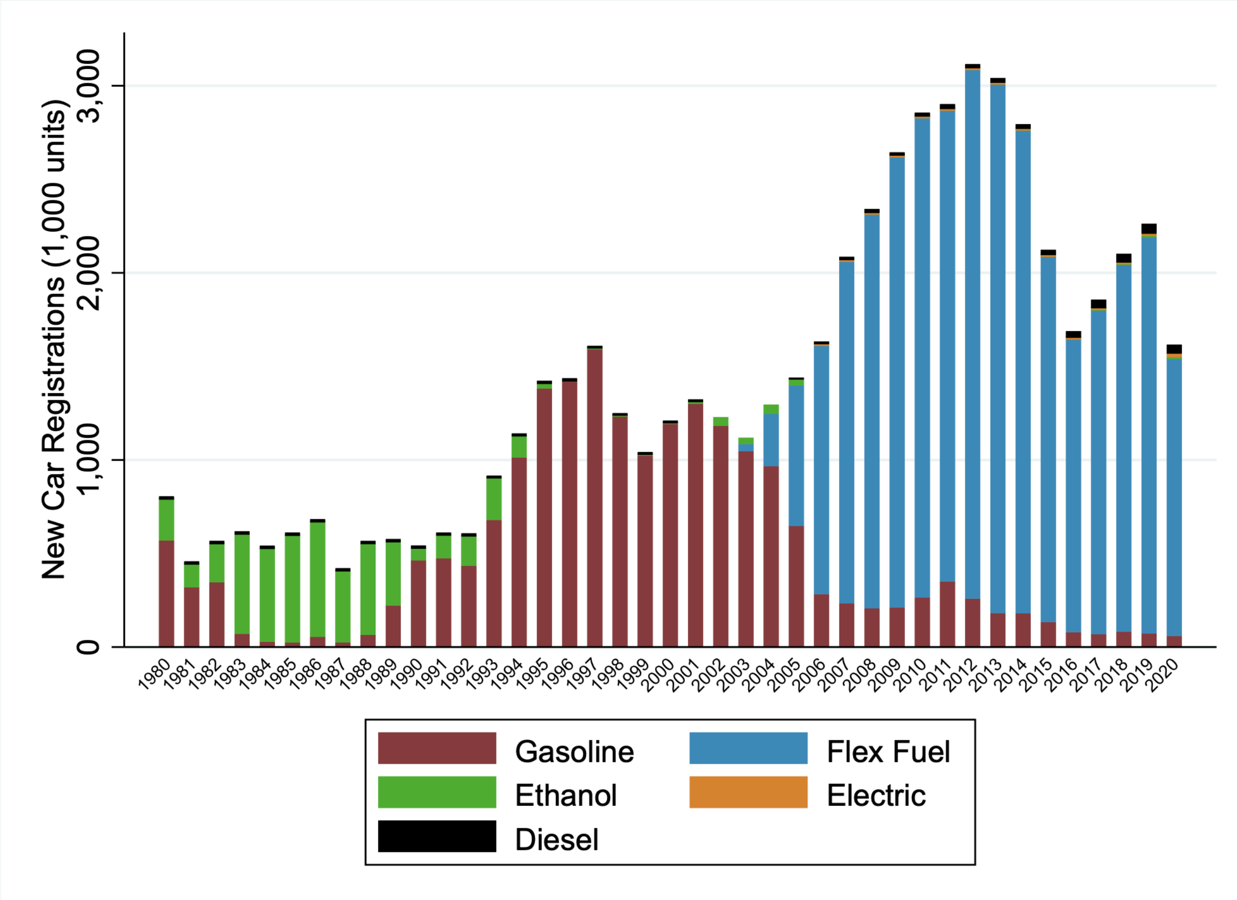

Figure 9.3: Car Registrations by Type of Fuel

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.

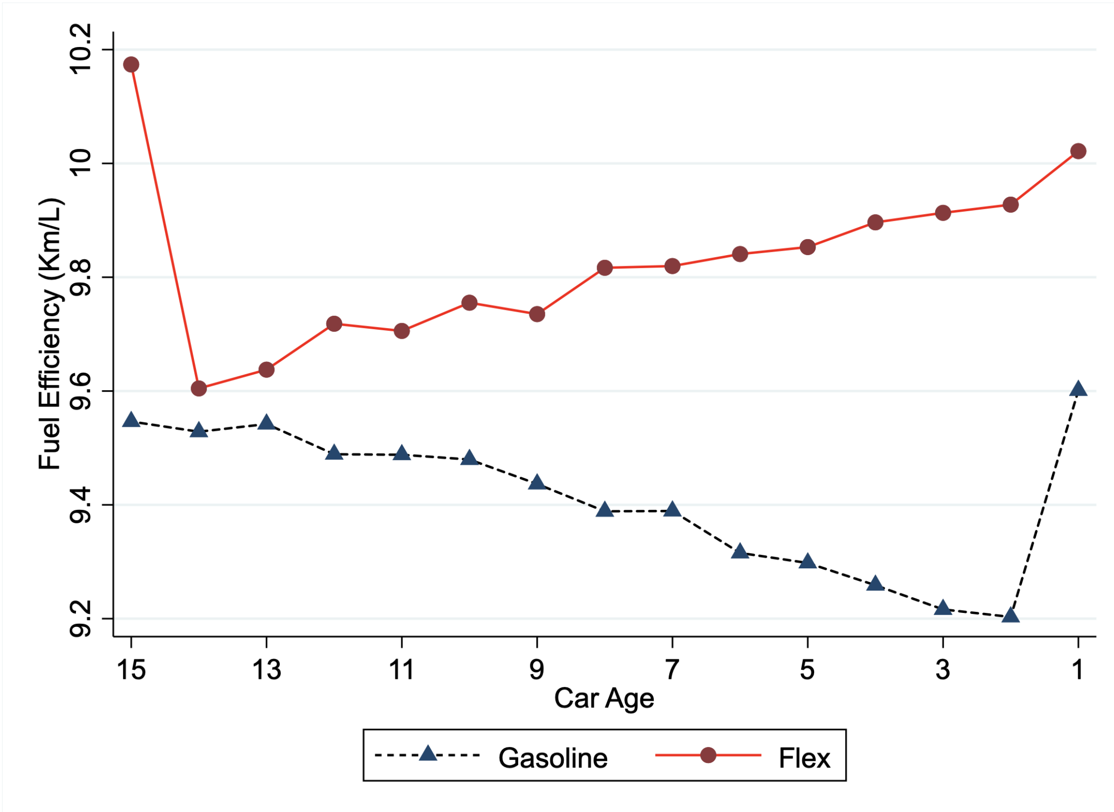

Figure 9.4: Fuel Efficiency of Gasoline and Flex-Fuel Vehicles by Age

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 improve its efficiency over time.

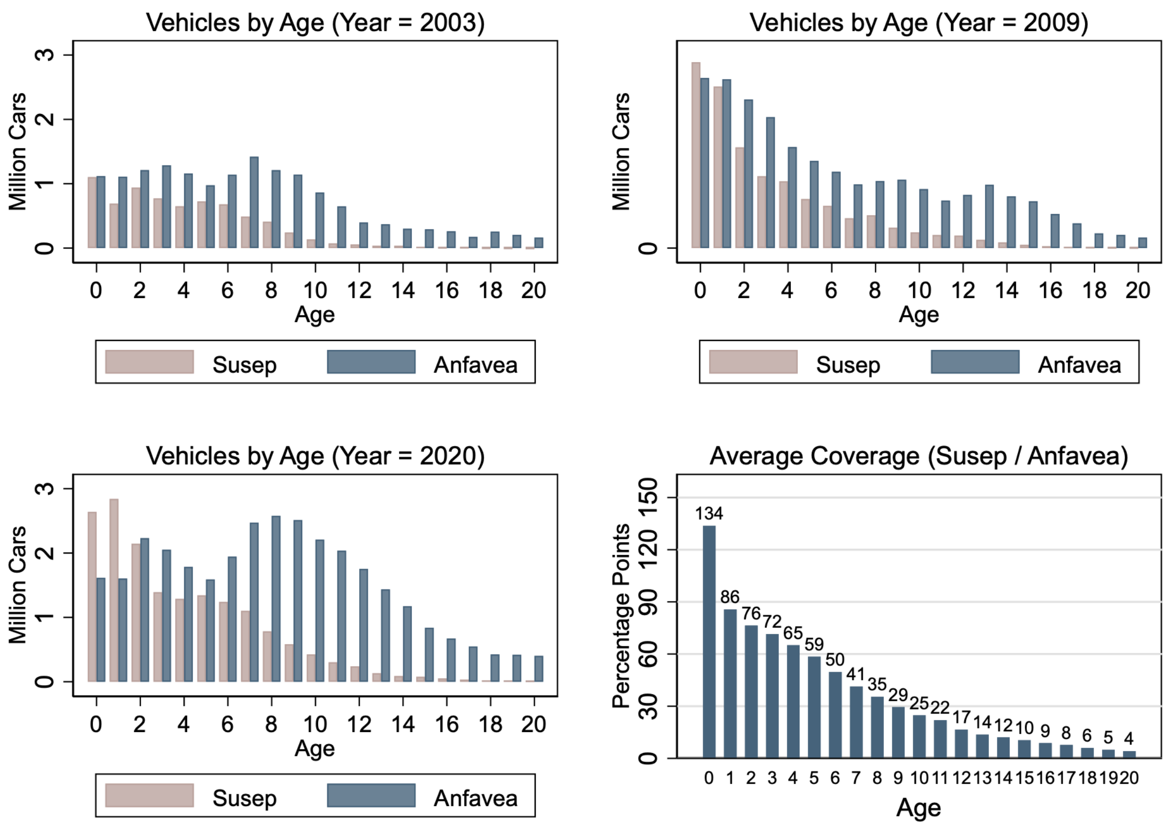

Figure 9.5: Number of Vehicles by Age for Different Years

Notes: This figure displays the evolution of the number of vehicles in the fleet and the number of insurance contracts by age and for different years. Overall, virtually all new vehicles are insured during their first year of usage, diminishing significantly the number of insured vehicles as they age. Cases in which the number of insured vehicles is higher than the estimated fleet using sales records suggest that ANFAVEA records may not contain information from all sales in the market. The last graph shows the average market coverage of insured vehicles by age for the period 2002 to 2020.

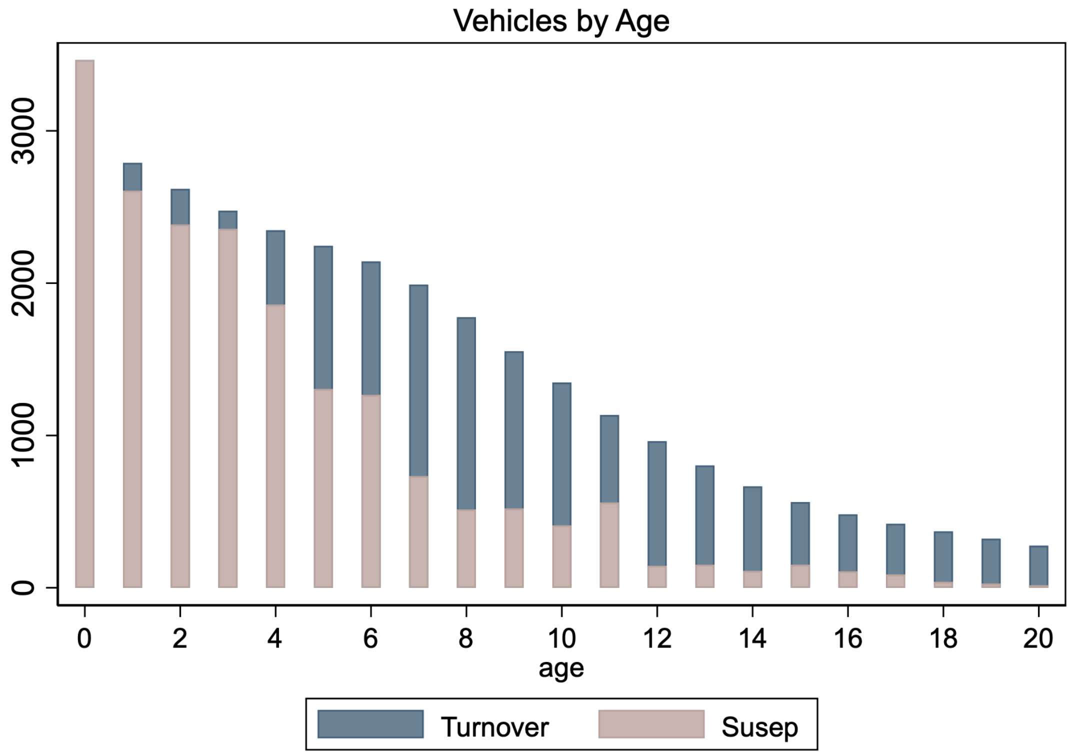

Figure 9.6: Average Turnonver of the Fleet

Notes: This figure displays the average insured vehicles and the expected current fleet, after adjusting for vehicles pre-2002 (ANFAVEA sales records) and using estimations of vehicle survival rates (see Mattos and Correia (1996)). The difference represents the turnover of the insured fleet. Taking into account that new vehicles are virtually 100% insured in their first year, this turnover represents all vehicles that either were scrapped or sold to a non-insured agent. In recent years, after flex-fuel vehicles became the majority of new vehicle sales, this turnover expresses how fast the new technology is spread across the population.

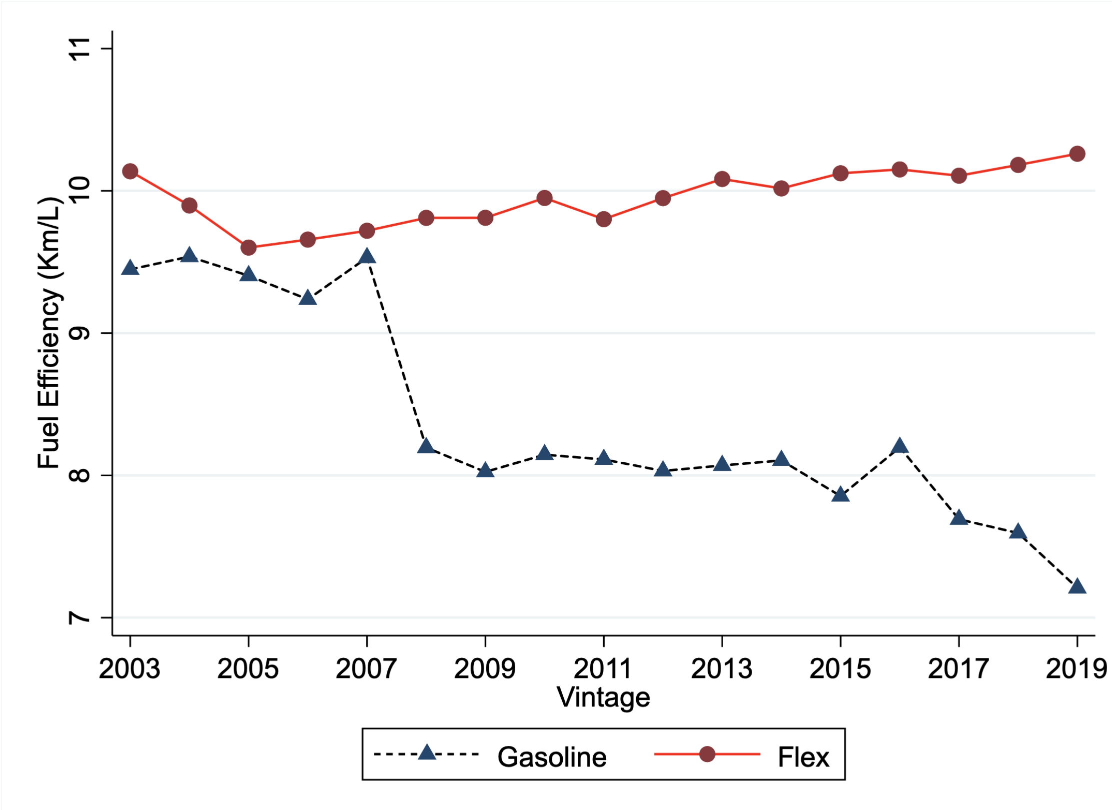

Figure 9.7: Fuel Efficiency of Gasoline and Flex Fuel Vehicles by Vintage

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 was replaced by the bi-fuel vehicles. At this point, the gasoline models left in the market had a significantly lower fuel economy level.

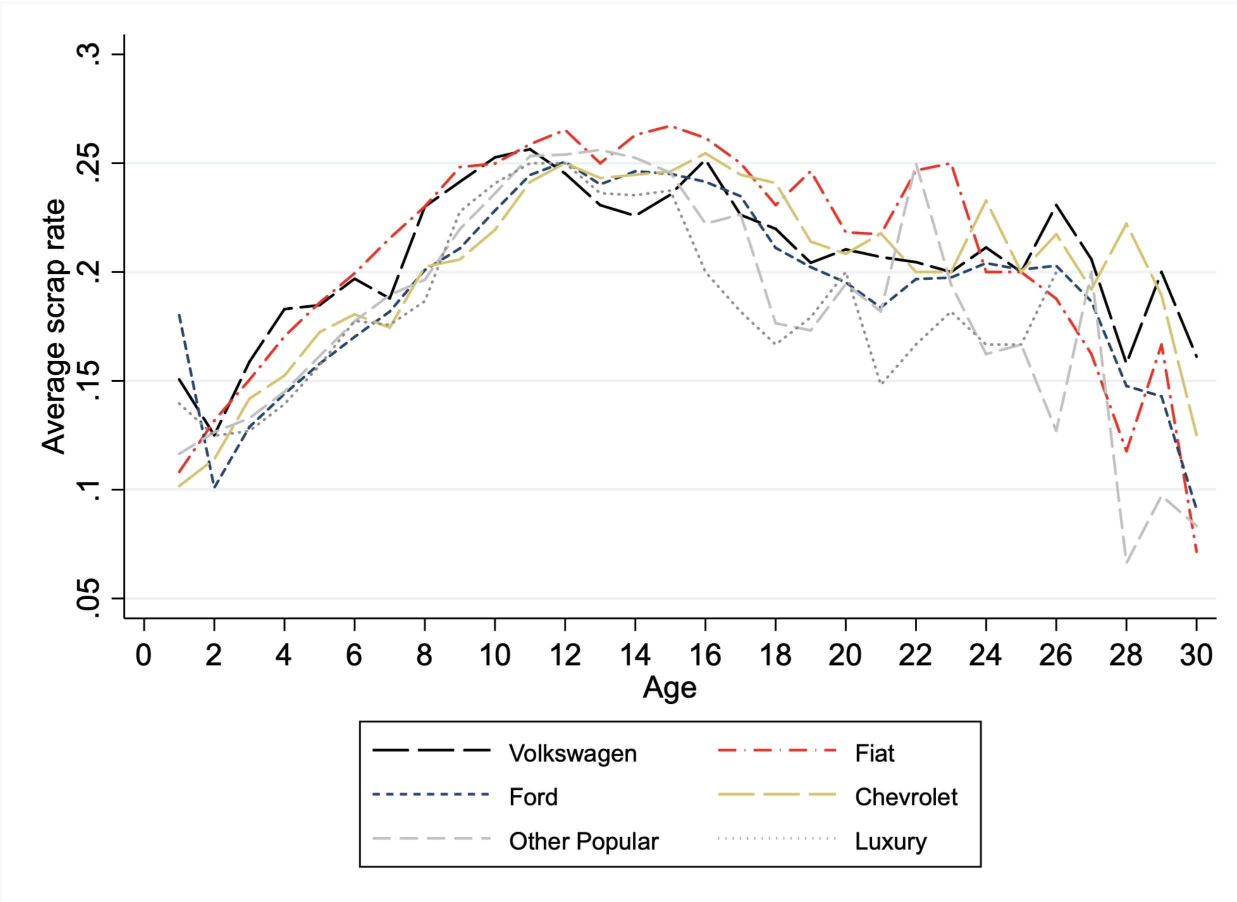

Figure 9.8: Median Turnover Rates by Vehicle Age and Maker

Notes: This figure shows the median scrap rates by vehicle age. Opposite to many other countries, the pattern of turnover rates for Brazil presents a decay after vehicle ages 15 years. This behavior could be associated with 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.

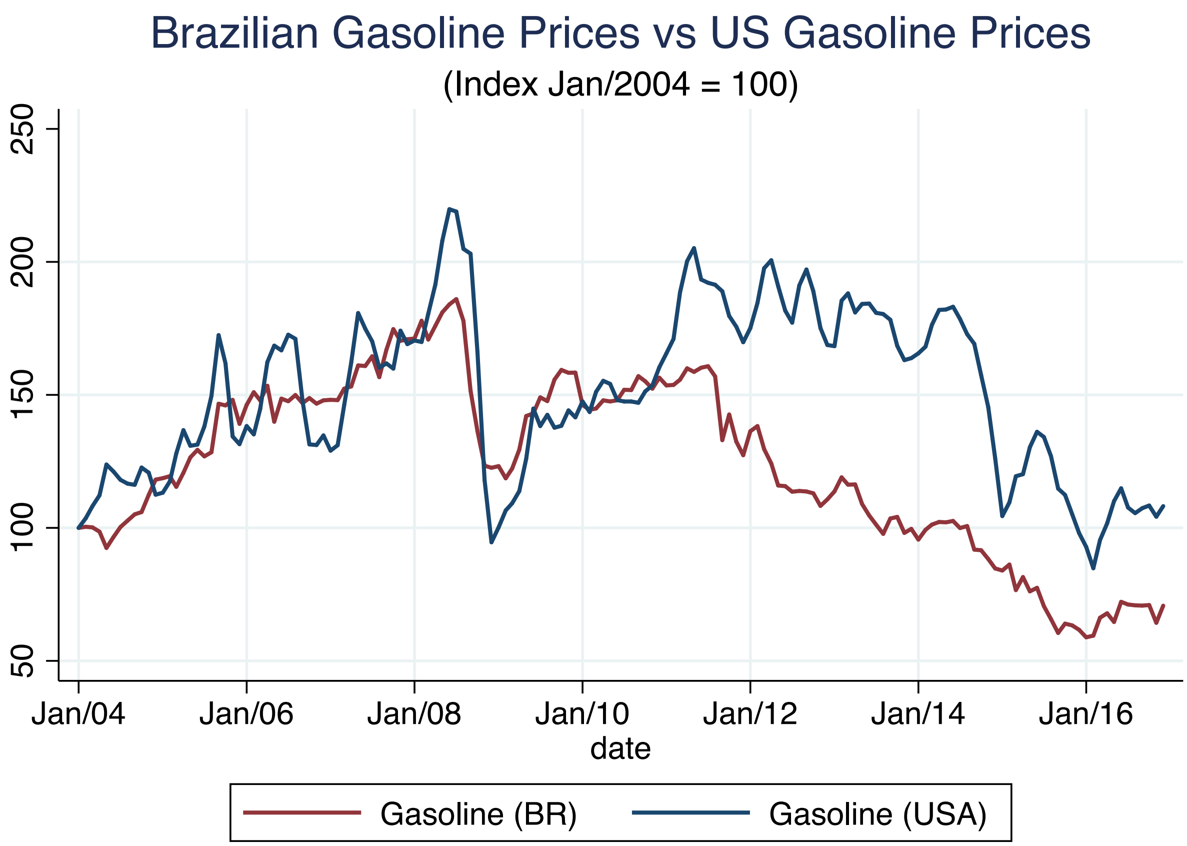

Figure 9.9: Real Gasoline Prices: Brazil and US

Notes: This figure shows the evolution of real gasoline prices for both Brazil and US. Prices were normalized into an index, with a base of 100 in January 2004. Up to the moment of the explicitly (nominal) price ceiling policy in 2011, Brazil's gasoline price used to follow the average of the US prices. Price controls were used to mitigate oscillations in oil prices. After the price ceiling policy, Brazilian gasoline prices remained at an artificially lower level for over 5 years, until the international price parity policy, mostly effective after 2017, reverted this scenario.

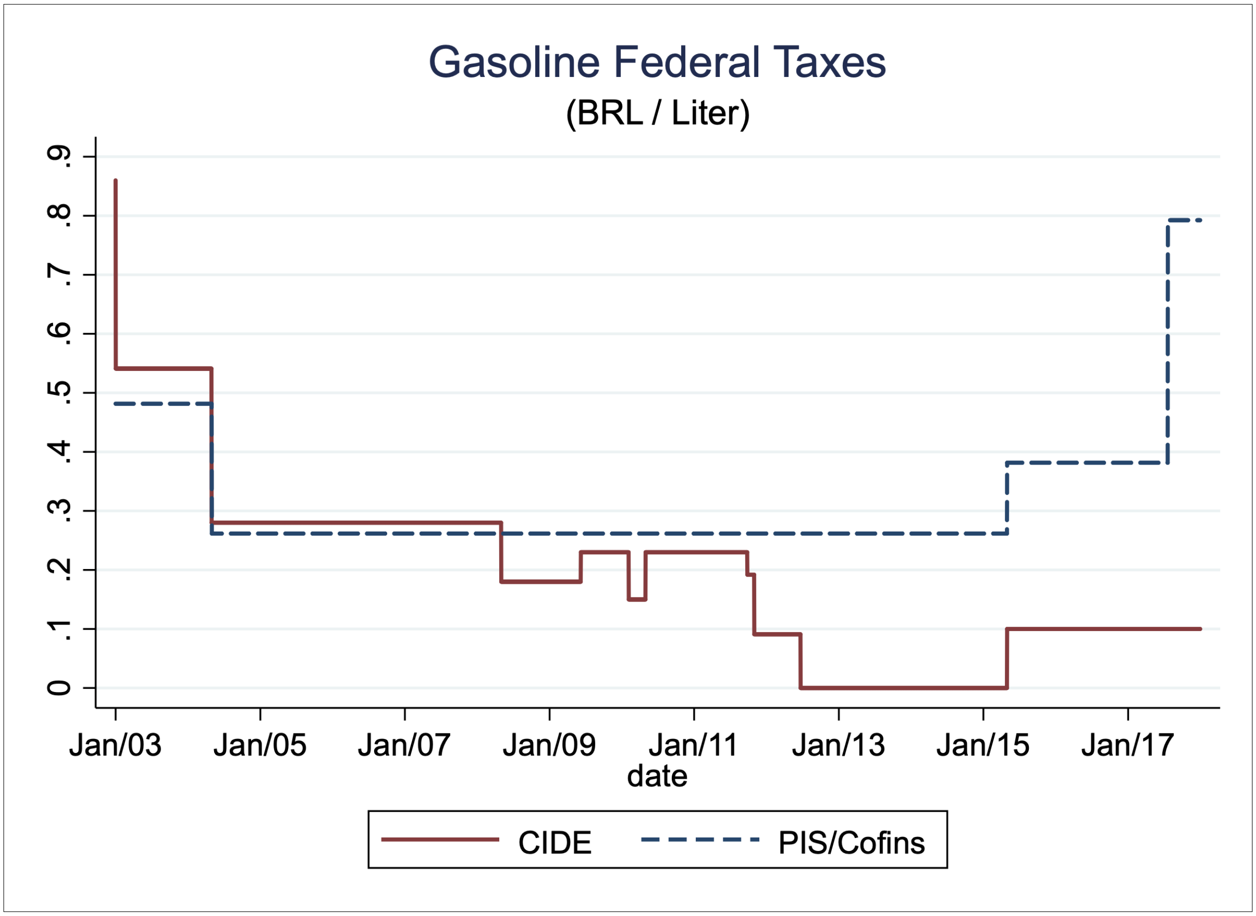

Figure 9.10: Gasoline Federal Taxes in Brazil

Notes: This figure shows the evolution of federal taxes present in gasoline prices in Brazil. The two types of taxes, PIS/COFINS and CIDE, have different purposes. The former is related to social security and other public social assistance programs available to employees. The latter is related to infrastructure investments and other environmental projects linked to transportation and petroleum usage. In practice, both taxes have been used as instruments to control prices and minimize the impacts of oil price oscillations.

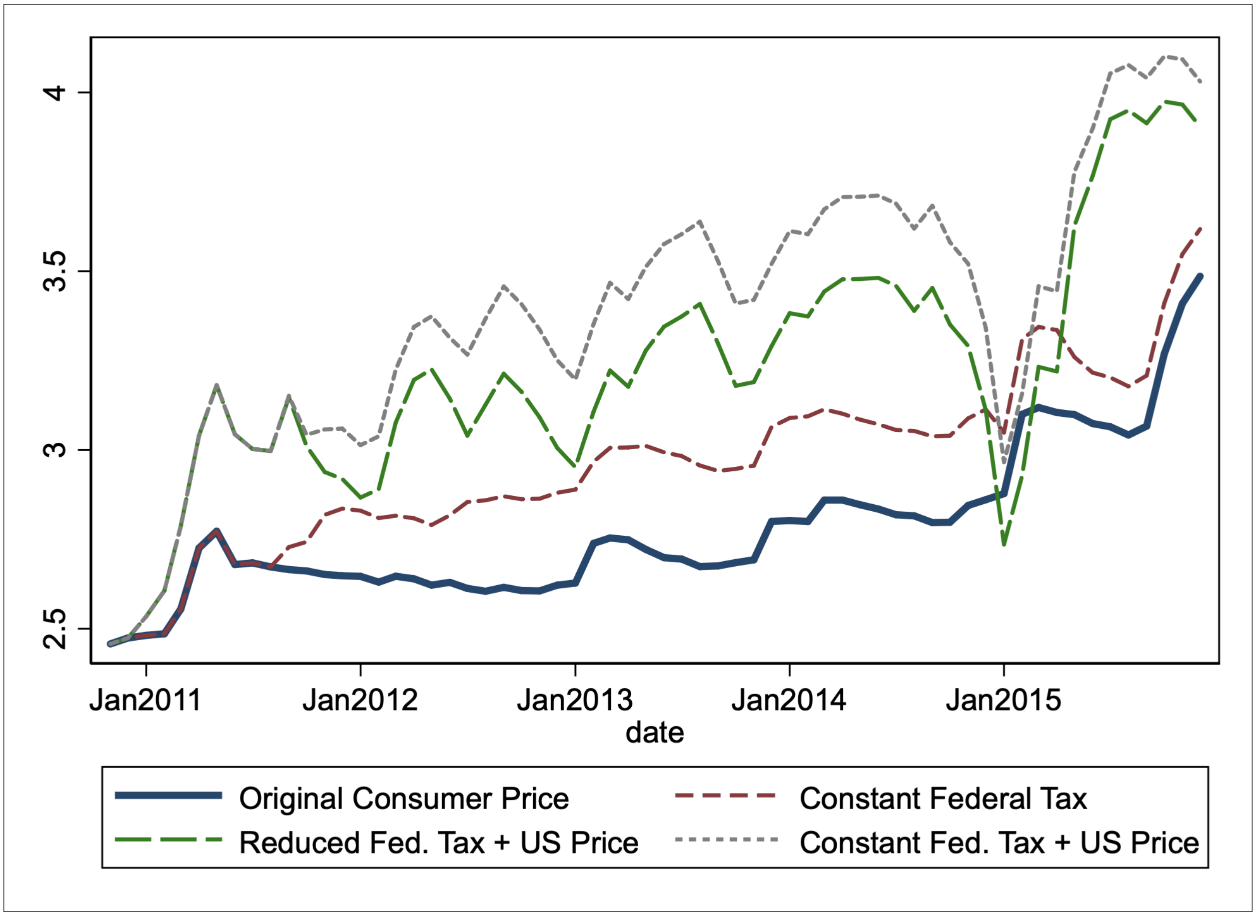

Figure 9.11: Nominal Gasoline Prices - Counterfactual

Notes: This figure shows gasoline price evolution and three counterfactual prices: (i) one considering no federal tax reduction during the period of 2011 to 2014, (2) a second counterfactual adjusting Brazilian gasoline prices to the level of US prices, and (iii) a third gasoline price combining the first two events. These counterfactuals were created to investigate the possibility of the gasoline price ceiling policy (2011-2014) not being implemented.

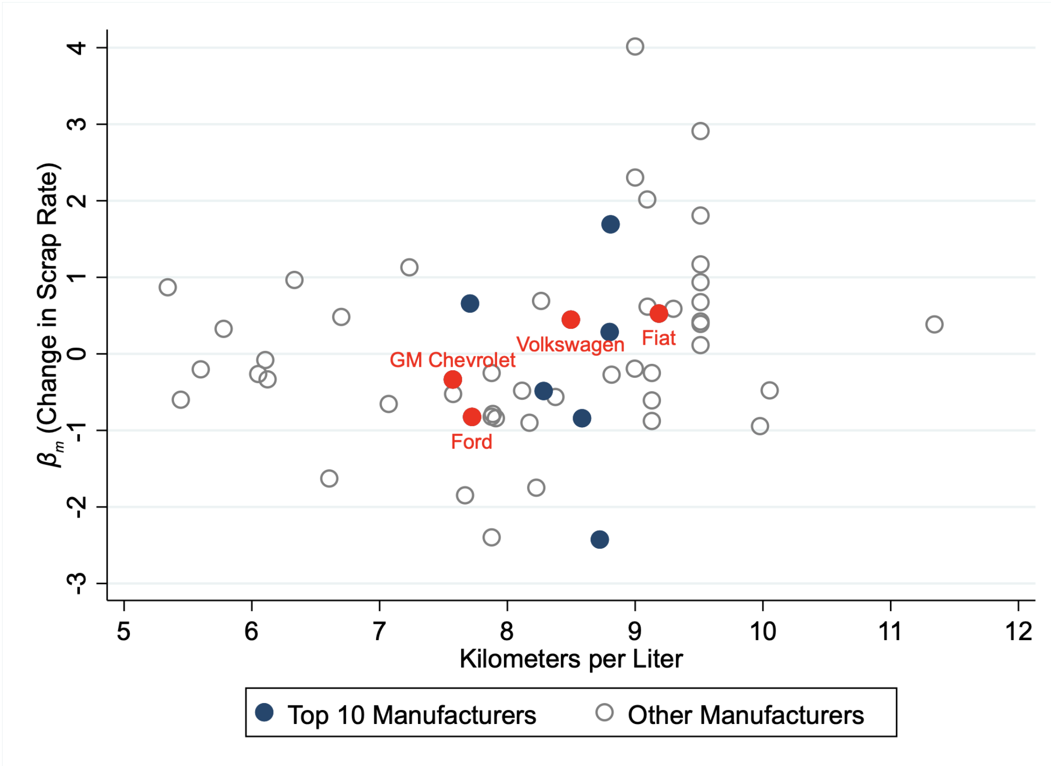

Figure 9.12: Coefficients from the First Stage

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 turnover rates on car prices. The figures highlight 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.

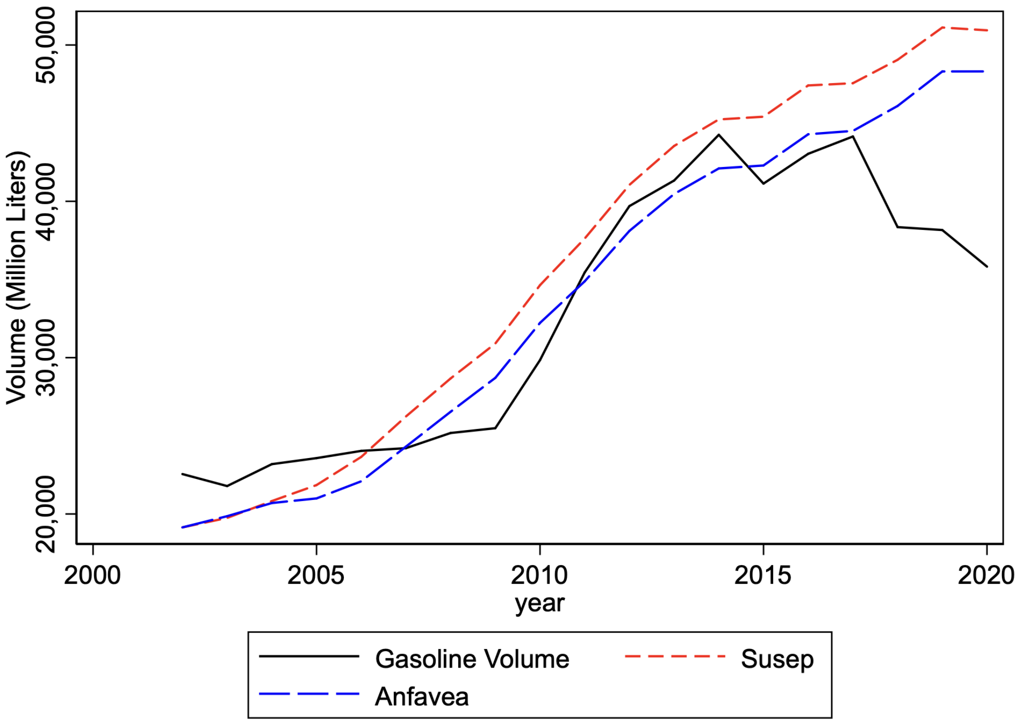

Figure 9.13: Gasoline Volume based on VKT estimates

Notes: This figure shows the amount of gasoline necessary to accommodate the average vehicle kilometer traveled according to equation 20. Susep estimates are based on the fleet obtained using private insurance information, while Anfavea estimates use Anfavea's new sales registration numbers.

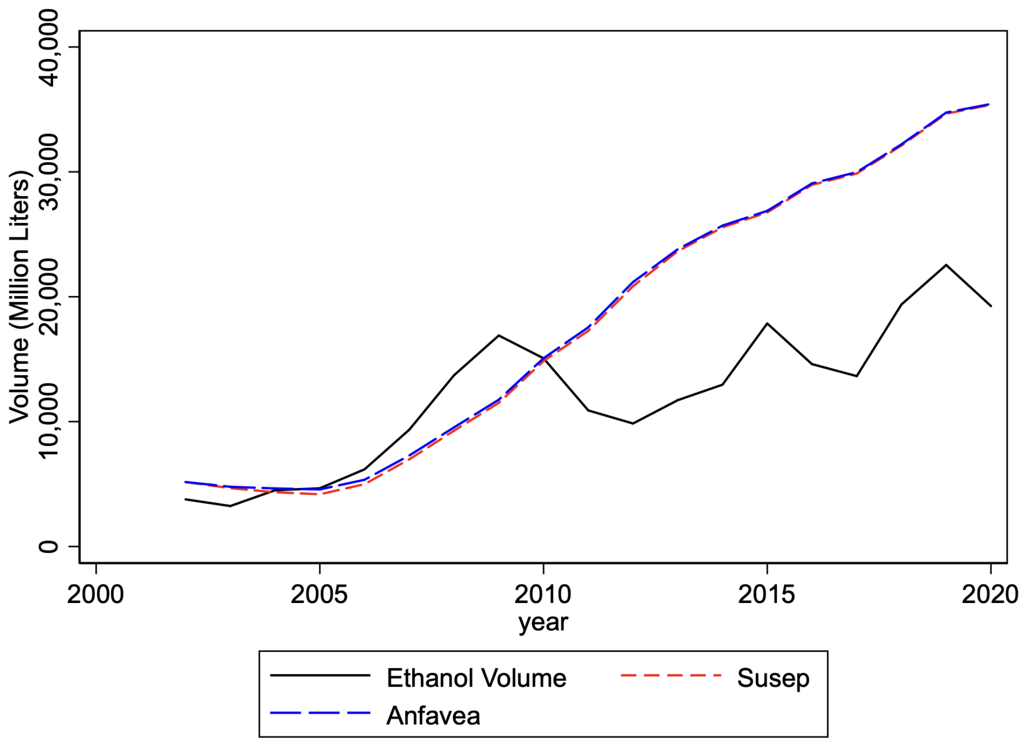

Figure 9.14: Ethanol Volume based on VKT estimates

Notes: This figure shows the amount of ethanol necessary to accommodate the average vehicle kilometer traveled according to equation 20. Susep estimates are based on the fleet obtained using private insurance information, while Anfavea estimates use Anfavea's new sales registration numbers.

Appendix A.1

Autoseg (SUSEP) Database and Adjustments

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

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

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

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

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

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

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

Table A.1: Insurance Data Submitted

Reference year: 2008

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

Source: Autoseg (SUSEP)

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

Notes: This table represents the number 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 with a potential update of the number of contracts that were effective in each semester.

Table A.2: IPI Tax for New Vehicles

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

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

Table A.3: Used Vehicle Price Elasticity of Turnover

Panel A: All Cars					
	up to 150k	up to 300k	up to 400k	up to 500k	any price
Turnover 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
Turnover 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 turnover rates. Turnover elasticity represents the elasticity of turnover used in car prices. The instrument used for car prices is fuel prices weighted by vehicle efficiency. Panel A focuses on all light-duty cars, popular or luxury, while panel B focuses only on popular cars. Pickups, vans, minibuses, and other light commercial vehicles are not included in these estimations. The "share of total" row represents the amount of vehicles in each valuation category, compared to the total number of vehicles in my database. Clustered on make-model-(car age) and tax brackets
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.4: Used Vehicle Price Elasticity of Turnover

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

Notes: The dependent variable is vehicle turnover rates. Turnover elasticity represents the elasticity of turnover used in car prices. The instrument used for car prices is fuel prices weighted by vehicle efficiency. Panel A focuses on light-duty cars, while panel C focuses on all vehicles, which include pickups, vans, minibusses, and other light commercial vehicles. Clustered on make-model-(car age) and tax brackets.
Each column represents a different combination of the potential datasets submitted to the governmental agency. Insurance firms must submit twice a year (June and December) a dataset with all vehicle contracts from the past three semesters. This creates an overlapping of information in each semester. To avoid duplicity of information, I aggregate only one set of information per semester to obtain the annual vehicle fleet. Each column in this table uses a different set of data as follows: column "Main" uses data from the dataset with more information for each semester (this is the database all the estimations in the paper are based); column "Report A" uses data from the first semester for which database A (submitted in June) is complete; column "Report B" uses data from the first semester for which database B (submitted in December) is complete; and column "Most Recent" uses data from the most recent semester for which database (June or December) is complete.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.5: Used Vehicle Price Elasticity of Turnover

	Full Sample		Excluding 2009, 2012-2014	
	Cars	All Vehicles	Cars	All Vehicles
Introduction (2003 to 2006)				
Turnover Elasticity	-0.4114***	-0.4104***	-0.4191***	-0.3651***
	(0.0727)	(0.0609)	(0.0783)	(0.0712)
Diffusion (2007 to 2010)				
Turnover 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)				
Turnover 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)				
Turnover 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 turnover rates. Turnover elasticity represents the elasticity of turnover used in car prices. 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 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 2009 and 2012 to 2014, which represent years when the federal government implemented reduced sales taxes for new vehicles. Besides cars, regressions from the columns "all vehicles" also include pickups, vans, minibusses, 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

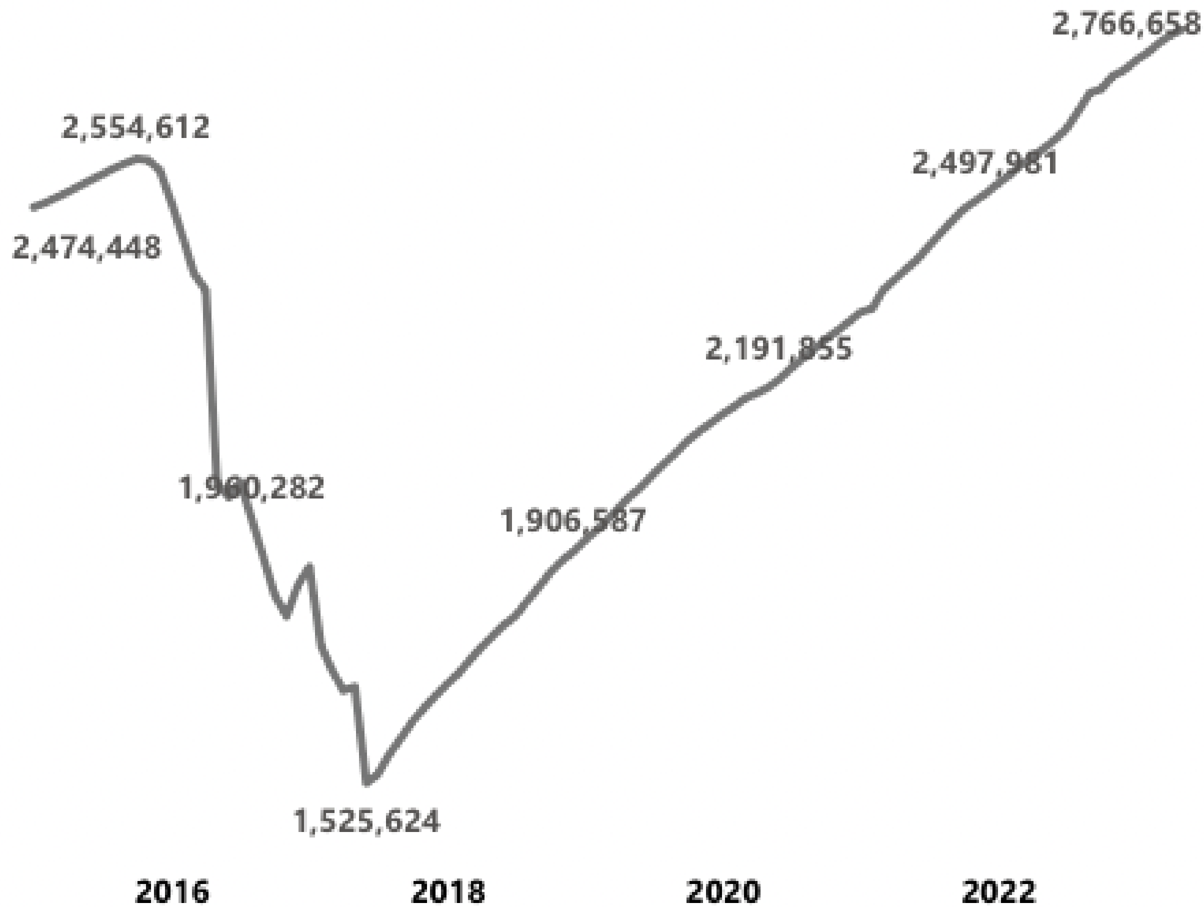

Figure B.1: Mandatory Truck Registration Renewal

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 a drop in the official numbers as seen in the figure. Registration records usually only accumulate new registrations and never deduct trucks that were scrapped and are not in the actual fleet anymore. This mandatory renewal of the register was the first in the category and evidences the overestimation of official records.

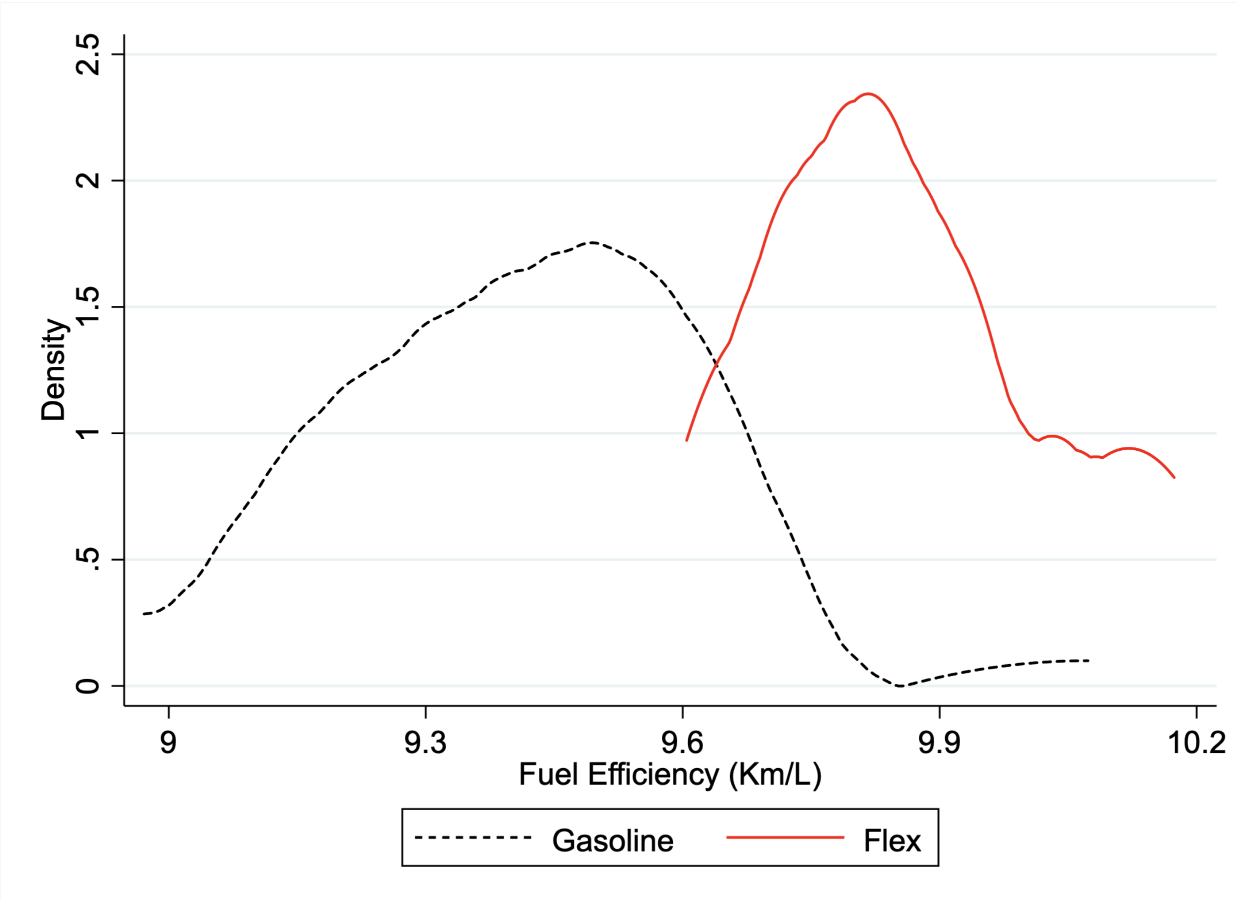

Figure B.2: Fuel Efficiency of Gasoline and Flex Fuel Vehicles - Density

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