# Three Essays on the Economics of Energy Markets

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# Abstract

This thesis examines the complex interactions between government policy, market structure, and societal outcomes in Brazil's fuel markets through three complementary empirical studies. The Brazilian fuel sector provides a unique laboratory for understanding these relationships due to its distinctive institutional features: a state-owned dominant producer (Petrobras), a mature biofuel market with ethanol as a close substitute to gasoline, the widespread adoption of flexible-fuel vehicle technology since 2003, and a history of significant government intervention through price controls and merger policy. Collectively, these three chapters demonstrate how policy interventions in fuel markets generate far-reaching consequences that extend beyond immediate economic effects to encompass public health, environmental quality, and the distribution of welfare between consumers and firms. By leveraging comprehensive datasets and employing rigorous econometric methods, this thesis contributes to our understanding of how market structure, technological innovation, and government policy interact to shape outcomes in a critical sector of the economy, with implications that extend well beyond Brazil's borders to other emerging economies facing similar policy challenges.

My first chapter examines the impacts of gasoline price stabilization policies on vehicle fuel demand, air pollution, and the consequent externality on infant health across Brazilian municipalities from 2005 to 2016. I leverage comprehensive data on fuel prices and consumption from the National Petroleum Agency, satellite-derived pollution data, and administrative health records to implement an instrumental variables approach that exploits supply-side cost shifters for retail gasoline prices. The identification strategy builds on refinery prices plus federal fuel taxes as instruments, conditional on municipality, month-of-year, and state-by-year fixed effects. The results indicate that gasoline consumption becomes increasingly price-responsive with the diffusion of flexible-fuel vehicles, with overall price elasticity of demand estimated at -1.46, jumping from -0.90 in 2005-2009 to -2.56 in 2010-2016 when flex-fuel vehicles became the majority of Brazil's automobile fleet.

The results also reveal substantial negative externalities from gasoline consumption: a 1% increase in monthly gasoline sales leads to a 0.22% increase in satellite-derived PM2.5 concentration and a 1.46% increase in hospitalization rates for respiratory conditions among children aged 0-5 years. These health impacts translate into over 67,000 additional pediatric hospitalizations annually, representing a significant burden on Brazil's publicly-funded universal healthcare system. In this context, gasoline price stabilization policies create a fiscal double burden for the federal government by reducing revenue through price controls and tax reductions while simultaneously increasing healthcare spending due to pollution-driven hospitalizations. Interestingly, hospitalization increases are smaller in poorer municipalities, suggesting that despite generating federal deficits, these policies may reduce health disparities, though they also discourage substitution toward cleaner biofuel alternatives.

My second chapter provides the first comprehensive retrospective evaluation of horizontal mergers in Brazil's gasoline distribution sector, examining four major concentration acts that occurred under the country's pre-2012 antitrust framework: the Ipiranga split (2008), Ipiranga-

Texaco acquisition (2009), Ipiranga-DNP acquisition (2011), and Shell-Cosan joint venture (2011). Using a unique dataset of weekly retail gasoline prices and detailed market structure information spanning 2008-2012, I employ a difference-in-differences approach with multiple control groups, including main competitors and unbranded retailers to identify the causal effects of mergers on both retail prices and margins. My analysis reveals substantial heterogeneity in merger outcomes across transactions and geographic regions, driven by differences in downstream market competitiveness and the nature of the concentration acts themselves.

Most notably, I document an asymmetric transmission mechanism whereby competitive downstream markets prevent the pass-through of both upstream cost increases and efficiency gains to consumers. The Ipiranga-Texaco acquisition created upstream market power that was absorbed by competitive downstream retailers through margin compression rather than being passed to consumers, while the Ipiranga-DNP acquisition in less competitive northern markets allowed retailers to capture efficiency gains rather than passing them through as lower prices. My joint analysis of price and margin effects reveals important distributional consequences that would be missed by traditional approaches focusing solely on consumer prices. These findings demonstrate that downstream market structure plays a crucial mediating role in determining how merger-related welfare effects are distributed between consumers and firms, with significant implications for antitrust policy in vertically related markets and geographic market definition in merger evaluation.

My third chapter examines the Brazilian experience with flex-fuel vehicle technology and evaluates its impact on reducing carbon emissions from 2003 to 2020 through three complementary analyses. First, I investigate technology diffusion by estimating fleet turnover elasticity, understanding how tax policies and promotion of flex-fuel cars induced a faster replacement and scrappage of old vehicles. For this analysis, I used vehicle insurance contract data and applied a panel instrumental variable approach. This analysis is restricted to insured vehicles, and covers 100% of new registrations but only one-third of the total fleet. It can, however, be taken as an upper-bound for the turnover effect. I obtain a turnover elasticity of -0.43, which is significantly smaller than scrappage elasticities found in developed countries, reflecting emerging market characteristics such as lower average income and credit restrictions. Tax reduction policies (IPI) were particularly effective for owners of older vehicles, contributing to the replacement of approximately 185,000 cars per year and accelerating clean technology diffusion.

The second part of the chapter focuses on impacts of flex-fuel diffusion on consumer choices and consequent carbon emissions. The introduction of flex-fuel technology fundamentally transformed fuel market dynamics by shifting consumer fuel choice from the time of vehicle purchase to the moment of refueling. Using data from 2003 to 2020, I found that price elasticities changed from inelastic (-0.50 for gasoline, -0.47 for ethanol) to highly elastic (-2.18 for gasoline, -3.67 for ethanol) as flex-fuel vehicles became dominant in the fleet. Counterfactual simulations demonstrate that flex-fuel technology avoided 149 billion tons of $CO_2$ emissions between 2003 and 2020, representing a 28% reduction compared to a scenario without this technology. However, the gasoline price ceiling policy implemented during 2011-2014 contributed to 137 billion tons of additional $CO_2$ emissions, nearly offsetting the environmental benefits of flex-fuel adoption. These findings highlight both the potential of alternative fuel technologies in mitigating climate change and the critical importance of appropriate pricing policies in maintaining their environmental effectiveness.

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# Chapter 1

# Price Stabilization Policy, Gasoline Consumption, and Health Externality: Evidence from Brazil

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## 1.1 Introduction

Petroleum products' price controls are prevalent around the world. They are often justified as a means to curb inflation and/or help the poor cope with the adverse effects of higher oil prices (Kojima, 2013). Like any other price control policies – e.g., minimum wage, rent control, and agricultural price floors – a price ceiling for petroleum products may lead to reallocation, misallocation, and externalities.[2] Its effects can be even more consequential in the presence of a well-developed market for biofuels, which are less polluting substitutes, and market power in

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[2]Minimum wage has been shown to lead to reallocation of workers to high-paying firms (Dustmann et al., 2022), rent control to misallocation of housing units (Glaeser and Luttmer, 2003) and externalities to neighboring units (Autor, Palmer and Pathak, 2014), and agricultural price floors to distortion of farmer behavior (Annan and Schlenker, 2015).

production and/or distribution.

In this study, we examine the impacts of gasoline price stabilization policies on vehicle fuel demand, air pollution, and infant health across municipalities in Brazil over the period 2005-2016. The Brazilian federal government has pursued gasoline price stabilization via direct price controls and reductions in federal fuel taxes. Brazil has a state-owned oil company – Petrobras – which is a dominant player on the production and imports of petroleum products. In addition, Brazil has a mature market for the biofuel ethanol, which has been developed since the 1980s, and for flexible-fuel vehicles (FFV), which were introduced in 2003 and run smoothly on gasoline and/or ethanol. Hence, there is ample opportunity for fuel substitution.

We leverage comprehensive data to obtain instrumental variable estimates of the causal effects of interest. Our data for fuel prices and fuel consumption come from a representative survey of gas stations across the nation, our pollution data come from satellite-derived particle pollution, and our health utilization data come from administrative records of the Brazilian Ministry of Health. Our instrumental variable approach builds on Levin, Lewis and Wolak (2017) and rests mostly on supply (cost) shifters for retail gasoline prices. In fact, the main instruments are refinery (production) oil prices plus federal fuel taxes.

Our identifying assumption is that conditional on municipality, month-of-year, and state-by-year fixed effects, and additional climatic and economic control variables, our instrument only affects gasoline demand via gasoline prices, and only affects air pollution and pediatric hospitalization for respiratory illnesses via gasoline consumption. This assumption appears to be supported by auxiliary analysis showing that our instruments have relatively low predictive power for changes in municipal population, GDP, and hospital beds – which would reflect local economic conditions and amenities – conditional on our fixed effects and other covariates.

We highlight three main findings. First, gasoline consumption seems to become more responsive to prices with the diffusion of flexible-fuel vehicles. The overall price elasticity of demand for gasoline during our sample period 2005-2016 is estimated to be -1.46, but jumps from -0.90 in 2005-2009 to -2.56 in 2010-2016, when the majority of the Brazilian automobile fleet turns flex-fuel. These estimates suggest that price stabilization policies may have become more effective in altering consumer behavior more recently.

Second, gasoline consumption generates sizable negative externalities. Increases in gasoline consumption lead to both higher air pollution and higher pediatric hospitalization. A 1% increase in monthly gasoline sales in a typical municipality in Brazil leads to a 0.22% increase in satellite-derived PM2.5 concentration.[3] Similarly, a 1% increase in monthly gasoline sales leads to a 1.46% increase in hospitalization rates for respiratory conditions for children aged 0 to 5 years, which is commonly used as an indicator of pollution effects. This translates into over 67,000 additional pediatric hospitalizations annually.

Third, the negative health externalities of gasoline consumption may reinforce the fiscal effects of gasoline price stabilization policies in Brazil. On the one hand, direct price control at the federally-owned oil company – Petrobras – reduces federal corporate revenue, and fuel tax reduction decreases federal tax revenue. On the other hand, about half of the additional pollution-driven hospitalizations are paid for by the federal government because of the publicly-funded universal health care system (Ministério da Saúde, 2006). Thus, not only federal revenue decreases, but federal spending also increases. It is important to point out that the hospitalization increases are smaller in poorer municipalities, as measured by an indicator for below the national median of municipal GDP. Therefore, despite generating federal deficit, price stabilization policies might reduce health disparities.

Our study makes three main contributions to the literature. First, it contributes to the literature on the consequences of price stabilization policies – e.g., minimum wage (Cengiz et al., 2019; Dustmann et al., 2022), rent control (Autor, Palmer and Pathak, 2014; Diamond, McQuade and Qian, 2019), and agricultural price floors (Annan and Schlenker, 2015). These papers have shown evidence of the following responses: misallocation, reallocation, and spillovers. To the best of our knowledge, we provide the first analysis of vehicle fuel price stabilization policies, which

[3]Particulate matter 2.5 (PM2.5) refers to fine particles or droplets in the air that are two and a half microns or less in width.

are ubiquitous around the world. We show that governments may not only lose revenue because of gasoline tax reduction or direct price control, as in Brazil, but may also increase spending in publicly-funded healthcare because of potential pollution impacts on public health.

Second, our study contributes to the literature estimating the paramount price elasticity of demand for gasoline (Hughes, Knittel and Sperling, 2008; Alves and Bueno, 2013; Levin, Lewis and Wolak, 2017) and investigating vehicle fuel choices among consumers (Salvo and Huse, 2011, 2013; Salvo, 2018). The more recent literature has highlighted aggregation bias in previous work leading to the underestimation of elasticities, and the role of new technologies in making consumer responses more elastic. We provide evidence indicating that the estimation with more granular data and the diffusion of flexible-fuel vehicles are indeed associated with larger price elasticities of demand for gasoline.

Third, our study contributes to the literature examining the impacts of transportation emissions on air pollution and health (Currie and Walker, 2011; Schlenker and Walker, 2016; Marcus, 2017; Salvo and Wang, 2017; He, Gouveia and Salvo, 2018; Alexander and Schwandt, 2022; Hansen-Lewis and Marcus, 2025). This literature has demonstrated the deleterious effects of transportation emissions, mostly in developed countries or in large cities in the developing world. We provide the first nationwide estimates of the effects of vehicle emissions on air pollution and infant health in a large developing country, where environmental quality is relatively poor and the willingness to pay for environmental improvements might be relatively lower (Greenstone and Jack, 2015).

The paper proceeds as follows. Section 1.2 provides background information on price stabilization policies in Brazil. Section 1.3 introduces a conceptual framework to understand the effects of price control and taxes on the adoption of clean(er) driving and health outcomes. This framework generates negative selection in the adoption of gasoline with respect to hospitalization. Section 1.4 describes the comprehensive data used in the analysis, and discusses some descriptive statistics. Section 1.5 presents the empirical strategy based on instrumental variables. Section 1.6 reports and discusses the results, including robustness checks and heterogeneity analysis. Lastly, Section 1.7 provides some concluding remarks.

## 1.2 Background

The period 2000-2016 was eventful for fuel markets in Brazil. It witnessed the end of the legal monopoly held by Petrobras – the Brazilian state-owned refinery,[4] the introduction of a new flexible-fuel vehicle technology allowing for easy substitution between gasoline and ethanol at the pump, changes in wholesaler competition, and a series of price controls exerted by the federal government.

The end of the legal monopoly did not translate into the end of Petrobras' leadership. Instead, it motivated a series of research and development projects that led to the discovery of new oil fields, expanding Petrobras' relevance and making Brazil self-sufficient in oil production by 2005. Because of its state-owned status, Petrobras has not been free from political influences. In fact, because most of the gasoline and other fossil fuels consumed in Brazil come from Petrobras, price control has been an instrument that the federal government has used to minimize oscillations of international oil prices and keep inflation under control.

Figure 1.1 displays nominal prices for domestic gasoline and Brent crude oil, and highlights how Petrobras kept prices virtually constant for long periods of time. Inflation reached 12.53% in 2002 and 9.3% in 2003, during the presidential transition from a more centrist party to the leftist Labor Party. Keeping inflation under control and close to the target imposed by the Brazilian Central Bank was crucial for the success of the new government. Thus, controlling fuel prices became a tool to isolate Brazil from external oil price oscillations.

Another source of price control is fuel tax reduction. Figure 1.2 shows how federal taxes have been used to control gasoline prices. The Brazilian tax system is highly complex and some taxes generate a cascading effect. On gasoline, for instance, there are PIS/COFINS and CIDE

[4]Up to 1997, Petrobras held monopoly over research, extraction, production, and refinery of petroleum in Brazil. Petrobras is still the major producer and refiner, responsible for around 94% of all the petroleum produced.

(federal taxes)[5] and ICMS (state taxes).[6] While PIS/Cofins and CIDE are paid by the refinery, ICMS is applied over the final consumer prices and generates a cascade effect.[7]

Figure 1.3 illustrates the influence of Petrobras production price and federal fuel taxes on retail gasoline price. The decomposition in the figure is for December 2012. At that time, Petrobras price represented almost 48% of the gasoline retail price, and federal fuel taxes almost 10%. Notice that anhydrous ethanol also helps determine gasoline retail price. Since the 1970s the Brazilian government has made it mandatory to blend anhydrous ethanol with gasoline.[8] In the past two decades, the blend has been kept around 25%.

On top of the direct and indirect fuel price controls, there was a key technological change in the automobile market in the 2000s. Figure 1.4 shows the evolution of the Brazilian car fleet. In 2003, the first flex-fuel vehicle (FFV) was introduced in Brazil, allowing for easy substitution between gasoline and ethanol. The main contribution of this new engine was to allow for the decision on which fuel to use to be made at the pump, instead of forcing consumers to decide it only when purchasing a new vehicle. Flex-fuel cars were being developed simultaneously by many manufacturers, which resulted in a relatively fast adoption. According to the Brazilian Association of Automotive Vehicle Manufacturers (ANFAVEA), by 2010 above 95% of the new cars produced and sold were FFV. By 2011, the FFV fleet was already larger than the gasoline-only fleet.

[5]PIS (Program of Social Integration) and COFINS (Contribution for the Financing of Social Security) are federal taxes based on monthly billings of companies, defined as the turnover of sales of goods and services. PIS is intended to finance the unemployment insurance system, and COFINS to fund Social Security. CIDE (Contribution for Intervention in the Economic Domain) is an instrument of economic policy to deal with situations that may require government intervention in the economy. It can be levied in many sectors of the economy. The CIDE-fuels targets importation and commercialization of oil, natural gas, and others fuels in the internal market. It aims at financing environmental projects and transportation infrastructure, but also at providing subsidies for fuel prices and transportation.

[6]ICMS (Tax on the Circulation of Goods and Services) is a state-level value added tax applied to the commerce of any goods or services. To minimize tax evasion, the refinery is the statutory payer of the ICMS due to its goods and services and the ICMS for all other players in the chain (called ICMS-ST, for distributors and retailers in the case of gasoline).

[7]Total ICMS = Petrobras' ICMS + ICMS-ST.

[8]Ethanol raises the octane rating of unleaded gasoline, so it boosts the performance of the engine. Also, because of its high oxygen content, ethanol burns more completely than ordinary unleaded gasoline and reduces harmful tailpipe emissions.

Regarding market structure, as a result of the Petroleum Law of 1997, in the early 2000s the Brazilian fuel market experienced a period of increasing competition in the distribution and retailer segments. This was followed by an intense concentration process by the end of the decade. There were changes in competition in both segments. In addition, up to 2019 Petrobras was the owner of the leading distributor and retailer brand called BR Distribuidora.[9] The relevance of Petrobras in all segments of the Brazilian fuel market reinforces any price policy enforced by the refinery.

Finally, there is the International Price Parity (PPI) policy enacted in 2015, at the end of the period of our analysis. This policy mandated that Petrobras would follow international oil prices to adjust domestic fuel prices. It was approved after the end of the Labor Party government to minimize political influence over Petrobras. Since the first effects of this law were felt only by the end of 2016 and beginning of 2017, we do not investigate further into this policy. But it provides context on the political pressures related to fuel markets in Brazil.[10]

## 1.3 Conceptual Framework: Health Investment and the Adoption of Gasoline vs. Ethanol for Driving

To fix ideas and set the stage for the empirical analysis, we develop a simple model that generates selective adoption of gasoline vs. ethanol for driving. Gasoline is considered a relatively dirtier and less sustainable vehicle fuel than ethanol, both in terms of local pollution and greenhouse gas emissions (Coelho et al., 2006; Goldemberg, 2007; Goldemberg, Coelho and Guardabassi, 2008).

Suppose that health capital is a function $f(\alpha, A)$ of latent health at birth, $\alpha$, and defensive investments, $A$, chosen by a representative individual (or by their parents). Defensive investments refer to various actions individuals can take to protect themselves from the negative effects

[9]Petrobras owned BR Distributor until 2021, but started the process of selling its stocks in 2019.
[10]The PPI policy was abolished by the current Lula administration on May 16, 2023.

of pollution. These investments can include avoiding outdoor activities altogether, consuming medication to attenuate the consequences of pollution exposure, or adopting practices aimed at reducing emissions during highly polluted days such as carpooling or working from home. Suppose further that $f(\alpha, A)$ is a strictly concave function with $f_\alpha(\alpha, A) > 0$, $f_A(\alpha, A) > 0$, and $f_{A\alpha}(\alpha, A) > 0$ (so the marginal value of defensive investments is higher for high latent health endowment individuals).[11] Then if $w$ is the market return to health capital and $s$ is the per unit cost of defensive investment, individuals maximize lifetime utility, given by

$$U(A) = wf(\alpha, A) - sA. \tag{1.1}$$

Individuals choose the level of defenses that solves $wf_A(\alpha, A^*) = s$. Standard arguments lead to sensible comparative statics: $\frac{\partial A^*}{\partial w} > 0$, $\frac{\partial A^*}{\partial s} < 0$, and $\frac{\partial A^*}{\partial \alpha} > 0$.

With this basic model of health capital accumulation in mind, consider a decision of driving with gasoline vs. ethanol. Like other defenses, driving with ethanol would constitute a form of investment. In particular, consider a representative individual of a city experiencing a dirty environment (e.g., bad air quality), who needs a higher return on health capital to compensate for the environmental disamenity: $w_D > w_C$. If individuals incur the cost $r$ of adopting cleaner driving via ethanol consumption, they would enjoy a cleaner environment (e.g., better air quality). Thus, individuals compare utility in a dirty versus a cleaner environment, i.e.,

$$U_D^* = w_D f(\alpha, A_D^*) - sA_D^*, \quad \text{and} \tag{1.2}$$

$$U_C^* = w_C f(\alpha, A_C^*) - sA_C^* - r, \tag{1.3}$$

[11] Relatedly, Pope et al. (2015) have pointed out that although there is strong evidence that fine particulate matter (PM2.5) air pollution contributes to increased risk of disease and death, recent evidence suggests that the concentration–response function between PM2.5 and mortality risk may be *concave* across wide ranges of exposure. In their words, "[s]uch results imply that incremental pollution abatement efforts may yield greater benefits in relatively clean areas than in highly polluted areas" (p.516). Similarly, Miller, Molitor and Zou (2021) provide the first causal estimates of the concentration-response function of PM2.5 exposure, leveraging wildfire smoke that produces ground-level air quality shocks of widely varying intensity. They find that small air pollution shocks have disproportionately larger mortality effects than large air pollution shocks. Again, "[t]his *concave* concentration-response relationship points to large benefits of additional air quality improvements in the U.S. despite pollution levels being already low" (our emphasis).

where defensive investment is chosen optimally in each case, which for any $\alpha$ gives $A_D^* > A_C^*$.

This model predicts "selective adoption of gasoline vs. ethanol for driving." Let $\hat{\alpha}$ be the level of latent health endowment such that a representative individual is indifferent between adopting gasoline and ethanol, i.e., the value of $\alpha$ for which (1.2) and (1.3) are equal. Then individuals with latent health endowment lower than $\hat{\alpha}$ will drive with ethanol, while those with higher health endowment will drive with gasoline. This selection complicates attempts to empirically evaluate the effect of gasoline-driven pollution on individual health outcomes. Observed differences in characteristics between individuals using gasoline vs. ethanol – in terms of income, health, etc. – could be the consequence of city residents' vehicle fuel choices, but could also be due to unobserved differences in traits of adopters and non-adopters of gasoline. Within this framework, we are interested in estimating an effect that might reasonably be thought of as "the causal impact of gasoline-driven air pollution on hospitalization." In so doing, we want to allow for the possibility that hospitalization, $y$, is negatively related to latent health endowment or health capital more generally, both of which are unobservable.

The key to identifying causal effects of pollution is to exploit variation in fuel prices. This is a consequence from the following comparative static,

$$\frac{\partial \hat{\alpha}}{\partial r} = \frac{1}{w_C f_\alpha(\hat{\alpha}, A_C^*) - w_D f_\alpha(\hat{\alpha}, A_D^*)} < 0; \tag{1.4}$$

an increase in the cost of adopting cleaner driving $r$ – say an increase in the relative price of ethanol – shifts downward the cleaner driving threshold.

To see how variation in fuel prices helps with identification, suppose that there are only two relative prices for ethanol: low and high. Let $\alpha_0$ be the health endowment threshold for cleaner driving for individuals facing low relative price of ethanol and let $\alpha_1 < \alpha_0$ be the corresponding threshold for those facing high relative price. We can divide individuals into three groups. First, those whose latent health endowment level is above $\alpha_0$ are "never adopters" of ethanol, who do not use ethanol even when its relative price is low. Conversely, this could be seen as the group of "always adopters" of gasoline, set $A$. Second, those whose latent health endowment is below

$\alpha_1$ are "always adopters" of ethanol, who would use ethanol regardless of high relative prices. Similarly, this could been seen as the group of "never adopters" of gasoline, set $N$. Finally, individuals for whom $\alpha_1 < \alpha < \alpha_0$ are "compliers," set $C$. This group is so named because conceptually they are people who "comply" with the proposed instrument – adopt gasoline if its relative price is low, but adopt ethanol if the relative price of gasoline is high.

Now let $D = 1$ designate a representative individual's decision to adopt gasoline for driving and $D = 0$ the decision to adopt ethanol. Let $y_{D=1}$ be the hospitalization status for an individual if she uses gasoline, while $y_{D=0}$ is the hospitalization status if she uses ethanol – noting that one of these is observed, while the other is an unknown counterfactual. Notice that we are considering the behavior of a representative individual; hence, the choice reflects adoption of gasoline vs. ethanol at a city level. We can estimate $E(y_{D=1}|A)$ and $E(y_{D=0}|N)$, respectively, by means $\bar{y}_{D=1,Z=0}$ and $\bar{y}_{D=0,Z=1}$, where $Z = 1$ indicates low relative price of gasoline and $Z = 0$ high price. Remarkably, simple algebra shows that we can recover both $E(y_{D=1}|C)$ and $E(y_{D=0}|C)$, under the following assumptions: the relative price of gasoline, $Z \in \{0, 1\}$, induces some individuals to adopt gasoline for driving who otherwise would have not adopted (as predicted by our model), and it is statistically independent of $(y_{D=1}, y_{D=0})$.

The Wald estimator $\frac{\bar{y}_{Z=1}-\bar{y}_{Z=0}}{\bar{D}_{Z=1}-\bar{D}_{Z=0}}$ for $E(y_{D=1}-y_{D=0}|C)$ recovers an estimate of the "local average treatment effect (LATE)" (Imbens and Angrist, 1994; Angrist, Imbens and Rubin, 1996). The term "local" emphasizes the fact that the estimate pertains to a particular subset of the population, and the term "treatment effect" refers to the impact of gasoline-driven air pollution. Indeed, as clarified by our theoretical setup, our estimate applies to the middle-health endowment group only; impacts might differ for higher- and lower-endowment individuals. Furthermore, the estimated effect includes the impact of behavioral responses made in anticipation of adoption of gasoline for driving (e.g., increased defensive investments in some margins). Lastly, if adopters are negatively selected into gasoline consumption, the LATE estimate will be *larger* than the corresponding OLS coefficient of the regression of hospitalization on gasoline sales.

Because we will be using a continuous instrument, the probability of adopting gasoline for driving $p(z) = E[D|Z = z]$ is also a continuous function of $z$. In this case, we use infinitesimal changes in the adoption probability to uncover LATE. Heckman (1990), Heckman and Vytlacil (1999, 2001), and Carneiro, Heckman and Vytlacil (2003) use a selection model to interpret such a marginal effect. In this case, adoption of gasoline for driving is a function of $Z$ and unobservable component $\lambda$. That is, $D = 1$ if $g(z) - \lambda \geq 0$, and $D = 0$ otherwise.

Under the usual instrumental variable assumptions, the latent model implies that we can rank individuals according to the unobservable component. If such component for individual $i$ is smaller than for individual $j$ (i.e., $\lambda_i < \lambda_j$), then $D_i(z) \geq D_j(z)$ for all $z$. Given this ranking, we can define the marginal treatment effect (MTE) conditional on $\lambda$ as $\beta(\lambda) = E[y_{i,D=1} - y_{i,D=0}|\lambda_i = \lambda]$. This effect relates directly to the limit of the LATE defined for values of $\lambda$ such that there exists a value $z$ that satisfies $g(z) = \lambda$. That is, $\beta(\lambda) = \beta(z)$ for $g(z) = \lambda$.

To understand this parameter as LATE, let's consider the simpler case where $g(Z)$ is a linear function of $Z$. In this case, the LATE estimator for two points in the distribution of $z$ can be expressed as

$$\beta^{LATE}(z, z^*) = \frac{E[y|Z = z] - E[y|Z = z^*]}{E[D|Z = z] - E[D|Z = z^*]}, \tag{1.5}$$

and we can think of the MTE as the LATE estimator when $z$ gets arbitrarily close to $z^*$. That is,

$$\beta^{MTE}(z) = \frac{\partial E[y|Z = z]}{\partial E[D|Z = z]}. \tag{1.6}$$

## 1.4 Data

We use three main sources of data to estimate the impacts of gasoline price stabilization policies on vehicle fuel demand, air pollution, and infant health across municipalities in Brazil from 2005 to 2016.

Fuel market data are provided by the National Petroleum Agency (ANP). Price data are collected weekly through surveys of a rotating sample of gas stations in representative cities across

Brazil. The survey covers a total of 555 cities, including state capitals and the Federal District, and represents approximately 70% of Brazil's annual gasoline consumption. The data obtained includes retail prices, wholesale distribution prices, and Petrobras refinery prices categorized by state.[12] All data have been deflated. Additionally, the survey captures information such as the date of the survey and the brand of the gas station. Volume data are sourced from self-reported sales by wholesale distributors, allowing for identification at the city and month level. To visualize the sample, Figure 1.5 illustrates the geographical distribution of all 555 municipalities included in our study, along with the respective annual gasoline volumes for 2015.

Health data come from the SUS Department of Informatics (DATASUS), the Ministry of Health's agency responsible for gathering information from all publicly-funded healthcare providers. There is universal health coverage in Brazil. We obtained detailed data on hospitalizations of children aged 0 to 5 years, with any respiratory illnesses.[13] Pediatric hospitalization for respiratory conditions is commonly used to assess the impacts of pollution, as children are often considered the proverbial "canary in the coal mine." Additionally, concerns about the history of exposure are minimal, as the data primarily reflects contemporary exposure. We also obtained patient demographics – age, gender, city of residence, etc. – and the costs associated with hospitalizations and other treatments.

Air pollution and climatic data come primarily from the Global Modeling and Assimilation Office (GMAO) and Goddard Earth Sciences Data and Information Services Center (GES DISC). They provide particulate matter (PM 2.5) data and other atmospheric information (temperature, precipitation) using satellite data (MERRA-2).

Regarding control variables, GDP and population come from the Brazilian Institute of Geography and Statistics (IBGE). Research centers such as UNICA/CEPEA/ESALQ have provided

[12]Petrobras is the major producer of gasoline in Brazil, refining around 98% of all gasoline consumed. Its price policy is set according to the state of the distributor and type of transportation.

[13]The list of respiratory illnesses includes asthma, bronchitis, pneumonia, rhinitis, sinusitis, tuberculosis, influenza, among others. Many respiratory diseases can be treated without the need for hospitalization. Thus, our estimates should be seen as a lower bound for the true impact of PM 2.5 on infant health, because we are only considering the cases when hospitalization was necessary.

information on ethanol and sugar prices. We have also obtained commodity prices from the International Monetary Fund (IMF) and U.S. gasoline prices from the U.S. Energy Information Administration (EIA).

For the instruments used in the analysis, we gathered Petrobras producer prices, federal fuel taxes, and a measure of sugarcane quality. Producer price has wholesaler-level variability, comprising a total of 18 states and 38 wholesaler centers. We used the average price by state, averaging from neighboring states when a specific state does not receive fuel directly from Petrobras. Sugarcane quality is a measure of sugarcane crop potential. To assess the quality of the sugarcane production, we used a measure of the total recoverable sugar (ATR, in Portuguese) that evaluates the monetary potential of each crop production according to the quality of its energy content. It represents the total value of sugar production – sucrose, glucose, and fructose – that can be transformed either into sugar or ethanol. Sugarcane production data come from the National Supply Company (CONAB), a public organization under the Brazilian Ministry of Agriculture. The ATR information comes from the National Association of Bioenergy (UDOP). To create the measure of sugarcane quality, we obtained the total crop by state, adjusting for each region's seasonality, and three distinct sugarcane quality prices: from Northern Brazil (Alagoas), Central (São Paulo), and Southern Brazil (Paraná).

Regarding summary statistics, the bottom of Table 1.1, Panel A, shows that the average monthly gasoline and ethanol sales for the 555 municipalities in our sample are 3.74 and 1.44 million liters, respectively. The share of gasoline sales increased slightly from 2005-2009 to 2010-2016, but remained around 70%. The average monthly pediatric hospitalization rate per million population is 215.32. Hospitalization rate is measured as the number of hospital admissions for respiratory illnesses for children aged 0 to 5 years per million population. The average monthly PM2.5 from the satellite-derived data is $8.6\mu g/m^3$, ranging from 2.4 to 240.5 $\mu g/m^3$. For comparison, the average satellite-derived PM2.5 concentration in China over the period 1990-2019 was about $25\mu g/m^3$, peaking at $28.9\mu g/m^3$ in 2010 (**?**). For India, the decadal satellite-derived PM2.5 concentration was $23.51\mu g/m^3$ in 1990, $34.38\mu g/m^3$ in 2000, $37.76\mu g/m^3$ in 2010, and $44.91\mu g/m^3$ in 2021 (**?**). For the United States, the satellite-derived PM2.5 concentration dropped from $9.2\mu g/m^3$ in 2003 to $7.5\mu g/m^3$ 2012 (**?**).[14]

## 1.5 Empirical Strategy

In order to quantify the extent to which gasoline price control may worsen the negative externalities of pollution and the fiscal standing of the federal government, we proceed in three steps. First, we estimate the price elasticity of demand for gasoline to assess the responsiveness of consumers to gasoline prices. Second, we estimate the effect of gasoline consumption on air pollution, as measured by satellite-derived particulate matter. Third, we estimate the impact of gasoline consumption on pediatric hospitalizations due to respiratory illnesses.

Our ultimate goal is to quantify the fiscal effects of the price control policy. The federal government is a majority shareholder of Petrobras – the petroleum dominant player in Brazil – and funds the Sistema Único de Saúde (SUS) – Brazil's national health system that reaches universal health coverage. Armed with the price elasticity of demand, we can assess how much the gasoline price control affects gasoline consumption. Then, we can plug the estimated change in gasoline consumption in the other estimated equations, and measure the effects on air pollution and pediatric hospitalization. We can then perform back-of-the-envelope calculations to quantify both the revenue loss from the price control policy and the increased health expenditures resulting from higher pollution levels.

### 1.5.1 Estimating the price elasticity of demand for gasoline

We use an instrumental variables approach to estimate the price elasticity of demand for gasoline. The estimating equation is

[14] **?** compares the satellite-derived PM2.5 concentrations across the globe in 2010. They report, for example, $59.8\mu g/m^3$ in East Asia, $58.3\mu g/m^3$ in South Asia, $15.1\mu g/m^3$ in Western Europe, $8.5\mu g/m^3$ in Latin America, and $7.9\mu g/m^3$ in the United States and Canada.

$$ln(Q_{it}^G) = \alpha + \eta_G ln(P_{it}^G) + \eta_E ln(P_{it}^E) + X_{it}\gamma + \theta_i + \delta_t + \phi_{sy} + \epsilon_{it}, \tag{1.7}$$

where $Q_{it}^G$ denotes gasoline consumption for municipality $i$ in month-of-sample $t$, $P^G$ the price of gasoline, and $P^E$ the price of ethanol. Ethanol is a close substitute to gasoline in Brazil, especially after the introduction of flex-fuel vehicles (FFV), which has given drivers the option to choose the fuel at the pump. $X$ represents the following control variables: ln(GDP), ln(population), and climatic variables (minimum and maximum temperatures, and precipitation). $\theta_i$ represents a set of municipality fixed effects, $\delta_t$ month-of-sample fixed effects, $\phi_{sy}$ state-by-year fixed effects, and $\epsilon_{it}$ the error term.

The main parameter of interest is $\eta_G$, the price elasticity of demand for gasoline, which is expected to be negative. The cross-price elasticity regarding ethanol, $\eta_E$, will be positive if gasoline and ethanol are substitutes, as expected, or negative if they are complements.

We instrument the price of gasoline with the Petrobras production price plus federal fuel taxes. As previously explained, Petrobras supplies gasoline at different prices across Brazilian states, primarily due to variations in transportation costs, so gasoline price varies by state $s$ and month-of-sample $t$. We use Petrobras refinery prices because of the political control that the Brazilian federal government has over their pricing policy. Also, there is considerable variation in federal fuel taxes over time, as displayed in Figure 1.2. Under the assumption that the state variation in Petrobras prices plus federal taxes is relatively unaffected by temporary city-specific demand fluctuations, using this IV approach helps eliminate any remaining endogeneity generated by the correlation between city-level prices and local demand shocks. This identification strategy builds on Levin, Lewis and Wolak (2017), who use spot market (wholesale) gasoline prices from three large regional refining centers (New York Harbor, the Gulf Coast, or Los Angeles) as instruments for local retail prices.[15]

[15] Other previous work has used as instruments wholesale prices (Cuiabano, 2018; Anderson, 2012), diesel, kerosene, and oil prices (**?**Ramsey, Rasche and Allen, 2011), disruptions in supply (Coyle, DeBacker and Prisinzano, 2012), and changes in gasoline tax (Davis and Kilian, 2011).

Notice that we do not model the change in technology induced by the introduction of FFV, but instead focus on the change of elasticities along that transition. Having been introduced in 2003, many car manufacturers rapidly switched production to FFV, partially motivated by tax incentives and subsidies to diffuse the new technology. Consumer adoption happened organically, buying FFV when they were on the market for new cars. The Brazilian fleet was over 50% FFV already in 2010, as shown in Figure 1.4. Based on this, we will explore the heterogeneity of our results regarding two periods – 2005-2009 and 2010-2016 – to understand how elasticities evolved as FFV became the majority of the fleet.

The flex-fuel engine changed consumers' decision making process by allowing the choice of fuel to happen at the pump rather than when they purchase a new car. This change has implications for fuel substitutability. Consumers do not need to lock-in to a durable and expensive asset to reap the savings of the best cost-benefit fuel.

Yet, the efficiency of gasoline and ethanol is not the same. Ethanol contains about one-third less energy than gasoline. Ethanol prices must be equal or lower than 70% the gasoline prices for consumers to benefit from its use. More recent engines and changes in the composition of gasoline have raised that threshold to roughly 75%. Under this scenario, we expect a considerable increase in the price elasticities of demand due to the increase in fuel substitutability.

For the price of ethanol, we use as instrument the regional value of the total recoverable sugar (ATR, in Portuguese) – sucrose, glucose, and fructose – from the sugar cane production. ATR is a measure of sugarcane quality, which depends on weather, soil quality, fertilizers, and other production inputs. In Brazil, ethanol is made out of sugar cane, so its distillation competes directly with sugar production. Like in Levin, Lewis and Wolak (2017), we have monthly variation in ATR value from three regions: Northern Brazil (Alagoas), Center Brazil (São Paulo), and Southern Brazil (Paraná).

### 1.5.2 Estimating the impacts of gasoline consumption on air pollution and pediatric hospitalization

We use a similar instrumental variables approach to estimating the extent of the negative externalities of gasoline consumption. For the impacts on air pollution and pediatric hospitalization, this is the estimating equation:

$$ln(Y_{it}) = \alpha + \beta ln(Q^G_{it}) + X_{it}\gamma + \theta_i + \delta_m + \phi_{sy} + \epsilon_{it}, \tag{1.8}$$

where $Y_{it}$ represents satellite-derived PM2.5 or pediatric hospitalization in municipality $i$ in month-of-sample $t$. $Q^G$ denotes gasoline consumption, and $X$ represents ln(GDP), ln(population), hospital beds per 1 million population, and climatic variables (minimum and maximum temperatures, and precipitation).[16] $\theta_i$ represents a set of municipality fixed effects, $\delta_m$ month-of-year fixed effects, $\phi_{sy}$ state-by-year fixed effects, and $\epsilon_{it}$ the error term.

Following the same strategy from the estimation of price elasticity of demand for gasoline, we instrument gasoline consumption by the state-level Petrobras gasoline price plus federal fuel taxes. Our identification assumption is that the instrument would affect PM2.5 or pediatric hospitalization only through gasoline consumption.[17] Because gasoline prices could affect local economic activity more broadly, we control for municipal GDP and population, as mentioned above. These variables should capture several dimensions of local economic shocks.

It is important to recognize the challenge of identifying the impact of gasoline consumption on pediatric hospitalization only through its effect on fine particle pollution. The concentra-

[16] In robustness checks, we also control for ethanol consumption and the results are relatively similar. We do not add ethanol to our main specification because it does not seem to affect air pollution levels (PM2.5 and ground-level ozone) when both gasoline and ethanol are included in the same equation, as reported in Appendix Table A.1.7. Furthermore, gasoline and ethanol consumption have a high positive correlation (0.815), which could generate collinearity issues.

[17] This assumption seems backed by additional analysis, presented in Appendix Table **??**, indicating that our instruments exhibit relatively limited predictive capability concerning shifts in municipal population, GDP, and hospital bed counts. The first stage F-statistics are just a fraction of the F-statistic from our main analysis, which is reported in the first column. These factors typically mirror local economic circumstances and amenities, conditional on the fixed effects and other variables.

tion of one air pollutant is usually highly correlated to the concentration of a number of other pollutants. The use of fine particle pollution (PM2.5) as our main pollution variable, however, should address some of those issues because it represents a variety of pollutants. As explained by EPA, particulate matter is a mixture of solid particles and liquid droplets found in the air. These particles come in many sizes and shapes and can be made up of hundreds of different chemicals. Some are emitted directly from a source, such as construction sites, unpaved roads, fields, smokestacks, or fires. Most particles, however, form in the atmosphere as a result of complex reactions of other chemicals such as sulfur dioxide (SO2) and nitrogen oxides (NOx), which are pollutants emitted from power plants, industries, and automobiles. Notwithstanding, we provide evidence that gasoline consumption may affect ground-level ozone as well, but decreasing rather than increasing its concentration.[18]

## 1.6 Results

We present the results in four parts. First, we report the estimates of the price elasticity of demand for gasoline. Second, we present the estimated impacts of gasoline consumption on air pollution and pediatric hospitalization. Third, we discuss the fiscal implications of gasoline price stabilization policies. Lastly, we discuss some distributional impacts of price controls.

### 1.6.1 Price elasticity of demand for gasoline

Table 1.1, Panel A, column 2, reports the IV estimated price elasticity of demand for gasoline of approximately -1.46.[19] In column 1, the OLS estimate is slightly smaller (-1.19), but we cannot rule out it is identical to the IV estimate. Prior studies have focused on different locations and

[18]This evidence is consistent with **?**, who show that ground-level ozone concentrations fell by about 20% as the share of flex-fuel vehicles burning gasoline rather than ethanol rose from 14 to 76%. A similar pattern is found in Salvo and Wang (2017): increased ethanol use in the gasoline-ethanol vehicle fleet leads to higher ozone concentrations in urban Sao Paulo's ambient air. Interestingly, however, they find no significant relationship between ethanol versus gasoline use and PM2.5 levels.

[19]Our main analysis uses an unbalanced panel of municipalities, but results are similar if we restrict our sample to a balanced panel (about 30% of our main sample), as reported in Appendix Table A.1.1.

time periods, have used different methodologies, and have reported estimates ranging from about -0.5 (Alves and Bueno, 2013, time series analysis for Brazil over the period 1974-1999) to about -3.0 (Salvo, 2018, price field experiment in Sao Paulo from May 2011 to March 2012).[20]

The price elasticity of gasoline seems to have increased over our sample period 2005-2016. In column 3, the estimate for the earlier period 2005-2009 drops by about 40%. In column 4, the estimate for the later period 2010-2016 is closer the largest elasticity reported in the literature. Recall that about half of car fleet in Brazil was FFV in 2010. Having the option to choose the fuel at the pump appears to have increased consumer sensitivity to gasoline prices.

The cross-price elasticity of demand regarding ethanol is estimated to be relatively low. Focusing on the estimate in Panel A, column 2, a 1% increase in ethanol prices increases demand for gasoline by 0.44%. Once more, we cannot rule out that the OLS estimate is identical to the IV estimate. Since ethanol and gasoline are primarily substitutes, a positive sign for the cross elasticity is expected. Although its value is slightly lower than the estimate of 0.48 reported by Alves and Bueno (2013), it seems to have increased over time as well.

The instruments generate relatively strong first stages for gasoline and ethanol prices in the main model, as reported in Panels B and C, respectively. The first stage F-statistic is close to 18 for the whole sample period, but falls below 10 for the subperiods 2005-2009 and 2010-2016. In Appendix Table A.1.2 we report estimates using alternative instruments such as Petrobras prices aggregated by region and sugar export prices. All price elasticities remain numerically similar and statistically the identical. Our choice for the preferred instruments was due to greater data variability across the country.

The first column in Table 1.1, Panel B, shows that the Petrobras gasoline price – which is a state-level price that includes production costs, federal fuel taxes, and transportation costs –

[20] Alves and Bueno (2013) estimated an elasticity of –0.46 using cointegration and error-correction models, based on annual, countrywide aggregated data from 1984 to 1999. Note, however, that their study does not account for the introduction of FFV in 2003, and uses aggregated data, which has been shown to make elasticities more inelastic (Levin, Lewis and Wolak, 2017). Cuiabano (2018) examined collusion among retailers in the southern cities of Londrina and Cambé using monthly data from 2007 to 2009, and found a price elasticity of -0.57. Her sample is small, and may not be representative for all cities in Brazil.

affects retail gasoline price positively. A 1% increase in Petrobras price increases the retail price by 0.44%. Likewise, in the first column of Panel C, sugarcane quality – which depends on weather, soil quality, fertilizers, and other production inputs – affects gasoline retail price positively as well. This is not surprising because, as shown in Figure 1.3, ethanol is added to gasoline for the retail market. A 1% in sugarcane quality increases gasoline retail price by approximately 0.02%.

Appendix Tables A.1.3 and A.1.4 reveal a similar pattern for the price elasticity of demand for ethanol. The estimate for the whole period of analysis is -1.95, but increases from -1.58 in 2005-2009 to -3.50 in 2010-2016. For comparison, Salvo (2018) reports estimates of up to -4.1 for his field experiment across four large cities in Brazil over the period May 2011 to March 2012. In contrast, the cross-price elasticity regarding gasoline is much larger, but still increases over time.[21]

Appendix Table A.1.6 shows that only a small portion of the more elastic demand for gasoline could be attributable to aggregation bias (Levin, Lewis and Wolak, 2017). The estimate of the price elasticity of demand for gasoline drops from -1.46 to -1.21 in Panel A, when we switch from analysis at the city-by-month to state-by-month level. We cannot rule out that they are statistically the same. This finding reinforces the prominence of FFV as a technological innovation that fostered fuel substitutibility and, consequently, more sensitive responses by consumers. Notice, however, that there does not seem to be aggregation bias for the cross-price elasticity regarding ethanol.

Gasoline and ethanol are not one-to-one substitutes because they differ in energy efficiency. When the price of ethanol is approximately 70% of the price of gasoline, the price of both fuels for a unit of energy are equivalent. Below this cutoff, ethanol has a better benefit-cost ratio. To test for consumer sensitivity to different prices, we perfomed additional tests.

Table 1.2, columns 2 and 3, show that consumers in poorer municipalities in Brazil – those

[21]Both gasoline and ethanol price elasticities of demand are estimated to be similar if we consider simultaneous estimation using a seemingly unrelated regression (SUR) approach, as reported in Appendix Table A.1.5.

below the national GDP median – are more sensitive to gasoline and ethanol prices. The interaction effects reinforce the absolute value of our main estimates for the price elasticity of demand for gasoline and the cross-price elasticity regarding ethanol, reproduced in column 1 for comparison.

Column 4 reports how the price elasticity varies if the price ratio of ethanol and gasoline falls into different quartiles of the distribution of relative prices. We observe a strong impact (-2.35) when ethanol has a better benefit-cost ratio (first quartile), a slightly inelastic impact when both are approximately equivalent (-0.95 between quartiles 1 and 4), and somewhat inelastic, though not statistically significant, when gasoline has a better benefit-cost ratio (-0.21, fourth quartile).

Results presented in column 5 follow a similar pattern. That column reports estimates regarding the gap between gasoline and ethanol prices instead of the quartiles of the relative price distribution. When the difference between gasoline and ethanol prices is large, the gasoline price elasticity is relatively elastic (-1.89). When that difference decreases, the elasticity drops to -0.83, becoming relatively inelastic.

### 1.6.2 Impacts of gasoline consumption on air pollution and pediatric hospitalization

Table 1.3 highlights the links between gasoline consumption, pollution concentration, and pediatric hospitalization.[22] Panel A reports a sizable response of pediatric hospitalization for respiratory illnesses to gasoline consumption. A 1% increase in monthly gasoline sales in a typical municipality in Brazil leads to roughly a 1.46% increase in hospitalization rates for respiratory conditions for children aged 0 to 5 years.[23] The average monthly gasoline sales in a typical

[22]This table presents results arising from our preferred specification without including ethanol consumption in the right-hand side. Again, this choice was guided by evidence pointing to gasoline consumption as the main driver of local pollution in a horse race with ethanol consumption, as shown in Appendix Table A.1.7. Nevertheless, the results are remarkably similar if we control for ethanol in our main specification, as reported in Appendix Table A.1.8.

[23]This estimate is remarkably stable as we include control variables one by one, as reported in Appendix Table A.1.9. Also, in Appendix Table A.1.10, we present separate estimates for children under 1 and children 1 to 5 years old. The main results for hospitalization and gasoline are somewhat similar, but the results for hospitalization and

municipality is about 9.4 million liters, so a 1% change means about 94,000 liters (or 25,000 gallons). The first stage is strong, with an F-statistic of the gasoline instrument of about 416. The OLS estimate is considerably smaller, consistent with the negative selection in the adoption of gasoline vs. ethanol for driving. Recall that our simple model predicted that gasoline adopters would be negatively selected into gasoline consumption, and the LATE estimate would be larger than the OLS estimate.

Panel B of the same table reports considerable impacts of gasoline consumption on air pollution. A 1% increase in monthly gasoline sales in a typical municipality in Brazil leads to a 0.22% increase in satellite-derived PM2.5 concentration. The first stage is also relatively strong, with an F-statistic of the gasoline instrument of about 69. The OLS estimate is also smaller than the IV estimate. This pattern is not surprising. Recall that our simple model predicted higher defensive investments (e.g., carpooling) when the air quality is bad. That generates a negative omitted variable bias. Table 1.4 reveals that most of the impacts on pediatric hospitalization are driven by asthma, bronchitis and pneumonia. Acute exacerbation of these illnesses have been linked to exposure to air pollution.

If a change in PM2.5 concentration is the only channel through which gasoline consumption affects hospital admissions for respiratory conditions, Panel C of Table 1.3 shows that a 1% increase in PM2.5 concentration increases pediatric hospitalization by about 0.28%.[24] This is a nontrivial effect. It is comparable to the magnitude of elasticity of infant mortality to total suspended particulates (TSP) estimated by Chay and Greenstone (2003) for the United States over the period 1980-1982. These authors find that a 1% reduction in TSP results in a 0.35% decline in the infant mortality rate at the county level.

pollution seem to be driven by children aged 1 to 5 years.

[24] Appendix Table A.1.7 provides evidence that there may be a trade-off between PM2.5 and ambient ozone as a consequence of gasoline use. These estimates are consistent with results from **?** and Salvo and Wang (2017), which show a reduction in ozone concentrations in the metropolitan area of Sao Paulo due to a shift from ethanol to gasoline use. On the other hand, Salvo and Wang (2017) find no significant relationship between ethanol versus gasoline use and PM2.5 levels.

### 1.6.3 Fiscal impacts of gasoline price stabilization policies

When the federal government uses gasoline price stabilization policies, there are sizable revenue losses. Notwithstanding, they have been used prominently in Brazil in the past two decades. Prices at the refinery have been controlled, and federal taxes have been lowered to keep prices stable.

Based on our estimated price elasticity of demand for gasoline, a 10% price reduction implies a 3.5 billion (2020 Reais) loss of federal revenue per year.[25] This loss is equivalent to about 20% of the budget allocated to the Brazilian Ministry of Transportation.[26] To make it easier to understand, a 10% of gasoline price implies an increase in gasoline consumption of about 9.3 liters (2.5 gallons) per family per month.[27]

Federal gasoline price stabilization policies also reduce state tax revenue. The ICMS (Tax on the Circulation of Goods and Services) is a state-level sales tax imposed on the commerce of goods and services. For gasoline, its calculation is based on the average retail price, surveyed biweekly by ANP, the Brazilian National Agency of Petroleum, Natural Gas, and Biofuels. Thus, the ICMS calculation includes the price at the refinery and the federal taxes. Any price reduction implemented at the federal level will have implications for state tax revenue.

The federal government does not only lose Petrobras corporate revenue and tax revenue, but also increases spending due to the negative health externalities of pollution. There is a publicly-funded healthcare system in Brazil, which covers all treatments, including surgeries and medications. For children aged 0 to 5 years – a subgroup of the population that is disproportionately sensitive to pollution and the focus of our analysis – hospitalizations rates for respiratory illnesses increase. Indeed, we have shown that higher gasoline consumption because of the price

[25]This calculation uses 2015 prices as the baseline prices, and considers \$0.26 reais per liter for PIS/COFINS and \$0.54 reais per liter for CIDE.

[26]See budget for 2012-2022 at https://www.gov.br/transportes/pt-br/assuntos/dados-de-transportes/bit/bit-publicacoes.

[27]A 10% reduction in the price of gasoline is not unreasonable. Comparing the price in December 2022 to December 2021, for example, there was a reduction of federal fuel taxes of \$0.69 reais per liter, which corresponds to a reduction of 10.2% in the price per liter.

stabilization policies leads to increases in PM2.5 concentration.

Based on our estimated hospitalization impacts, a 10% increase in monthly gasoline consumption in a typical Brazilian municipality leads to 67,350 additional pediatric hospitalizations for respiratory illnesses per year. This corresponds to a 26% increase in annual pediatric hospitalizations for respiratory conditions. At the average cost of hospitalization for those conditions, the additional expenditure is roughly 66.35 million (2020 Reais), representing approximately 6% of the budget allocated to the Brazilian Ministry of the Environment.[28]

### 1.6.4 Distributional impacts of gasoline price stabilization policies

Price control policies are often justified as a means to help the poor balancing their budget because of higher gasoline prices. But those policies may backfire, and disproportionately harm the poor. The car fleet might be older and more polluting among the poor. Thus, the additional gasoline consumption resulting from price controls might disproportionately increase pollution in poorer municipalities. As a consequence, hospitalization rates might be higher in those locations as well. Because of these trade-offs, this is an empirical question.

Table 1.5 reveals that pediatric hospitalization rates for respiratory illnesses are lower in poorer municipalities. The coefficient of the interaction between gasoline consumption and the indicator for municipal per capita GDP below the median is negative and statistically significant.[29]

One potential explanation for this pattern is the relatively lower level of gasoline consumption overall and per capita in poorer municipalities. As Panels B and C report, the average overall gasoline consumption in municipalities with per capita GDP below the median is less than a fourth of the municipalities above the median. In per capita terms, gasoline consumption is about half in poorer relative to richer municipalities. This pattern appears to spill over expo-

[28]See budget for 2010-2017 at https://antigo.mma.gov.br/mma-em-numeros/orçamento.html.

[29]As reported in Appendix Table A.1.11, the pattern of results is similar when we break down the analysis for children under 1 and children 1 to 5 years old.

sure to air pollution. Average PM2.5 concentration is about a fourth in poorer relative to richer municipalities.

## 1.7 Concluding Remarks

This study has examined the impact or gasoline price stabilization policies on fuel consumption, local air pollution, and pediatric hospitalization for respiratory conditions. We have estimated a rather elastic consumer response to gasoline prices – particularly in more recent years – which makes price control and tax reduction quite effective in altering fuel consumption patterns in Brazil. These policies can meaningfully shift consumption away from ethanol, the biofuel that competes closely with gasoline due to the widespread adoption of flexible-fuel vehicles.

We have also found that higher gasoline consumption leads to both higher fine particle pollution and higher pediatric hospitalization rates for respiratory conditions. These results suggest that fuel price stabilization policies generate nontrivial negative externalities from the transportation sector.

Taken these findings together, public sector deficits are likely to emerge from fuel price stabilization policies. Price control and tax reduction should decrease federal revenue from gasoline sales. Additional pollution-driven hospitalizations should increase federal spending, because they are covered by a publicly-funded universal health care system in Brazil. Therefore, the fiscal standing of the federal government should deteriorate with the implementation of those policies.

Two lessons could be drawn from the impacts of the Brazilian fuel price stabilization policies. First, fuel tax reduction to ease inflationary pressures on the poor may backfire. In the United States, for example, research has shown that transportation emissions can deteriorate public health (Currie and Walker, 2011; Knittel, Miller and Sanders, 2016; Schlenker and Walker, 2016; Marcus, 2017; Alexander and Schwandt, 2022; Hansen-Lewis and Marcus, 2025). Because individuals may take defensive actions to either avoid or remediate the consequences of exposure to pollution, their household finances may be affected. Moreover, to the extent that the the poor and the elderly are covered by Medicaid or Medicare, respectively, the additional spending by the federal and state governments may deteriorate their fiscal standing.

Second, fuel price stabilization policies may favor petroleum over alternative sources of energy in transportation. In Brazil, where most cars can run on gasoline and ethanol, those policies may induce substitution away from the most important biofuel in the country. In other settings, the alternative may be electricity or natural gas, for example. If society wants to transition to cleaner energy sources as fast as possible, such trade-offs should be considered in the policy debate.

# Figures and Tables

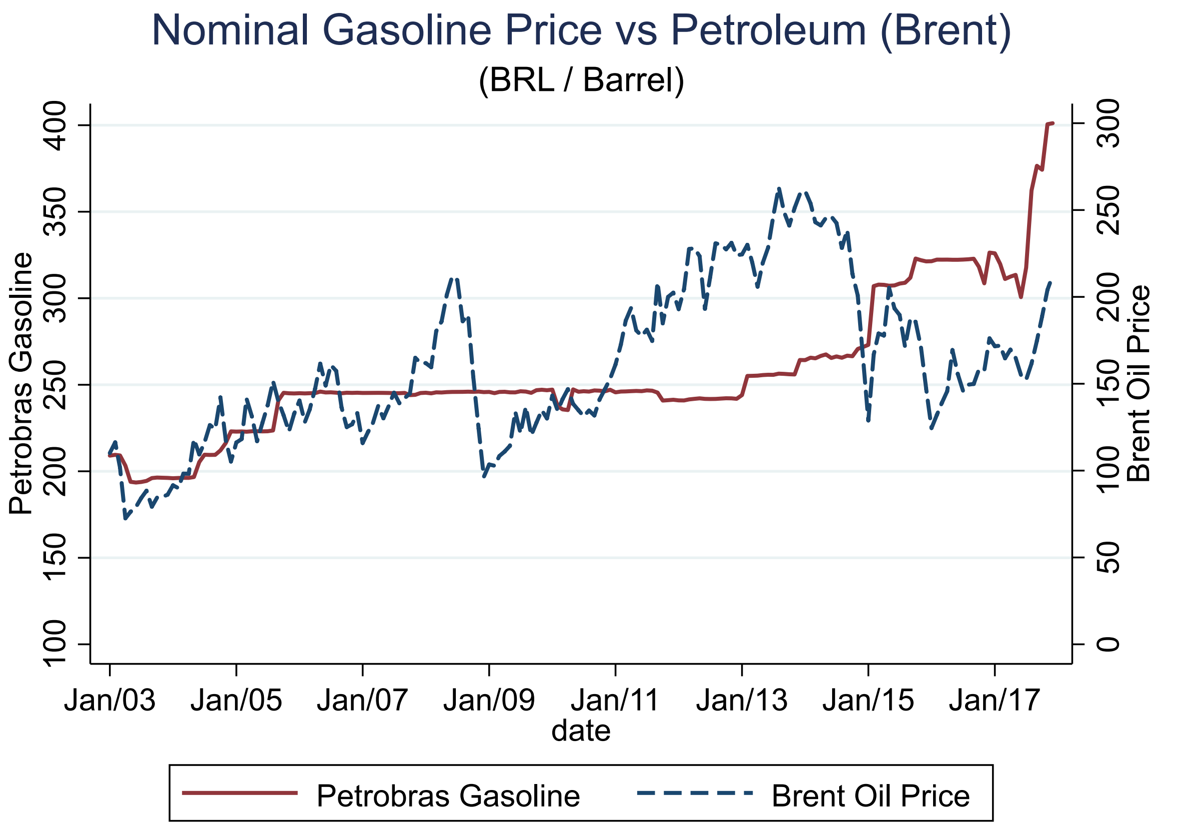


Figure 1.1: Nominal Gasoline Price and Brent Oil Prices (BRL / Barrel)

*Notes*: This figure shows the evolution of two price time series: Petrobras gasoline prices and Brent oil prices, both expressed in Brazilian real.

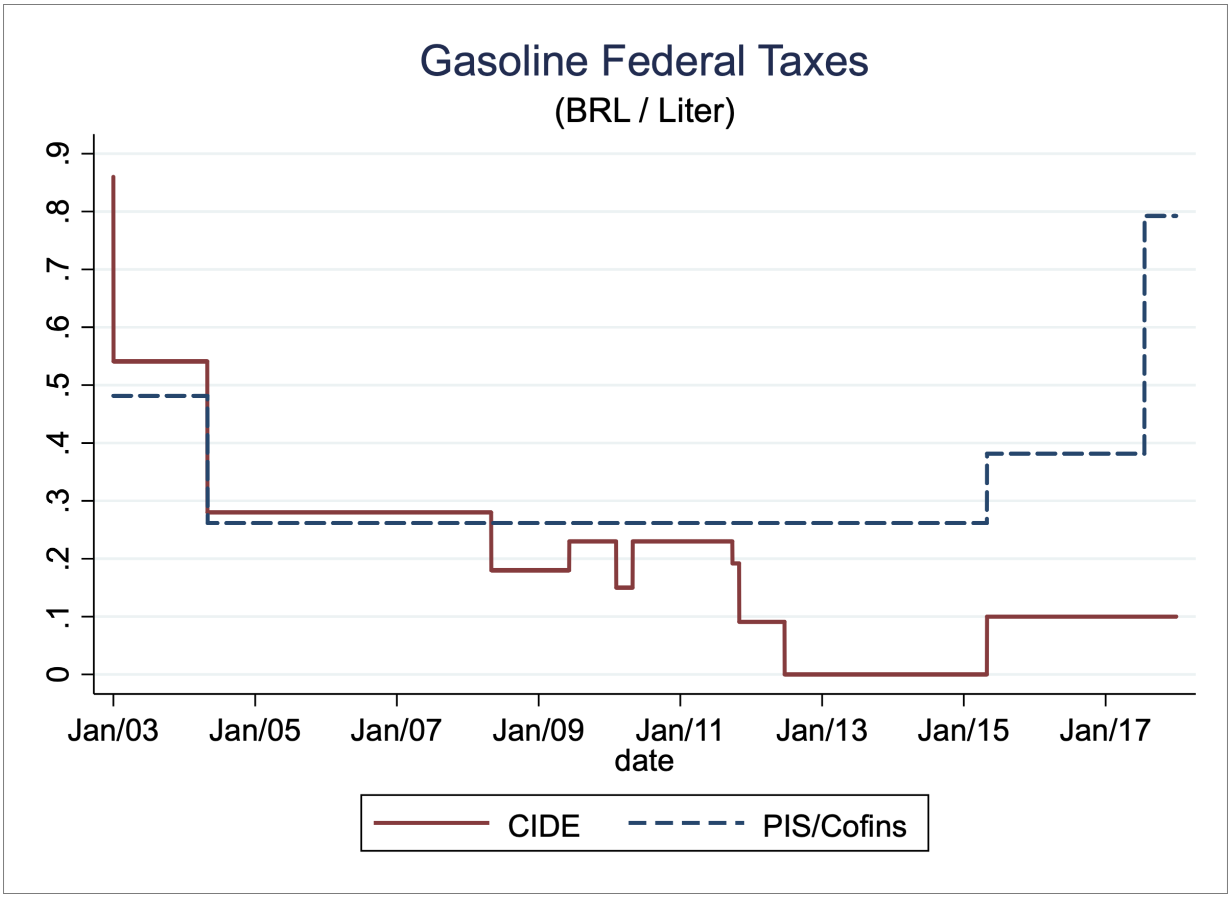


Figure 1.2: Federal Taxes Affecting Gasoline Prices

*Notes*: This figure displays the evolution of the two federal taxes that can influence the retail price of gasoline: CIDE and PIS/COFINS. CIDE (Contribution for Intervention in the Economic Domain) is an instrument of economic policy to deal with situations that may require government intervention in the economy. It can be levied in many sectors of the economy. The CIDE-fuels targets importation and commercialization of oil, natural gas and others fuels in the internal market. It aims at financing environmental projects and transportation infrastructure, but also at providing subsidies for fuel prices and transportation. PIS (Program of Social Integration) and COFINS (Contribution for the Financing of Social Security) are federal taxes based on monthly billings of companies, defined as the turnover of sales of goods and services. PIS is intended to finance the unemployment insurance system, and COFINS to fund Social Security.

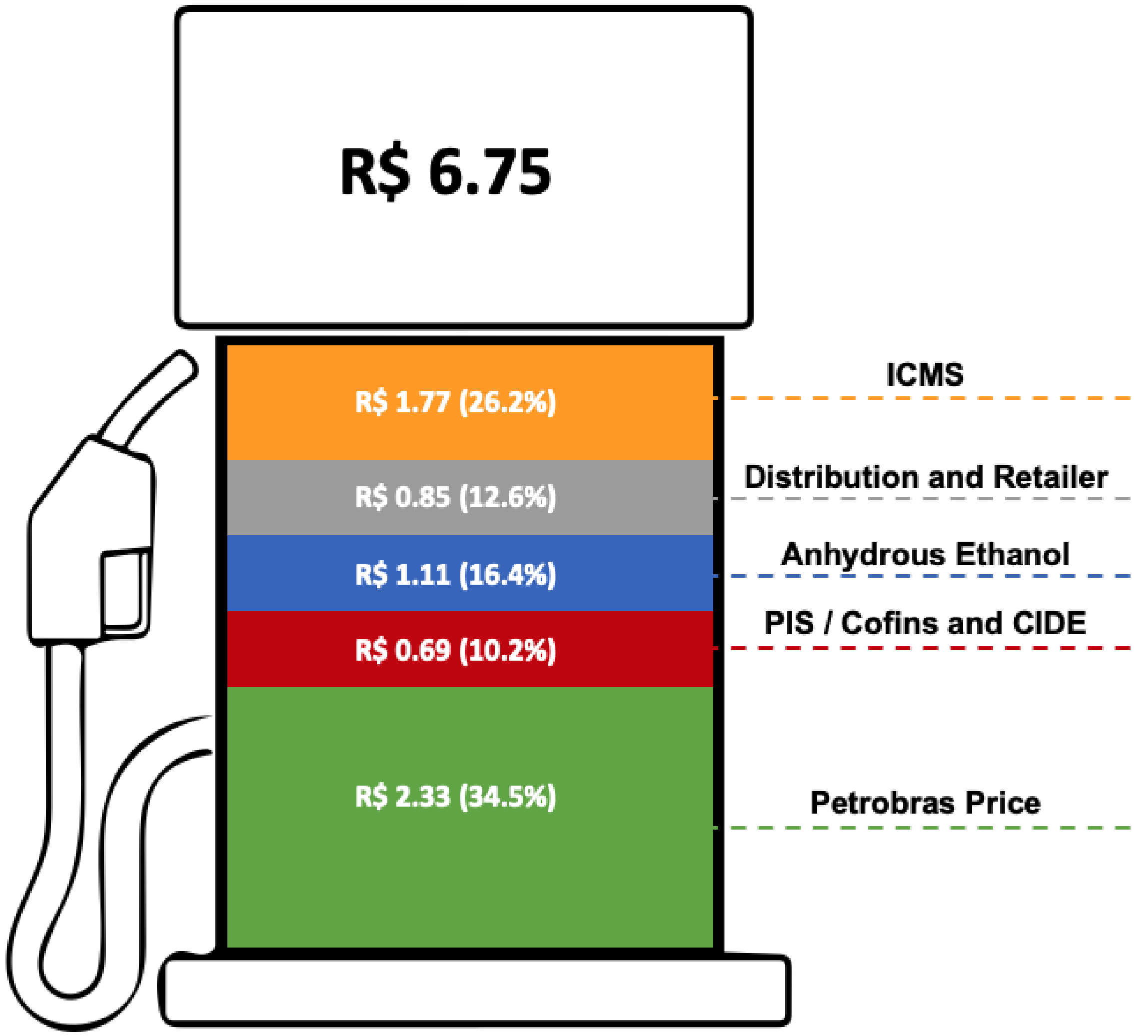


Figure 1.3: Gasoline Price Decomposition – December 2012 Example

*Notes*: This figure illustrates the influence of Petrobras' producer price and federal fuel taxes (PIS/COFINS and CIDE) on the retail price of gasoline, using December 2012 as an example.

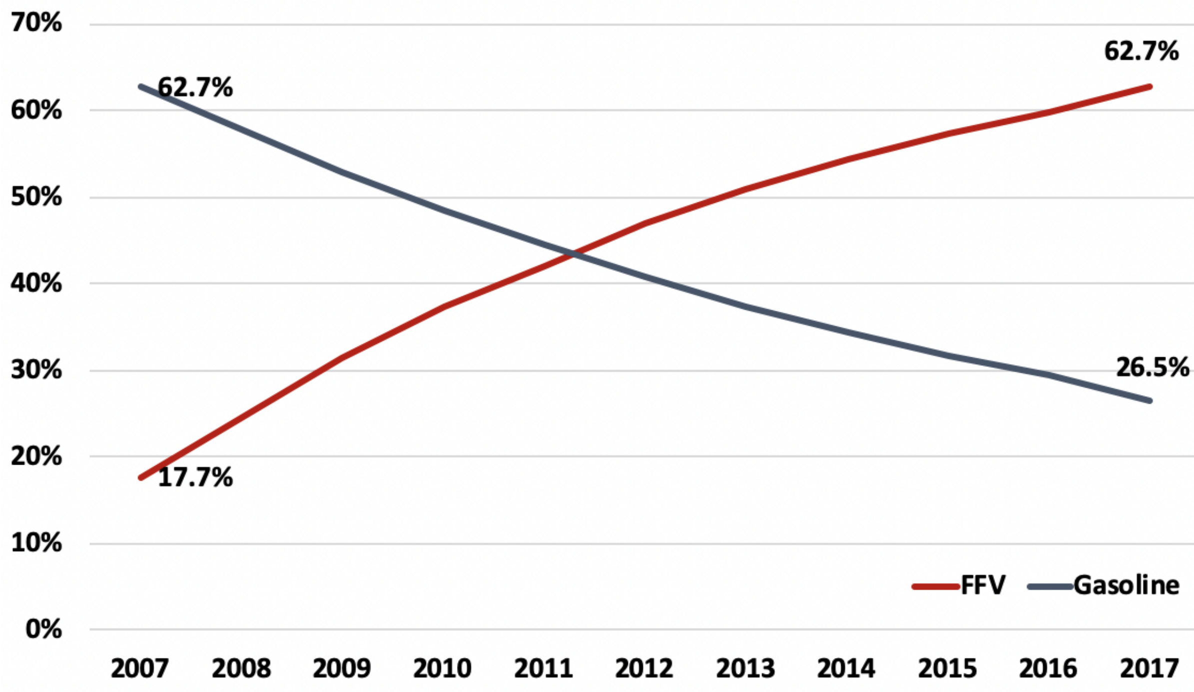


Figure 1.4: Diffusion of Flex Fuel Vehicles

*Notes*: This figure shows the evolution of the Brazilian passenger vehicle fleet, with a focus on the spread of flex-fuel vehicles, which can run on either gasoline or ethanol, giving consumers the option to choose their fuel at the pump. For a more detailed descriptive statistics of the passenger vehicle fleet, see Appendix Figure A.1.1.
*Source*: ...

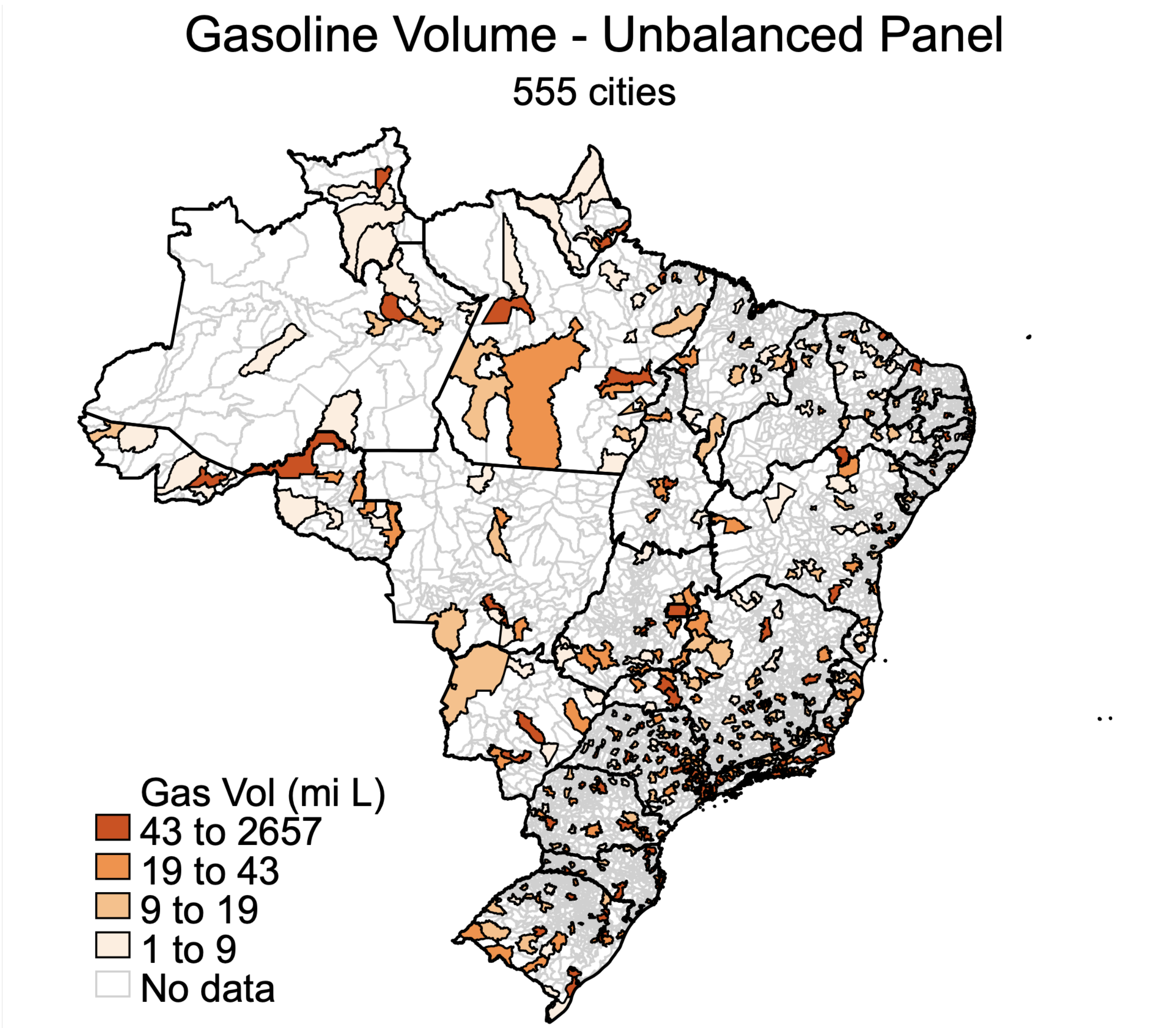


Figure 1.5: Annual Gasoline Sales – (Unbalanced) Sample of 555 Cities in 2015

*Notes*: This map highlights the cities in Brazil that were included in the 2015 gas station survey. It covers 555 municipalities, or about 10% of the total in Brazil, yet accounts for 70% of the country's annual gasoline consumption.

Table 1.1: Gasoline Demand Model

| ***Panel A: Gasoline Demand*** | | | | |
|---|---|---|---|---|
| | OLS: 2005-16 | IV: 2005-16 | IV: 2005-09 | IV: 2010-16 |
| Gasoline Price | -1.1944*** | -1.4559*** | -0.8950*** | -2.5586*** |
| | (0.1292) | (0.3052) | (0.3334) | (0.5673) |
| | [-1.4476,-0.9412] | [-2.0541,-0.8577] | [-1.5484,-0.2415] | [-3.6705,-1.4467] |
| Ethanol Price | 0.1228* | 0.4402*** | 0.2208** | 1.0062*** |
| | (0.0654) | (0.1026) | (0.1007) | (0.1572) |
| | [-0.0054,0.2510] | [0.2392,0.6413] | [0.0233,0.4183] | [0.6980,1.3143] |
| N | 73,353 | 73,353 | 30,019 | 43,334 |
| F-Stat | | 18.03 | 7.65 | 4.10 |
| Gas Vol (Mean & SD) | 3.74 (11.59) | 3.74 (11.59) | 2.82 (9.59) | 4.40 (12.81) |
| Etl Vol (Mean & SD) | 1.44 (6.55) | 1.44 (6.55) | 1.23 (5.85) | 1.59 (7.02) |
| Gas Price (Mean & SD) | 4.07 (0.46) | 4.07 (0.46) | 4.47 (0.38) | 3.78 (0.25) |
| Etl Price (Mean & SD) | 2.83 (0.64) | 2.83 (0.64) | 2.88 (0.74) | 2.79 (0.56) |
| ***Panel B: First Stage for Gasoline Price*** | | | | |
| | | GAS:05-16 | GAS:05-09 | GAS:10-16 |
| Petrobras Gasoline Price | | 0.4402*** | 0.7076*** | 0.2531** |
| | | (0.0734) | (0.0296) | (0.0973) |
| Sugarcane Quality | | 0.0199** | 0.0230*** | 0.0338** |
| | | (0.0086) | (0.0082) | (0.0132) |
| N | | 73,353 | 30,019 | 43,334 |
| ***Panel C: First Stage for Ethanol Price*** | | | | |
| | | ETL:05-16 | ETL:05-09 | ETL:10-16 |
| Petrobras Gasoline Price | | 0.1455 | 0.4356*** | 0.0426 |
| | | (0.1244) | (0.1626) | (0.1861) |
| Sugarcane Quality | | 0.2191*** | 0.2435*** | 0.2227*** |
| | | (0.0406) | (0.0625) | (0.0406) |
| N | | 73,353 | 30,019 | 43,334 |

*Notes*: The dependent variable is gasoline consumption under unbalanced panel. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. The F statistic shown is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 1.2: Gasoline Model – Interactions and Price Ratio tests

| Dependent Variable: Gasoline Demand | Main Model | + GDP | + Population | + Price Ratio | + Price Levels |
|---|---|---|---|---|---|
| Gasoline Price | -1.4559*** | -1.1514*** | -1.1687*** | | |
| | (0.3052) | (0.3132) | (0.3141) | | |
| Ethanol Price | 0.4402*** | 0.0561 | 0.0833 | | |
| | (0.1026) | (0.1347) | (0.1334) | | |
| Gas Price x 1(City GDP ≤ Median Brazil GDP) | | -0.6022*** | -0.7587*** | | |
| | | (0.1428) | (0.2212) | | |
| Etl Price x 1(City GDP ≤ Median Brazil GDP) | | 0.7904*** | 0.9964*** | | |
| | | (0.1868) | (0.2902) | | |
| Gas Price x 1(City Pop ≤ Median Brazil Pop) | | | 0.1958 | | |
| | | | (0.1850) | | |
| Etl Price x 1(City Pop ≤ Median Brazil Pop) | | | -0.2591 | | |
| | | | (0.2375) | | |
| Gas Price x 1(Pr Etl / Pr Gas ≤ Q1 (0.640)) | | | | -2.3474*** | |
| | | | | (0.4515) | |
| Gas Price x 1(Q1 (0.640) ≤ Pr Etl / Pr Gas ≤ Q3 (0.775)) | | | | -0.9530** | |
| | | | | (0.3646) | |
| Gas Price x 1(Pr Etl / Pr Gas ≥ Q3 (0.775)) | | | | -0.2084 | |
| | | | | (0.5467) | |
| Etl Price x 1(Pr Etl / Pr Gas ≤ Q1 (0.640)) | | | | 1.5270*** | |
| | | | | (0.3115) | |
| Etl Price x 1(Q1 (0.640) ≤ Pr Etl / Pr Gas ≤ Q3 (0.775)) | | | | -0.5060* | |
| | | | | (0.2602) | |
| Etl Price x 1(Pr Etl / Pr Gas ≥ Q3 (0.775)) | | | | -1.3170*** | |
| | | | | (0.4764) | |
| Gas Price x 1(Pr Gas - Pr Etl ≥ R$1.50) | | | | | -1.8874*** |
| | | | | | (0.4226) |
| Gas Price x 1(R$1.00 ≤ Pr Gas - Pr Etl ≤ R$1.50) | | | | | -1.5190*** |
| | | | | | (0.4096) |
| Gas Price x 1(Pr Gas - Pr Etl ≤ R$1.00) | | | | | -0.8313** |
| | | | | | (0.4047) |
| Etl Price x 1(Pr Gas - Pr Etl ≥ R$1.50) | | | | | 0.7728*** |
| | | | | | (0.1892) |
| Etl Price x 1(R$1.00 ≤ Pr Gas - Pr Etl ≤ R$1.50) | | | | | 0.2296 |
| | | | | | (0.2460) |
| Etl Price x 1(Pr Gas - Pr Etl ≤ R$1.00) | | | | | -0.5691* |
| | | | | | (0.2895) |
| N | 73,353 | 73,353 | 73,353 | 73,353 | 73,353 |

*Notes*: The dependent variable is gasoline consumption. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 1.3: Hospitalization Models – Children from 0 to 5 years old

| | | |
|---|---|---|
| ***Panel A: Hospitalization and Gasoline*** | | |
| | OLS | IV |
| | Log(Hosp Rate) | Log(Hosp Rate) |
| Log(Gas vol) | 0.0515** | 1.4550*** |
| | (0.0251) | (0.1914) |
| N | 67,554 | 67,554 |
| F-Stat | | 416.26 |
| ***Panel B: Pollution and Gasoline*** | | |
| | OLS | IV |
| | Log(PM 2.5) | Log(PM 2.5) |
| Log(Gas vol) | 0.0288*** | 0.2153*** |
| | (0.0093) | (0.0273) |
| N | 63,499 | 63,499 |
| F-Stat | | 68.61 |
| ***Panel C: Hospitalization and Pollution*** | | |
| | OLS | IV |
| | Log(Hosp Rate) | Log(Hosp Rate) |
| Log(PM 2.5) | -0.0025 | 0.2800** |
| | (0.0147) | (0.1111) |
| N | 57,226 | 57,226 |
| F-Stat | | 159.72 |

*Notes*: The dependent variable is infant hospitalization rate due to respiratory diseases (panels A and C), and PM 2.5 (panel B). Included controls: GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population. Panels A and B include fixed effects for year and year-by-state. Panel A includes month-of-year (seasonality) fixed effects while panel C includes month-of-sample. All panels include municipalities fixed effects. The F statistic shown refers to the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 1.4: Hospitalization Model by Categories of Illnesses

| | Asthma | Bronchitis | Pneumonia | Others |
|---|---|---|---|---|
| Log(Gas vol) | 1.5912*** | 1.6442*** | 1.4727*** | 0.6499** |
| | (0.2944) | (0.2941) | (0.2194) | (0.2608) |
| N | 43,433 | 41,925 | 65,314 | 50,782 |
| F-Stat | 216.79 | 169.72 | 371.00 | 223.60 |
| Gas Vol (Mean) | 3.74 | 3.74 | 3.74 | 3.74 |
| Gas Vol (SD) | 11.59 | 11.59 | 11.59 | 11.59 |
| Hospitalization (Mean) | 31.08 | 20.54 | 129.48 | 34.67 |
| Hospitalization (SD) | 59.28 | 35.55 | 147.42 | 66.53 |

*Notes*: This table shows the second stage results. The dependent variable is infant hospitalization rate for different respiratory diseases. Controls included: GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. The F statistic shown refers to the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 1.5: Hospitalization Model – Interactions – Children from 0 to 5 years old

| ***Panel A: Hospitalization Rates*** | | | | | |
|---|---|---|---|---|---|
| | Main Model | + Population | + GDP | + Hosp Beds | + Inf. Mortality |
| Log(Gas vol) | 1.4356*** | 1.4805*** | 0.8844*** | 0.6287* | 0.6479* |
| | (0.1892) | (0.2213) | (0.3101) | (0.3496) | (0.3557) |
| Log(Gas vol) x Population | | -0.1076 | 0.0483 | 0.0407 | 0.0401 |
| | | (0.0670) | (0.0729) | (0.0709) | (0.0707) |
| Log(Gas vol) x GDP | | | -0.1830** | -0.1535** | -0.1532** |
| | | | (0.0692) | (0.0697) | (0.0693) |
| Log(Gas vol) x H. Beds | | | | -0.1064** | -0.1071** |
| | | | | (0.0502) | (0.0501) |
| Log(Gas vol) x Infant Mortality | | | | | -0.0080 |
| | | | | | (0.0684) |
| N | 67,554 | 67,554 | 67,554 | 67,554 | 67,554 |
| *Kleibergen-Paap F-Stat by First Stage Regression* | | | | | |
| Gasoline Volume | 422.00 | 208.87 | 140.71 | 104.14 | 83.85 |
| Population Interaction | | 392.99 | 266.10 | 225.24 | 184.05 |
| GDP Interaction | | | 251.43 | 209.47 | 170.48 |
| Hospital Beds Interaction | | | | 110.26 | 87.91 |
| Log(Gas vol) x Infant Mortality | | | | | 270.60 |

**Summary Statistics**

| ***Panel B: observations below the median of GDP*** | | | | | |
|---|---|---|---|---|---|
| | Gasoline Consumption (1 MM Liters) | Gasoline Consumption (Liters / person) | Hospitalizations per 1 mi pop. | Pollution (PM 2.5) ($\mu$g/$m^3$) | Infant Mortality |
| Mean | 1.96 | 10.88 | 237.44 | 8.71 | 31 |
| SD | 6.25 | 4.75 | 219.24 | 4.35 | 15 |
| Q1 | 0.51 | 7.29 | 93.41 | 6.09 | 21 |
| Q2 | 0.97 | 10.87 | 173.52 | 7.87 | 26 |
| Q3 | 1.77 | 14.11 | 309.24 | 10.43 | 40 |
| ***Panel C: observations above the median of GDP*** | | | | | |
| | Gasoline Consumption (1 MM Liters) | Gasoline Consumption (Liters / person) | Hospitalizations per 1 mi pop. | Pollution (PM 2.5) ($\mu$g/$m^3$) | Infant Mortality |
| Mean | 5.69 | 20.69 | 174.37 | 8.55 | 29 |
| SD | 15.14 | 8.83 | 170.35 | 3.71 | 13 |
| Q1 | 1.25 | 16.00 | 66.58 | 6.10 | 20 |
| Q2 | 2.25 | 19.48 | 125.49 | 7.69 | 24 |
| Q3 | 4.99 | 23.94 | 221.78 | 10.28 | 36 |

*Notes*: This table shows the second stage results, and summary statistics for above and below the median GDP. The dependent variable is infant hospitalization rate due to respiratory diseases. First column represents original second stage. Other columns include interactions as additional controls. The F statistic shown refers to the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.

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

# Chapter 2

# The Effect of Mergers on Consumer Prices in a Developing Economy: Evidence from Gasoline Wholesale Distributors in Brazil

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## 2.1 Introduction

Mergers, acquisitions, and joint ventures are some of the most common ways that firms pursue to consolidate their presence and dominance in markets. To antitrust authorities, merger restropective analyses have become an essential tool for evaluating the effectiveness of antitrust enforcement and informing future policy decisions, particularly in industries where market concentration can directly impact consumer welfare (Ashenfelter, Hosken and Weinberg, 2013, 2014; Hosken, Olson and Smith, 2018). The choice of gasoline retail markets as a setting for this retrospective analysis is particularly compelling given their importance to economic activity, the frequency of merger activity in fuel distribution sectors globally, and the direct transmission of competitive effects to millions of consumers through daily price variations (Hastings, 2004; Hastings and Gilbert, 2005). The implications of inadequate merger enforcement in these markets extend beyond immediate consumer harm to broader macroeconomic effects through

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transportation costs, while the consequences of overly restrictive policies can stifle efficiency-enhancing consolidation and investment in distribution infrastructure (Knittel and Tanaka, 2021; Jacobsen and Van Benthem, 2015).

This paper provides the first comprehensive retrospective evaluation of horizontal mergers in Brazil's gasoline distribution sector, examining four major concentration acts that occurred under the country's pre-2012 antitrust framework. We analyze how these transactions affected retail prices and margins, with particular attention to the mediating role of downstream market structure in determining the ultimate distribution of merger-related welfare effects between consumers and firms.

Our analysis draws on a unique dataset combining weekly retail gasoline prices from Brazil's National Petroleum Agency (ANP) with detailed information on wholesale prices, fuel volumes, and market structure indicators spanning 2008-2012. The dataset covers approximately 70% of Brazil's total gasoline consumption and includes comprehensive information on retailer characteristics, geographic location, and brand affiliations, enabling precise identification of treatment and control groups across diverse market conditions.

Methodologically, we employ a difference-in-differences approach that exploits the discrete timing of merger events and geographic variation in their effects to identify causal impacts on market outcomes (Hastings, 2004; Ashenfelter and Hosken, 2010). Our identification strategy relies on the assumption that treated and control retailers would have evolved similarly absent the mergers, which is plausible given that all firms in our sample operated under identical regulatory environments and faced similar macroeconomic conditions. We strengthen this identification by using multiple control groups – including both main competitors and unbranded retailers – and implementing robustness checks that exclude periods immediately surrounding merger dates to address potential confounding events.

Our findings reveal substantial heterogeneity in merger effects across transactions and geographic regions. The Ipiranga split, driven by regulatory intervention, generated small but significant consumer benefits through price reductions. The Ipiranga-Texaco acquisition created upstream market power that was absorbed by downstream retailers rather than passed through to consumers, demonstrating how competitive retail markets can serve as a protective buffer. The Ipiranga-DNP acquisition in less competitive northern markets allowed retailers to capture efficiency gains rather than passing them to consumers, while the Shell-Cosan joint venture showed mixed effects reflecting the diverse competitive conditions across its national scope.

Most notably, we document an asymmetric transmission mechanism whereby competitive downstream markets effectively prevent the pass-through of both upstream cost increases and efficiency gains to consumers. While this mechanism can protect consumers from anticompetitive price increases, it simultaneously prevents them from benefiting from merger-generated efficiencies, creating a systematic bias in how vertical market structures mediate the welfare effects of horizontal consolidation.

This paper makes several important contributions to the mergers and acquisitions literature. First, we provide new evidence on the role of downstream market structure in mediating upstream merger effects, demonstrating that the same competitive forces that protect consumers from harm can prevent them from benefiting from efficiencies (Hosken, Olson and Smith, 2018). Second, we introduce a joint analysis of price and margin effects that reveals important distributional consequences masked by traditional approaches focusing solely on consumer prices (Ashenfelter, Hosken and Weinberg, 2013, 2014). Third, we contribute methodologically by showing how geographic heterogeneity in market structure can be exploited to understand the conditions under which concentration effects are transmitted to final consumers. Finally, our analysis represents the first comprehensive retrospective evaluation of multiple merger cases in Brazil's fuel distribution sector and among the first systematic post-merger evaluations conducted in a major Latin American economy, offering insights relevant to antitrust authorities in developing countries with concentrated distribution networks and heterogeneous regional market conditions.

The remainder of this paper is organized as follows. Section 2 provides institutional background on Brazil's gasoline distribution industry and the evolution of competition law that shaped the regulatory environment for our studied transactions. Section 3 describes the four merger cases selected for analysis, detailing their strategic rationale and regulatory treatment. Section 4 presents our data sources and the construction of key variables used in the empirical analysis. Section 5 outlines our econometric methodology and identification strategy. Section 6 presents our main results on price and margin effects, including an analysis of how these vary across different market structures. Section 7 concludes with a discussion of policy implications and directions for future research.

## 2.2 Background

### 2.2.1 Industry Background and the Evolution of Competition Law in Brazil

In Brazil, gasoline is produced or imported by a refiner, most likely Petrobras,[2], which is then transported to a wholesale distribution center. There are two types of gasoline: type A and type C. The latter is the pure gasoline produced by refineries and distributed to wholesalers. The former is a mixture composed of a percentage of anhydrous ethanol, destined for final consumers. Wholesale distribution centers are responsible for the preparation of this blended gasoline and its distribution.

Most of the production is offshore, with refineries located close to the coast or in strategic locations. Type A gasoline is transported to distribution centers by roads (trucks), railroads, water (especially cabotage sailing), and pipelines. Type C gasoline is transported to retailers only by trucks and, usually, within the same state.

There are two types of retailers, branded and unbranded, which dictate the type of relationship and contracts with distributors. Branded retailers will work under exclusivity contracts, selling products from one specific distributor and using their brand. Usually, these are long-term contracts and can include loans (from distributors) to upgrade or adapt the gas station to meet

[2]As of 2025, Petrobras produces approximately 85% of all gasoline in Brazil. Although the firm is publicly traded, the federal government retains majority ownership, maintaining control over the company's strategic decisions.

the distributors' branding and requirements. Unbranded retailers are independent brands with no exclusivity contracts. They can buy fuel from one or more distributors and usually work under short-term contracts, allowing them to switch suppliers more easily.

It is important to highlight that distributor firms are prohibited from owning their own retailers. Although vertical integration is allowed across fuel extraction, production, and distribution, it is not allowed between these sectors and the downstream retail segment. [3]

Differentiation in fuel markets tends to be limited. The National Petroleum Agency (ANP) supervises retailers to ensure minimum quality and compliance with requirements. Amenities such as branded convenience stores, fuel quality guarantees, and brand-specific products (additive [premium] gasoline, lubricants, and others) are among the main sources of differentiation among retailers.

In 1997, the Brazilian Congress approved the Petroleum Law (law 9,478/1997), which created the National Petroleum Agency. This law established regulations for new agents and ended Petrobras' monopoly on oil extraction, production, and refinery. The new regulations created an environment that promoted the expansion of the number of agents distributing liquid fuels, in particular, natural gas, gasoline, and diesel. While natural gas expansion is aimed at diverse industries and the generation of electricity, the distribution of diesel and gasoline is aimed at gas stations and the transportation sector.

The oil distribution sector, particularly for diesel and gasoline, went through many changes in the twenty years following the Petroleum Law. Initially, there was an expansion of activities, with close to 200 firms operating at the beginning of the 2000s. After 2005, this segment faced a series of mergers and acquisitions, concentrating activities and markets up to 2017. In 2010, there were around 150 firms that distributed gasoline, a number that was reduced to about 130 in 2017.

These distribution centers supplied fuel to over 41,000 retail stations, approximately 53.3%

[3] Among the three largest competitors, Petrobras used to be vertically integrated until 2021, Raizen has a refinery in Argentina, and Ipiranga is focused only on distribution.

of which were branded and 46.7% unbranded, with an uneven spatial distribution throughout the country. Specifically, while the Southeast region – home to 85 million people and with an area of 925,000 km$^2$ – accounted for 38% of all fuel retailers, the North region, with a population of 18.6 million and covering 3.85 million km$^2$, only hosted 9% of retailers. This disparity highlights the uneven distribution of retailers per unit area, with the Southeast region exhibiting a much higher retailer density. The lower retailer density in the North region reduces accessibility to fuel retail services and may also increase the market power of the few retailers operating in the region.

A topic of significant interest in antitrust is whether the concentration of retailers in certain locations has any implications for competition, particularly with regard to mergers in the upstream segments, which, in Brazil, are dominated by a few firms.[4] Up until 2017, the Brazilian antitrust authority had never blocked a merger in the liquid fuel distribution sector.[5] Before 2012, the agency's enforcement approach was considerably more lenient.

Until 2012, the Brazilian Antitrust Office (CADE) evaluated mergers and acquisitions in an *a posteriori* framework. Under the previous law (8.884/1994), firms could notify the authorities of a merger only after it had been concluded, which made the agency's task more difficult, especially in cases where the merger could have anticompetitive effects.[6] The new competition defense law (Law 12.529/2011) altered this scenario by requiring that all mergers with significant market concentration be notified to CADE prior to their completion. It also granted CADE greater autonomy to conduct economic analysis and enhance the efficiency of case adjudication.

The four transactions analyzed in this paper—Ipiranga and BR Distribuidora, Ipiranga and

[4]As of 2017, the four largest firms were BR (27.7%), Ipiranga (19.4%), Raízen (18.4%), and Alesat (3.4%).

[5]The first merger denied was between Ipiranga and Alesat, in August 2017. Although the marginal increase in concentration was relatively small, it has been argued that Alesat, the fourth-largest company in the segment, played a crucial role in disrupting concentration and fostering competition in the markets in which it operated. Although CADE refused to recognize Alesat as a *maverick firm*, it accepted the arguments that led to this conclusion and ultimately denied the merger.

[6]For instance, the Nestlé-Garoto case was a particularly complex merger in the chocolate industry, as the merger was finalized before the authorities were notified. The case sparked significant debate due to its high market concentration and the potential to reduce competition, as well as create barriers to entry for new competitors. In assessing the merger's efficiencies, CADE concluded that these would not be sufficient to prevent abuse of market power by the merged entity or to mitigate price increases and consumer harm. The case involved extensive litigation and judicial contestation, lasting 21 years, and was only concluded in 2023 with a series of remedies imposed by CADE to address the anticompetitive effects and restore competition in the relevant markets.

Texaco, Ipiranga and DNP, Esso and Cosan—happened before the new competition law was implemented and therefore occurred in a less stringent regulatory environment. The first case refers to Ipiranga's sale of assets to BR Distribuidora, which, at that time, was part of Petrobras. This transaction was treated as an acquisition, which generated significant concentration that could result in a welfare loss for consumers. To mitigate the impact, CADE allowed the sale of all assets from the North and Northeast regions (representing only 25% of Ipiranga's assets), while it denied the sale of assets in other regions to BR Distribuidora.

The second case, Ipiranga's acquisition of Texaco, marked the return of Ipiranga's operations in the North and Northeast regions through the purchase of Texaco's assets. Regionally speaking, this was a transfer of assets rather than an increase in market share. While it did not increase market concentration in those regions, it involved a shift in the management and control of key distribution centers. The third case involves Ipiranga's acquisition of DNP assets. Although this transaction led to a small increase in concentration, it was concentrated in the North region, where retailer competition was less intense than in other parts of the country. Lastly, the transaction between Esso and Cosan, which involved the formation of Raízen, was a merger that focused on assets in the South and Southeast regions—largely the largest consumer markets with a higher number of retailers in the downstream segment.

## 2.3 Cases Selected for Analysis

Before detailing the selected cases, it is necessary to clarify the terminology used throughout this paper. The term concentration acts — or simply concentrations — refers to events where two or more firms combine operations, whether through a merger, an acquisition of assets or control, or the formation of a joint venture. Concentration acts involve changes in the market structure by consolidating previously independent competitors or assets under shared or single ownership. This terminology follows the established usage in Brazilian and European competition policy frameworks and is adopted throughout this paper for conciseness.

This study focuses on two types of concentration acts: (i) acquisitions of assets or control, and (ii) the formation of joint ventures. Although each type involves some degree of consolidation between firms, they differ in important structural and operational aspects, as summarized below.

A merger occurs when two or more firms combine their operations into a single new entity, with none of the original firms continuing as independent market participants. All assets, liabilities, and operations are consolidated under the new firm, which assumes full control of the combined business activities. In Brazil, in the liquid fuel market, the most noticeable example of a merger in the 2000s would be the combination of Ale Combustíveis and Satélite, two firms in the distribution sector that combined activities in February 2007 to create a unified firm: Alesat. The reason why this paper does not focus on this case is that the assets of each firm had minimal overlap. The operation was mostly in complementary markets, which turned both Ale and Satélite from regional to national-level distributors.

An acquisition, by contrast, involves one firm purchasing assets, shares, or control of another firm. Typically, the acquiring firm continues to operate under its existing brand, while the acquired assets are integrated and may be rebranded under the acquirer's ownership and management.

Finally, a joint venture refers to a collaborative agreement in which two or more firms create and jointly control a separate business entity. In this arrangement, the parent firms maintain their independent operations but share control, governance, and profits over the newly created enterprise, usually focused on developing or commercializing specific products or services in a particular market. Although a joint venture represents a class of cooperative agreement,[7] authorities generally allow it provided that it generates pro-competitive benefits – such as promoting innovation, creating efficiencies, or facilitating the diffusion of technology – and does not lead to competition harms, such as enabling market coordination, excluding competitors, foreclosing access to essential inputs, or creating excessive market power.

[7]Other examples allowed by competition authorities such as CADE, the FTC, and the European Commission include research and development collaborations, production agreements, and standardization initiatives.

The cases selected for analysis in this paper include examples of each of these last two types of concentration acts. They were chosen based on their relevance to the Brazilian fuel distribution market, the timing of their consummation prior to the 2012 reform of antitrust laws, and the availability of data to measure their post-concentration effects.

The choice of fuel markets relates to the relative importance of this sector in terms of public policy and the transformations it has suffered in the past 30 years. From the end of Petrobras' monopoly over extraction and production, the expansion of distribution players and their subsequent concentration, to policies affecting fuel markets directly (fuel price controls) or indirectly (automobile's sales tax reduction), the level of concentration in the wholesaler distribution segment had deep impacts on consumers' welfare and indirect effect on many markets through their impact on transportation costs.

The Brazilian Antitrust Authority (CADE) has released two major reports on the fuel markets (Cade (2014) and Cade (2022)), focusing on both the retail and distribution segments. In these reports, CADE emphasizes that market concentration in the retail segment can arise either from concentration acts among retailers themselves or from concentration acts in the immediate upstream segment, among distributors that maintain brand exclusivity contracts with retailers. In the former case, concentration occurs through the ownership of retail establishments, while in the latter, it occurs through the consolidation of distributor brands under which some retailers operate.[8] In the distribution segment, between 1996 and 2021, there were 50 concentration cases judged by CADE, of which only one — the proposed acquisition of Alesat by Ipiranga in 2017 — was denied. Most cases (38) were approved without any restrictions.

### 2.3.1 Acquisition of Ipiranga's Assets by BR Distribuidora (Petrobras)

In 2007, Ipiranga's assets were strategically split among three major companies—Ultrapar, Petrobras, and Braskem—in a transaction valued at approximately US$4 billion, making it the

[8] It is important to emphasize that, in Brazil, distributors are prohibited from owning retail outlets, although they are permitted to hold exclusivity contracts with retailers.

largest merger or acquisition ever reviewed by CADE in Brazil's fuel and petrochemical markets, and one of the largest private-sector deals in the country's history. As part of the deal, Petrobras acquired Ipiranga's fuel distribution and retail assets in the North, Northeast, and Midwest regions, significantly expanding its downstream presence in markets where it previously had limited penetration.

The operation was structured to avoid excessive concentration at the national level. Ultrapar retained Ipiranga's operations in the South and part of the Southeast, where it was already established, while Braskem absorbed Ipiranga's petrochemical units. This geographic segmentation helped secure regulatory approval and provided a model for how large horizontal mergers in regulated sectors could be structured to mitigate antitrust risks.

CADE and the Ministry of Justice's economic bodies (SEAE and SDE) carefully evaluated the competitive effects of the asset division. In Petrobras's case, attention was focused on potential concentration in regional fuel retail markets, especially in municipalities where both BR and Ipiranga had strong presence. The deal ultimately allowed Petrobras Distribuidora to become more competitive in underserved regions without triggering the need for broader structural remedies at the national level.

### 2.3.2 Acquisition of Texaco's Assets by Ipiranga

In 2009, Ipiranga Produtos de Petróleo S.A. acquired the operations of Chevron in Brazil, including the Texaco brand. The transaction involved the purchase of Chevron Brasil Lubrificantes Ltda. and Chevron Brasil Ltda., encompassing Texaco's entire fuel distribution and retail activities in the country. As part of the deal, Ipiranga acquired retail contracts, distribution terminals, fuel inventories, and rights to the Texaco brand in Brazil. The consolidation involved two major players in the downstream fuel market, with Ipiranga already being one of the top distributors in the country. The scope of the transaction extended beyond retail fuel, also encompassing lubricants and industrial clients, although the primary competitive concerns focused on the retail gasoline and diesel segments.

The competition authority's analysis highlighted significant horizontal overlaps between Ipiranga and Texaco in several regions, particularly in the South and Southeast of Brazil. States such as Rio Grande do Sul, Santa Catarina, Paraná, and São Paulo were identified as having high levels of market concentration post-merger. In many municipalities, the transaction would substantially reduce the number of effective competitors, raising concerns about local market power, potential price increases, and reduced incentives for service quality and investment at the pump level. The merger raised red flags in areas where both firms had strong retail presence or supply relationships with branded and unbranded stations.

To address these concerns, the parties agreed to a set of remedies. These included the divestiture of assets or retail contracts in specific municipalities where the competitive effects were deemed most severe. Additionally, commitments were made to ensure non-discriminatory supply conditions for independent retailers and to preserve the possibility of market entry by rival distributors. These measures aimed to mitigate the risk of anti-competitive effects while allowing the broader transaction to proceed.

### 2.3.3 Acquisition of DNP's Assets by Ipiranga

In October 2010, Ultrapar, through its subsidiary Ipiranga, completed the acquisition of 100% of Distribuidora Nacional de Petróleo (DNP). The total transaction value was R$85 million, with R$47 million paid upfront in November 2010 and the remainder used for working capital adjustments. The deal officially closed and was consolidated from November 1, 2010.

The acquisition significantly bolstered Ipiranga's presence in Brazil's North region, adding approximately 110 service stations, increasing its regional volume by 40%, and elevating its market share to 14%, making it the second-largest fuel distributor in that region. This move complemented earlier expansion efforts—namely, the 2009 purchase of Texaco—and strengthened Ipiranga's strategic push into the North, Northeast, and Midwest, capitalizing on rapid regional demand growth.

Though smaller in scale compared to Ipiranga's landmark 2007 sale of assets to Petrobras, Braskem, and Ultrapar (a US$4 billion transaction), the R$85 million DNP deal was highly impactful at the regional level. It exemplified a targeted, efficient acquisition that leveraged local market momentum without unusual antitrust complexity.

### 2.3.4 Joint-Venture between Cosan and Shell

In early 2010, Cosan S.A. Indústria e Comércio and Shell International Petroleum Company Limited filed a notification with Brazilian competition authorities concerning the formation of a joint venture. The operation, initially formalized through a Memorandum of Understanding (MoU), aimed to integrate their downstream operations in Brazil. This included the merger of fuel distribution businesses under the Esso (Cosan) and Shell brands, with the potential to evolve into binding agreements such as a Joint Venture Agreement and a Framework Agreement. The resulting entity would concentrate activities across the distribution of gasoline, ethanol, diesel, and compressed natural gas (GNV), as well as retail operations at service stations throughout the country.

The Brazilian Secretariat for Economic Monitoring (SEAE) issued multiple requests for detailed market data from stakeholders, including SINDICOM, ANP, and ABEGÁS, covering market shares and supply structure for both liquid fuels and natural gas, segmented by state and municipality. The SEAE emphasized concern over horizontal overlaps, especially in municipalities with populations over 200,000, where both Cosan and Shell operated retail fuel stations. It sought granular data down to the neighborhood level in these urban centers to assess the degree of concentration. Furthermore, legal representatives of Shell submitted supporting documentation, including translated powers of attorney and authorizations, to facilitate the review process.

This merger represented a significant concentration in Brazil's fuel distribution and retail sector, prompting SEAE to demand detailed calculations, methodologies, and public and confidential versions of all submissions. The authorities underscored that failure to comply with information requests could result in penalties. The transaction signaled a major step toward consolidation in the downstream oil sector and triggered close scrutiny due to its potential competitive implications across several regional markets.

## 2.4 Data

***Retail Fuel Prices*** comes from Brazilian National Petroleum Agency (ANP). This data is obtained by a weekly survey from a set of representative cities, which comprises almost 70% of the total annual gasoline consumed in Brazil. We have information on retailers' brand name, day of the survey and location. In addition to these, we also obtained the national registry of legal entities number (CNPJ), which allow us to follow the precise gas station over time.

***Wholesaler Fuel Prices*** are also obtained from the survey mentioned above. This data is relevant to compute a gross margin for the the retailers, since represents the actual price paid by them. Other costs associated to the retailer activities are either fixed or negligible, having little to no influence in the analysis proposed here.

***Petrobras (Refinery) Fuel Prices*** are obtained directly from Petrobras and represent the producer (refinery) prices. These prices vary by macro region and are also used for complimentary analysis.

***Fuel Volumes*** are obtained from ANP and split into two different categories: retailer's and wholesalers' volumes. Retailer volumes are aggregated to city and month levels and represent the effective fuel sold to final consumers, being used here only for complimentary analysis. Wholesaler volumes are also in city and month level and represent the fuel sold by the wholesalers to the retailers. This later is split by wholesaler's brand, which allow us to (1) precisely check the period where firms effectively merged their activities, and (2) double-check the retailers' identification. We also use this wholesaler volume data for the concentration analysis using Herfindahl-Hirschman Index (HHI).

***Macroeconomic*** data such as inflation, GDP and population comes from the Brazilian Institute of Geography and Statistics (IBGE).

## 2.5 Empirical Approach

### 2.5.1 Methodology

The methodology applied in this study follows the established literature on post-merger evaluations using a difference-in-differences (DiD) approach. This reduced-form methodology has become the standard approach for policy evaluation in merger retrospectives, as it allows for the identification of causal effects by comparing outcomes between treated and control units before and after the merger event (Hastings, 2004; Ashenfelter, Hosken and Weinberg, 2013, 2014; Hosken, Olson and Smith, 2018).

The key identifying assumption underlying the DiD approach is that, in the absence of the merger, the treatment and control groups would have followed parallel trends. This assumption is particularly plausible in our setting because: (1) all retailers in our sample operate in the same regulatory environment and face similar macroeconomic conditions, (2) the timing of mergers was largely driven by strategic considerations at the corporate level rather than local market conditions, and (3) we include a comprehensive set of fixed effects to control for time-invariant heterogeneity.

The main methodological challenge in merger retrospectives lies in selecting an appropriate control group that provides a credible counterfactual for what would have happened to the merging parties' prices in the absence of the merger (Ashenfelter, Hosken and Weinberg, 2013). Following the established literature, we employ multiple control group strategies to test the robustness of our findings.

Our primary control group consists of two distinct types of retailers that provide varying degrees of competitive pressure on the merging parties:

1. **Main competitors:** Large branded retailers that compete directly with the merging parties in the same geographic markets. These firms face similar demand conditions and cost shocks but were not directly affected by the mergers under study. This approach follows Hastings (2004), who used competing branded stations as controls when analyzing the effects of independent station conversions.

2. **Unbranded retailers:** Independent gasoline stations that operate without exclusive contracts with any specific distributor. These retailers maintain flexibility to source gasoline from multiple suppliers and can switch brands based on wholesale price variations. As documented by Hastings (2004), independent retailers typically compete primarily on price with limited non-price differentiation, making them particularly sensitive to changes in competitive dynamics. The inclusion of unbranded retailers as controls follows Slade (1986) and Netz and Taylor (2002), who demonstrate that independent retailers serve as important competitive constraints in gasoline markets.

This dual control group strategy allows us to test whether merger effects vary across different types of competitors and provides a robustness check on our main results. The variation in competitive intensity between branded and unbranded retailers enables us to examine how merger effects depend on the degree of product differentiation, following the theoretical framework developed by Anderson, De Palma and Thisse (1992).

To address concerns about confounding events occurring simultaneously with the mergers, we implement two complementary temporal specifications:

1. **Full sample estimation:** We use a 12-month window around each merger (6 months before and after) to capture both short-term and medium-term price effects. This window length is chosen to minimize overlap between different merger events while providing sufficient observations for precise estimation.

2. **Event-time specification with "donut" periods:** Following Ashenfelter and Hosken (2010), we exclude observations from 2 months immediately before and after each merger to con-

trol for potential anticipation effects and contemporaneous shocks. This approach helps isolate the merger-specific effects from other market developments that might coincide with the merger timing.

For the price and margin regressions, we use weekly data, which allows us to have substantial variation and better capture the dynamics before and after the concentration acts. Our analysis focuses on four major cases in the Brazilian gasoline retail market, all occurring during the pre-2012 regulatory regime:

- **May 2008:** Ipiranga split – Following CADE's conditional approval of Petrobras's acquisition of Ipiranga, the company was split into two entities: Petrobras acquired operations in the central, north, and northeast regions, while Grupo Ultra (a new entrant to the liquid fuels market) acquired the south and southeast regions, maintaining the Ipiranga brand.
- **May 2009:** Ipiranga's acquisition of Texaco (Chevron) retail network, which represented the return of Ipiranga's brand presence in the central, north, and northeast regions. The overlap occurs mainly in the southeast region, where fuel distribution markets were already highly concentrated.
- **February 2011:** Ipiranga's acquisition of DNP (Distribuidora Nacional de Petróleo), reinforcing Ipiranga as a strong competitor in the north, especially in the Amazon area.
- **June 2011:** Shell-Cosan joint venture formation, creating Raízen, and consolidating it as the third largest distributor in Brazil.

All cases occurred under the more permissive pre-2012 antitrust framework, providing a consistent regulatory environment for comparison. The temporal spacing of these events allows us to study each case's effects while controlling for potential spillover effects from other consolidation activities.

### 2.5.2 Econometric Specification

Our baseline difference-in-differences estimating equation is:

$$\log(\text{Price}_{it}) = \alpha_i + \beta_t + \gamma\text{Merged}_{it} + \varepsilon_{it} \tag{2.1}$$

where $\text{Price}_{it}$ is the retail gasoline price charged by retailer $i$ on day $t$, $\alpha_i$ represents retailer fixed effects that control for time-invariant characteristics such as location, brand identity, and other station-specific factors, $\beta_t$ captures daily time effects including macroeconomic shocks, oil price movements, and seasonal patterns, and *Merged*$_{it}$ is an indicator variable equal to one for retailers involved in mergers in the post-merger period.

The coefficient $\gamma$ identifies the average treatment effect of the merger on retail prices, under the assumption that treatment and control groups would have evolved similarly in the absence of the merger (parallel trends assumption).

Following Hosken, Olson and Smith (2018), we also estimate models using margins (markups) as dependent variables to provide a more complete picture of how concentration acts affect market structure and competitive conduct:

$$\text{Margin}_{it} = \alpha_i + \beta_t + \gamma\text{Merged}_{it} + \varepsilon_{it} \tag{2.2}$$

Our analysis uses retailer-level price data collected on a random day of each week, providing high-frequency observations while maintaining computational tractability. The sample period covers 2008-2012, encompassing all merger events under the pre-2012 regulatory regime. All standard errors are clustered at the municipality-month level to account for potential serial correlation within markets and time periods, following the recommendations of Cameron, Gelbach and Miller (2011) for difference-in-differences estimation with panel data.

This comprehensive methodological approach allows us to provide credible estimates of merger effects while addressing the main identification challenges inherent in merger retrospective studies.

## 2.6 Results

### 2.6.1 Price and Margin Effects of Mergers

Figures 2.2 and 2.3 present the main results from our difference-in-differences estimation of concentration effects on retail gasoline prices and margins, respectively. The joint analysis of both outcome variables provides crucial insights into the mechanisms through which these cases affect market outcomes and reveals how the competitiveness of downstream retail markets mediates the transmission of upstream merger effects to consumers.

#### Case 1: Ipiranga Split - Minimal Market Impact

The Ipiranga split shows modest effects on both prices and margins. Compared to the main competitors, the acquisition of Ipiranga's assets by Petrobras resulted in small but statistically significant price reductions of approximately 0.2%, accompanied by small and nearly significant margin decreases. Results with respect to unbranded retailers show no price or margin changes.

These minimal effects are consistent with the nature of this regulatory intervention. While the split prevented excessive concentration by blocking Petrobras's full acquisition of Ipiranga, the resulting market structure change was relatively modest. Meanwhile, in the south and southeast regions, the entry of Grupo Ultra represented only a change of ownership of the Ipiranga brand, with no impact on upstream concentration or any downstream effects.

The small price reductions suggest that the regulatory intervention was successful in preventing potential anticompetitive harm without significantly disrupting existing market dynamics. The alignment of small price and margin decreases indicates that the limited competitive benefits were appropriately passed through to consumers rather than captured by retailers.

### Case 2: Ipiranga-Texaco Acquisition - Downstream Competition as Consumer Protection

The Ipiranga-Texaco acquisition presents a compelling case study of how downstream competition can protect consumers from upstream anticompetitive effects. While retail prices remained essentially unchanged for both main competitors and unbranded retailers, we observe substantial margin compression of approximately four percentage points.

This pattern strongly suggests that the merger generated upstream market power that increased wholesale costs for downstream retailers. However, the highly competitive nature of retail markets in the affected regions - which comprise more than 70% of Brazil's total gasoline consumption and include the most competitive metropolitan areas - prevented retailers from passing these cost increases through to consumers.

The significant margin compression indicates that retailers absorbed the upstream price increases at the expense of their own profitability. This downstream competitive pressure effectively served as a buffer that protected consumers from immediate price increases, demonstrating how retail market structure can mediate the transmission of upstream merger effects.

From an antitrust perspective, this case illustrates the complex interaction between upstream and downstream competition. While the merger appears to have created meaningful upstream market power (evidenced by the margin compression), the competitive retail environment prevented the full expression of this market power in consumer prices. However, this protection may not be sustainable in the long term if continued margin pressure leads to exit or reduced investment in retail markets.

### Case 3: Ipiranga-DNP Acquisition - Efficiency Gains Captured by Retailers

The Ipiranga-DNP acquisition shows no significant price effects for consumers but evidence of margin increases for retailers, particularly against unbranded competitors. This pattern suggests a fundamentally different mechanism from the previous cases.

The absence of price increases, combined with margin improvements, indicates that any efficiency gains generated by the concentration act were captured by downstream retailers rather than passed through to consumers. This outcome likely reflects the structural characteristics of the affected markets, which were primarily located in northern Brazil, including the Amazon region.

These markets are characterized by geographic dispersion, higher transportation costs, and naturally lower levels of retail competition due to barriers to entry and the challenges of fuel distribution in remote areas. The less competitive downstream environment provided retailers with sufficient market power to capture efficiency gains rather than compete them away through lower prices.

The regional concentration of this case in less competitive markets helps explain why retailers were able to retain efficiency benefits. Unlike Case 2, where intense retail competition forced margin compression, the weaker competitive pressure in northern markets allowed retailers to maintain or even improve their margins while keeping prices stable.

**Case 4: Shell-Cosan Joint Venture - Mixed Regional Effects**

The Shell-Cosan joint venture shows no significant price effects but some evidence of margin increases, particularly against main competitors. The pattern is similar to Case 3 but with smaller magnitudes, which is consistent with the broader geographic scope of this transaction.

The joint venture encompassed states from all Brazilian regions, creating a mix of highly competitive markets (such as São Paulo and Rio de Janeiro) and less competitive regional markets. This geographic diversity likely explains the intermediate results - efficiency gains were partially captured by retailers but the presence of highly competitive markets in the sample limited the extent of this capture.

The absence of price effects suggests that any upstream efficiencies generated by combining Shell's international expertise with Cosan's extensive Brazilian distribution network were not passed through to consumers. Instead, retailers in less competitive regional markets were able to capture these benefits, while intense competition in major metropolitan areas prevented significant price increases.

### The Role of Downstream Market Structure and Implications for Antitrust Analysis

The heterogeneity in results across cases can be largely explained by differences in downstream market competitiveness in the affected regions:

**Highly competitive markets (Case 2):** In Brazil's most competitive regions, downstream competition was sufficient to prevent price increases even when upstream market power was created. However, this protection came at the cost of retailer profitability through margin compression.

**Less competitive markets (Case 3):** In geographically dispersed northern markets with higher barriers to entry, retailers had sufficient market power to capture efficiency gains rather than compete them away through lower prices.

**Mixed competitive environments (Case 4):** The combination of highly competitive and less competitive markets resulted in intermediate outcomes, with limited efficiency capture by retailers.

This pattern demonstrates that downstream market structure plays a crucial mediating role in determining how upstream merger effects are transmitted to consumers. Competitive retail markets can provide important consumer protection against upstream anticompetitive effects, but may not ensure that efficiency gains are passed through to consumers.

These results also provide several important insights for antitrust authorities regarding concentration evaluations in vertically related markets:

**Geographic market definition matters:** The variation in effects across regions with different competitive characteristics underscores the importance of careful geographic market definition in merger analysis. Mergers affecting primarily competitive markets may have different welfare implications than those affecting less competitive regions.

**Asymmetric transmission of upstream effects:** While competitive downstream markets can protect consumers from upstream anticompetitive effects (Case 2), they may also prevent consumers from benefiting from upstream efficiency gains (Cases 3 and 4). This asymmetry is particularly pronounced in concentrated upstream markets, where efficiency gains from mergers are less visible to consumers compared to cost increases. Unlike highly publicized upstream cost shocks (such as refinery price increases that receive extensive media coverage and create consumer expectations for price adjustments), efficiency gains from concentration acts operate through opaque wholesale pricing mechanisms that lack transparency. This information asymmetry enables downstream retailers to capture efficiency benefits without consumer awareness or competitive pressure to pass them through. The result is a systematic bias where competitive retail markets effectively transmit upstream cost increases to protect producer margins but retain upstream cost savings to enhance retailer profitability, leading to an inequitable distribution of concentration-related welfare effects.

**Importance of regional market analysis:** The concentration of concentration effects in specific geographic regions with distinct competitive characteristics suggests that antitrust authorities should pay careful attention to regional variations in market structure when evaluating mergers in geographically dispersed industries.

**Long-term sustainability concerns:** The margin compression observed in Case 2 raises questions about the long-term sustainability of downstream competitive protection. Continued pressure on retailer profitability could lead to exit or reduced investment, potentially undermining the competitive protection over time.

These findings highlight the complexity of merger effects in vertically related markets and demonstrate the value of analyzing both price and margin outcomes to understand the full impact of horizontal mergers on market outcomes and welfare distribution.

## 2.7 Concluding Remarks

In this paper we analyzed four concentration acts, each involving at least one large firm in the wholesale distribution segment of fossil fuels in Brazil. All cases selected had regional or national relevance, and happened prior to the antitrust reform (2012). Under this previous regulatory regime, firms were allowed to merge (or acquire others) before notifying the authorities or waiting for approval.

The first of these cases was related to the split of Ipiranga's assets and purchase by Petrobras (BR). Despite the concerns raised, the Brazilian antitrust office (CADE) was successful in preventing an increase in concentrations that could lead to relevant unilateral price pressures. The limitation of the assets that Petrobras would be able to purchase did not significantly change the market structure of those regions. It even resulted in a slight price reduction to consumers.

The second case, Ipiranga-Texaco, happened in the largest fuel markets in Brazil. The result had an apparent success, with no price increase to final consumers. However, analyses of retail margins show that this apparent success was possible due to the high level of competition in the downstream segment, which reduced their profitability to prevent price increases to consumers. In other words, CADE's analysis of the acquisition per se was unsuccessful, creating excessive market power that allowed for an increase in prices in the wholesale segment. Consumers remained unharmed due to the degree of competitiveness among retailers.

The third case refers to a minor concentration in northern Brazil, a region represented mainly by the Amazon area. In this region, markets are more dispersed, the number of competing retailers is smaller than in the southern regions, and distribution costs are higher. This configuration gives a large market power to the downstream segment, which was able to capture all of the efficiency gains from the acquisition in the upstream market. Any resulting wholesale price reduction effects were not passed through to consumers, but absorbed my retailers in the form of higher margins.

The result of the last case (Shell-Cosan) represents a mix of cases 2 and 3. It was a national-level joint venture, encompassing 21 states plus the federal district, of which all southern states ( containing more competitive downstream markets) and many northern states (less competitive) were put together in this case. Similar to case 3, it resulted in no significant price increases to consumers, but small increase in retail margins.

These findings underscore the importance of examining not only the final impact on consumers but also the effects on all agents involved in a vertically integrated market. While consumer prices are often the focal point of antitrust scrutiny, our results show that critical distributional shifts – such as margin compression or expansion – may occur beneath the surface, masking an increase in harmful market power. These shifts reveal how cost burdens or efficiency gains are transmitted along the supply chain and whether welfare gains accrue to consumers, retailers, or upstream suppliers. A focus solely on consumer price outcomes risks underestimating both harm and benefit, especially in vertically structured markets with heterogeneous competitive conditions across regions.

More broadly, the study demonstrates the importance of institutional design in merger review policy. The pre-2012 Brazilian framework allowed for post-hoc notification, which in several cases enabled structural changes to materialize before a competitive assessment was conducted. This institutional delay may have limited the effectiveness of enforcement even in cases where competitive harm was identified ex-post. By combining detailed transaction-level data with regionally disaggregated analysis, this paper contributes a methodological template for retrospective merger evaluations in concentrated, multi-tiered industries. The evidence calls for nuanced, region-specific antitrust assessments that consider not only concentration levels, but also the ability of downstream market forces to constrain or amplify the effects of upstream consolidation.

# Figures and Tables

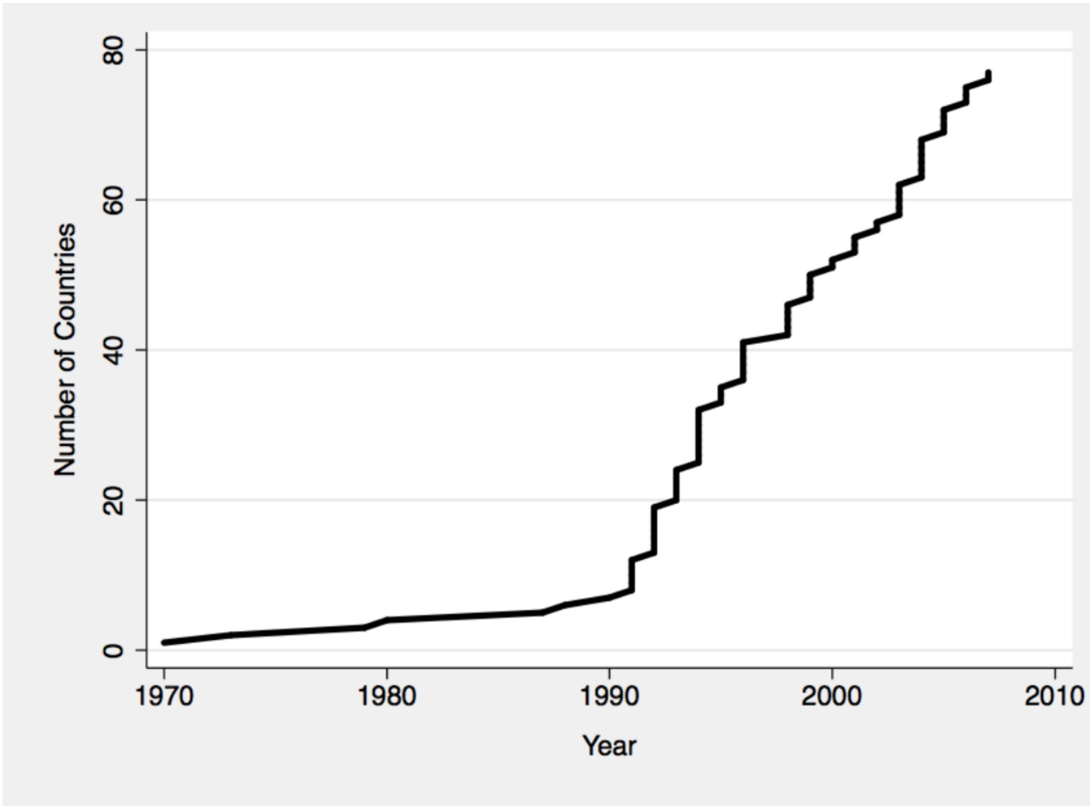


Figure 2.1: Adoption of Antitrust Laws in the Developing World

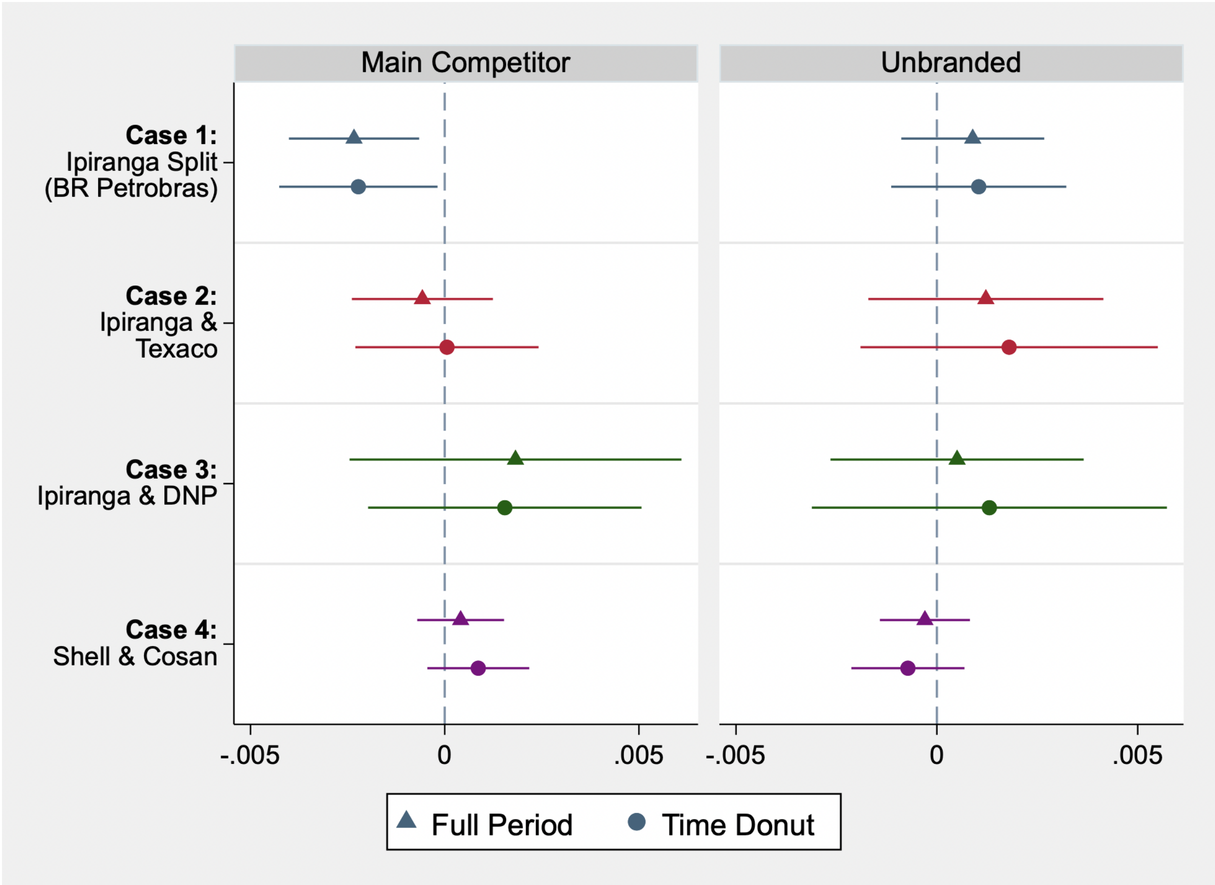


Figure 2.2: Difference-in-Differences Price Models

*Notes*: This figure shows the results from the difference-in-differences models using gasoline price as dependent variable. The panel on the left shows results using as control the respective main competitor, while the panel on the right uses unbranded retailers as control. Triangular marks represent full period regressions (12 months window), while circle marks represent donut time regressions (excluding 2 months around the merger to control for potential confounds at the time of the merger). All models use retailer-by-municipality and week-by-municipality fixed effects. Clustered by municipalities.

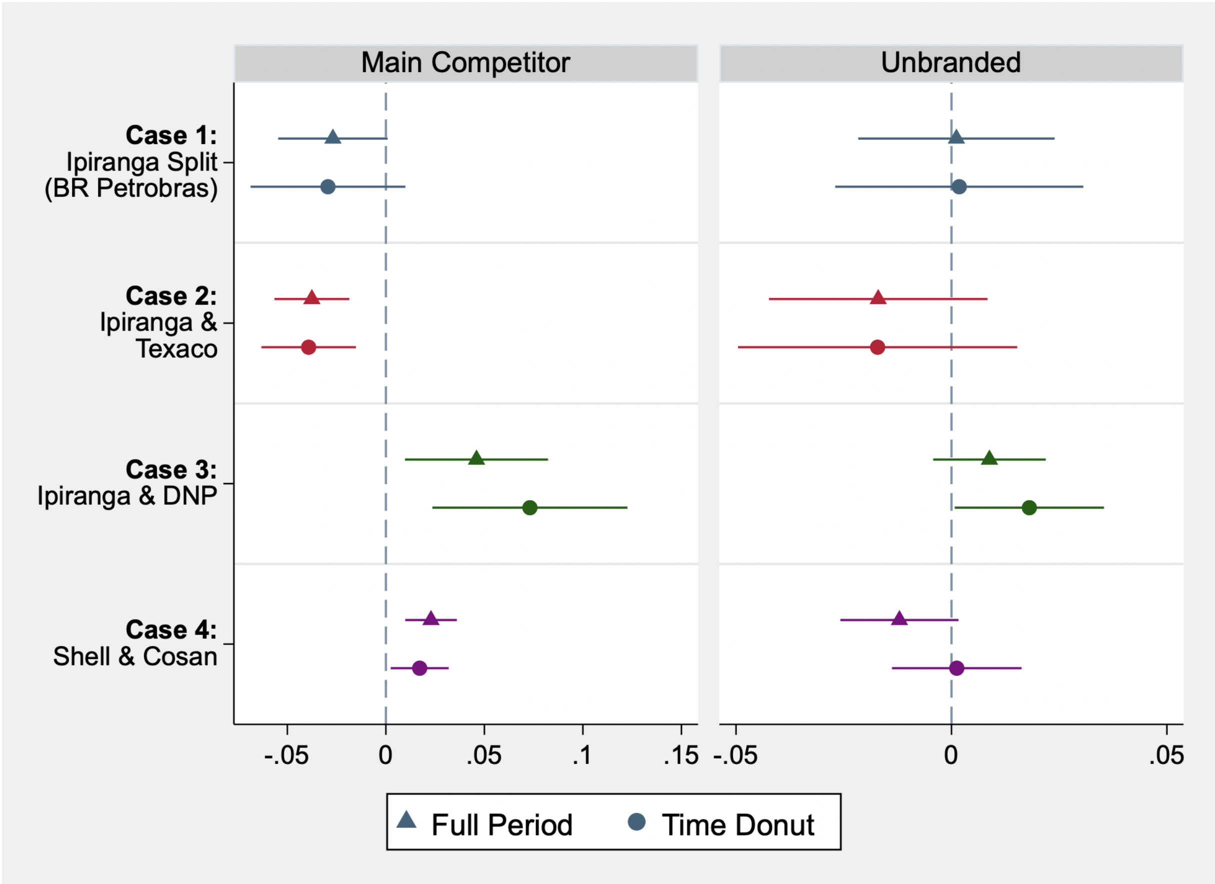


Figure 2.3: Difference-in-Differences Margin Models

*Notes*: This figure shows the results from the difference-in-differences models using gasoline margin as dependent variable. The panel on the left shows results using as control the respective main competitor, while the panel on the right uses unbranded retailers as control. Triangular marks represent full period regressions (12 months window), while circle marks represent donut time regressions (excluding 2 months around the merger to control for potential confounds at the time of the merger). All models use retailer-by-municipality and week-by-municipality fixed effects. Clustered by municipalities.

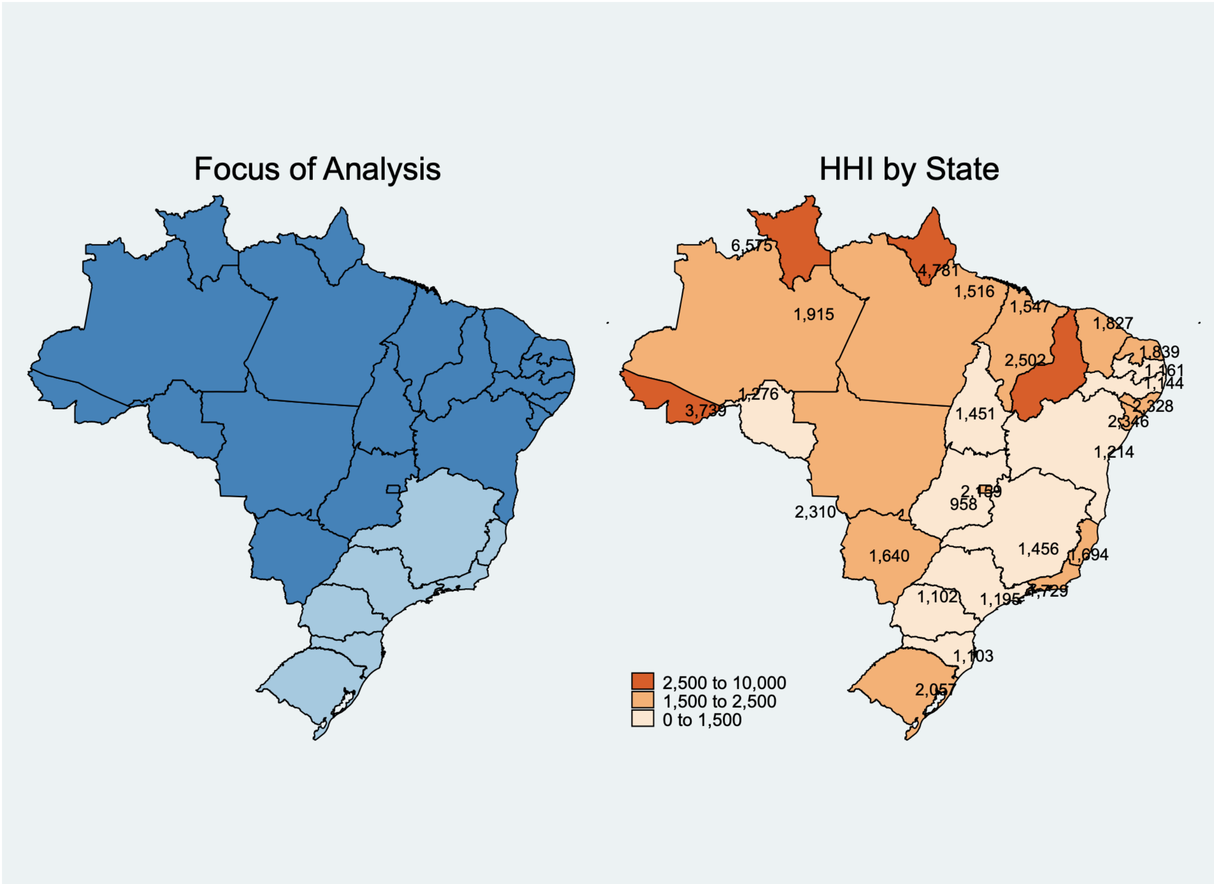


Figure 2.4: Geographic Overlap and Market Concentration – Case 01: Ipiranga Split

*Notes*: The left map shows the geographic presence of the merging firms. Dark blue states represent joint operations, medium blue states show presence by only one firm. The right map displays state-level HHI: darker areas denote more concentrated distribution markets. Several states in the North and Northeast exceed the 2,500 threshold, signaling high pre-merger concentration. Despite moderate overall concentration, the merger's regional intensity suggests varying competitive risks across states.

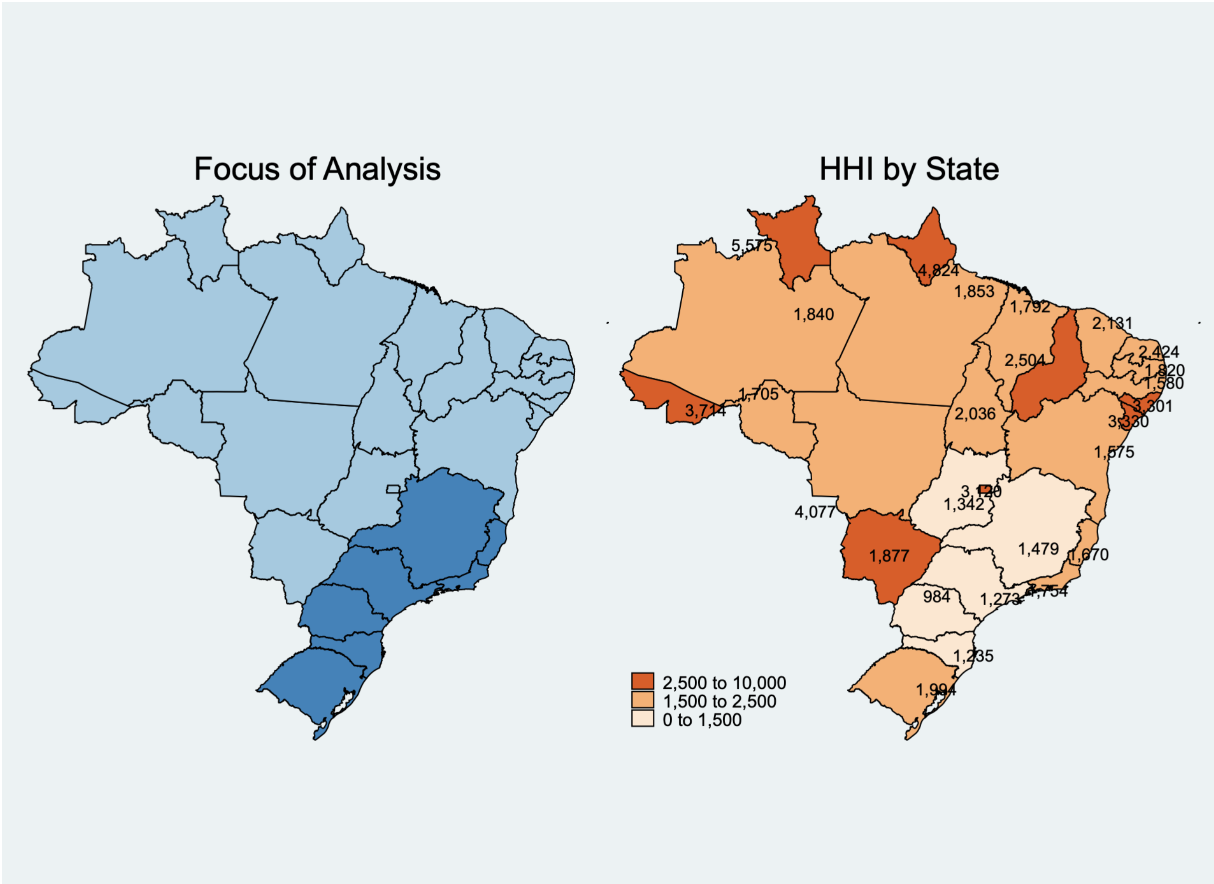


Figure 2.5: Geographic Overlap and Market Concentration – Case 02: Ipiranga and Texaco (Chevron)

*Notes*: The left panel highlights the merging firms' shared operations, concentrated in the Southeast and South regions (in dark blue). Lighter shades denote only one firm, hence no competition concerns. The right map shows HHI levels, with some states near or above 2,500. Most of the states affected by this merger show a low level of concentration.

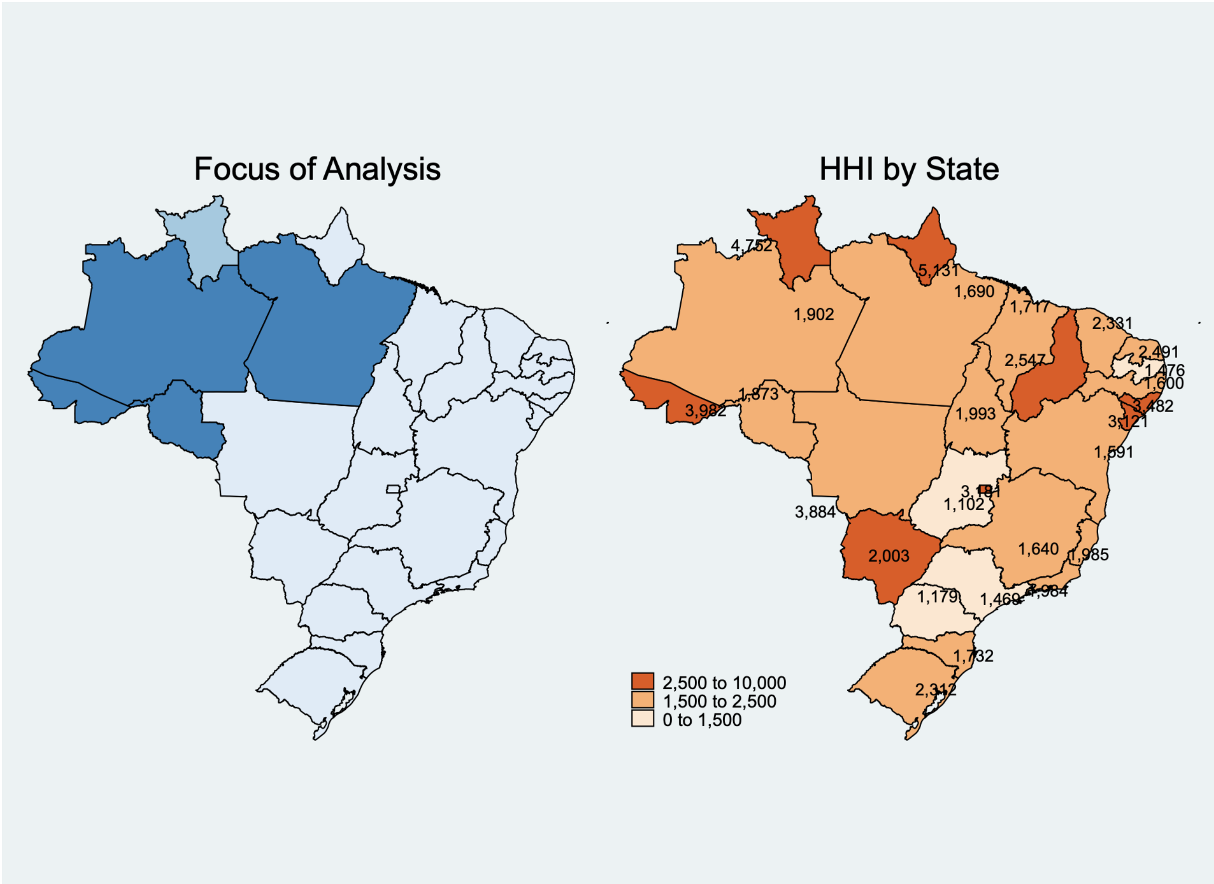


Figure 2.6: Geographic Overlap and Market Concentration – Case 03: Ipiranga and DNP

*Notes*: The map on the left indicates that the merging firms primarily operated in the North and parts of the Midwest. In contrast, the Southeast and South regions show no competition concerns. The right panel reveals that several of these operational states are already highly concentrated (HHI ¿ 2,500), raising potential red flags for antitrust enforcement in affected areas.

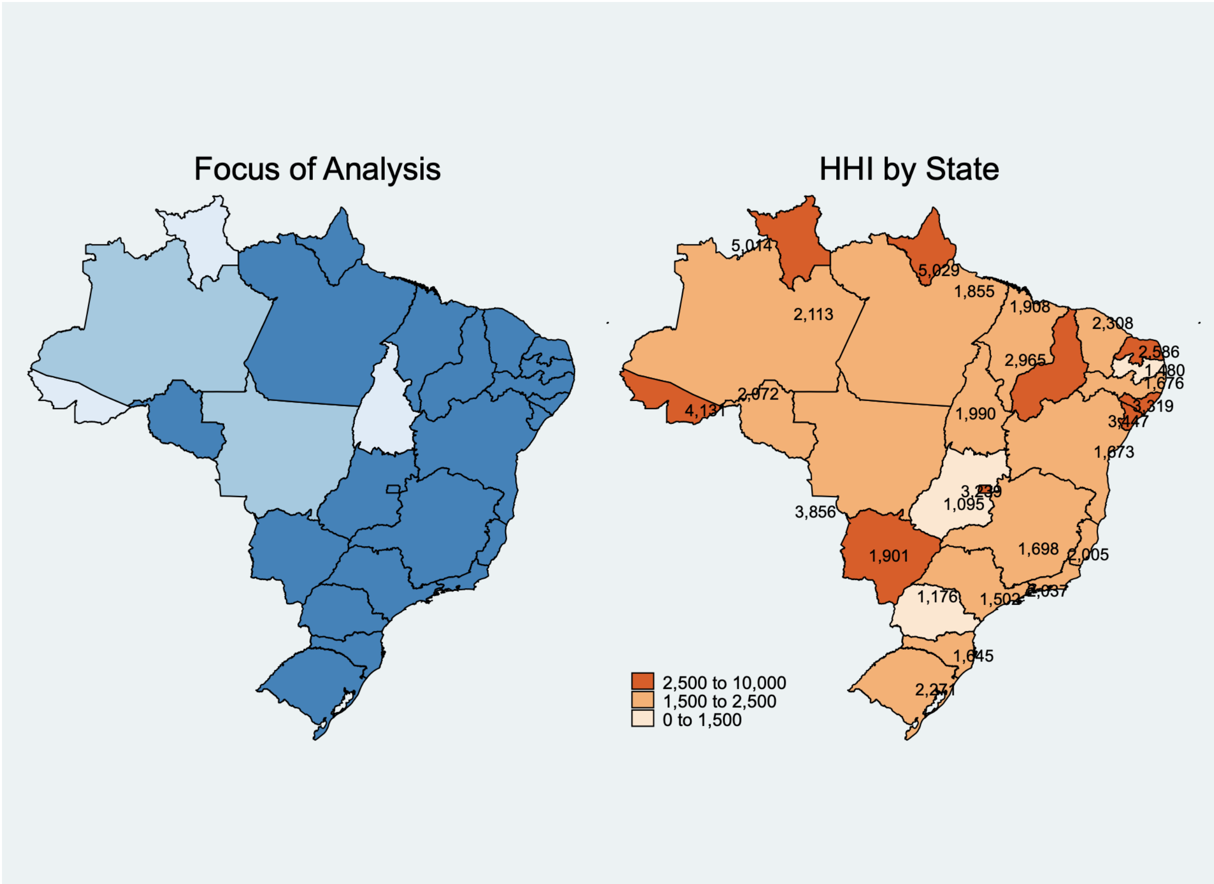


Figure 2.7: Geographic Overlap and Market Concentration – Case 04: Cosan and Shell

*Notes*: The map on the left illustrates the overlap in operations between the merging firms. Dark blue states indicate joint presence in distribution or retail segments; medium blue shows presence by only one firm; light blue indicates no presence. The map on the right shows the Herfindahl-Hirschman Index (HHI) by state: darker tones reflect higher concentration levels. According to antitrust guidelines, HHI values above 1,500 raise competitive concerns.

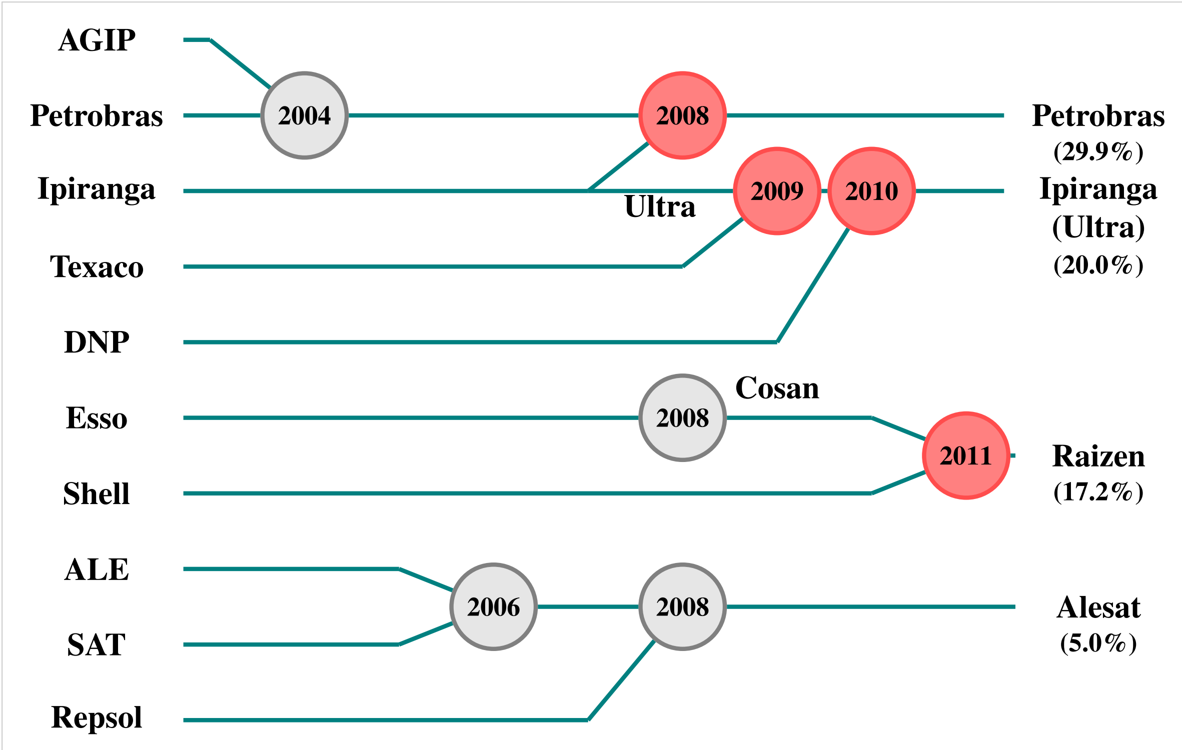


Figure 2.8: Timeline of main mergers and acquisitions between 2004 and 2011

*Notes*: This figure shows the largest mergers and acquisitions in the distribution fuel market between 2000 and 2012. The market share is calculated considering the national level market for December 2012. Data source: ANP.

# Chapter 3

# Technology Innovation and Climate Change Mitigation: The Case of Flex-Fuel Cars in Brazil

## 3.1 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, with 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

[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.

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 flex-fuel technology in reducing GHG emissions.

I use the information on Brazilian-insured vehicles to construct a novel database with detailed information on vehicle models and insurance characteristics. This database covers the period 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 on 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 strategy used for the turnover model is a panel instrumental variable approach, with the first stage exploring the relationship between used vehicle prices and a measure of fuel

[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.

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 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 ($-0.36 \times -0.17$), and for personal versus firm use, especially for older vehicles ($-0.47 \times -0.62$). The results indicate that tax reduction policies were responsible for the replacement of an average of 185,000 cars per year.

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 results from the turnover model, and estimates of average scrap rates from Mattos and Correia (1996) to construct an estimative for 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. Lastly, I 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 some studies focus on estimating survival curves and lifetime usage of vehicles (Hao et al. (2011*a*) Greene and Leard (2023)), other studies examine the effect of fuel prices and other policies on scrappage (Bento, Roth and Zuo (2018), Jacobsen and Van Benthem (2015), Baltas, Xepapadeas et al. (2001)). My work extends to the literature by including the replacement of used vehicles and by analyzing data from an emerging country with a sizable automobile market.

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)). Particularly, my work also relates directly to others investigating mitigation scenarios (Hao et al. (2011*b*), Alam et al. (2017), Palencia, Furubayashi and Nakata (2012)). I estimate that the contribution of the flex-fuel technology reduced $CO_2$ 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 3.2 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 3.3 I describe the data used in this paper. Section 3.4 presents my empirical strategy while section 3.5 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 3.8.

## 3.2 Background

### 3.2.1 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

[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), **?**)

[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.

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 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].

[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”,

### 3.2.2 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 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 3.4 and 3.7). 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

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

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 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 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 done 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.

### 3.2.3 Evolution of Automobile and Fuel Markets

At the end of the 1970s, after both petroleum shocks, manufacturers found the perfect conditions in Brazil 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 3.3 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 3.1.

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]

[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".

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 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.

## 3.3 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 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

[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.

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.

### 3.3.1 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 3.1 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. 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 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 3.3). 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 3.5.

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 3.2). 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. 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 3.6.

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 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

[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.

agents ends up being sold to non-risk-averse agents after one or more years of usage, and this turnover rate captures this movement.

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]

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

[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 higher maintenance costs.

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:

$$y_{amt} = \frac{n_{am(t-1)} - n_{am}}{n_{am(t-1)}}|_{(t-v)=a} \tag{3.1}$$

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 3.2 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 3.8 and table 3.2 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 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 also be 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 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-

[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.

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.

## 3.4 Methodology

### 3.4.1 Technology Diffusion of Flex-Fuel Vehicles

Like any traditional durable good, automobiles are purchased with the expectation that they will be consumed (or used) over a certain amount 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.

An extra factor in automobiles could be a second-hand vehicle with new technology. This product offers the same features as a new vehicle but at a lower cost. It offers the experience of trying new technology without incurring the high cost of a brand-new vehicle.

As highlighted previously, the main suppliers in the Brazilian automobile market opted to replace 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 the consumers' side since no other viable choices were available.

To facilitate the transition, the four manufacturers established that their flex-fuel vehicles had the same average price as their gasoline-driven vehicles. In addition, campaigns explained the difference in the technology and how to decide when ethanol had a higher cost-benefit ratio. The government also applies the same tax cutoff to 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.

### 3.4.2 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 3.1 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.

#### 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 3.2. Here, $Y_{amt}$ represents the turnover rate, $P_{amt}$ is the used vehicle price, and $\alpha_{am}$ and $\alpha_{at}$ 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.

$$ln(Y_{amt}) = \gamma_1 ln(\hat{P})_{amt} + \alpha_{am} + \alpha_{at} + \epsilon_{amt} \tag{3.2}$$

$$ln(P_{amt}) = \Sigma_{m=1}^{M} \beta_m Z_{mt} + \alpha_{am} + \alpha_{at} + \mu_{amt} \tag{3.3}$$

**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 3.2, 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 3.3. 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 3.12. 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 3.3 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 3.12 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.

#### 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 3.4.2 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 3.12).

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.

### 3.4.3 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]

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 3.4, where the functions $a(p)$ and $b(p)$ follow a second-order approximation as represented in 3.5 and 3.6. I will suppress individual and time for simplicity of notation.

$$log(c_i(p, u_i)) = (1 - u) \times log(a(p)) + u \times log(b(p)) \tag{3.4}$$

$$log(a(p)) = a_0 + \sum_{k \in (g,e)} a_k log(p_k) + \frac{1}{2} \sum_k \sum_k \gamma_{k,j} log(p_k) log(p_j) \tag{3.5}$$

[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.

$$log(b(p)) = log(a(p)) + \beta_0 exp\left(\sum_{k\in(g,e)} beta_k log(p_k)\right) \tag{3.6}$$

Substituting the functions 3.5 and 3.6 in the equation 3.4, I obtain the AIDS cost function 3.7. 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 3.7 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 3.8.

AIDS cost function:

$$\begin{aligned} log(c_i(p,u_i)) = a_0 + \sum_{k\in(g,e)} a_k log(p_k) + \frac{1}{2}\sum_{k\in(g,e)}\sum_{j\in(g,e)} \gamma_{k,j} log(p_k) log(p_j) + \\ +(1-u)\beta_0 exp\left(\sum_{k\in(g,e)} beta_k log(p_k)\right) \end{aligned} \tag{3.7}$$

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

$$\frac{p_g \times q_g}{c(p,u)} = w_g = a_g + \gamma^*_{ge} log(p_e) + \gamma_{gg} log(p_g) + u\beta_0\beta_g exp\left(\beta_g log(p_g) + \beta_e log(p_e)\right) \tag{3.8}$$

For a utility-maximizing consumer, the total expenditure $w$ should equate to $c(u,p)$. By defining a price index $P$ as in 3.9, I can invert equation 3.8 and solve it for the utility as a function of prices and demand for fuel.

$$P = a_0 + \sum_{k\in(g,e)} a_k log(p_k) + \frac{1}{2}\sum_{k\in(g,e)}\sum_{j\in(g,e)} \gamma_{k,j} log(p_k) log(p_j) \tag{3.9}$$

$$log(x) = log(P) + u\beta_0 exp\left(\beta_g log(p_g) + \beta_e log(p_e)\right) \tag{3.10}$$

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

$$u = log\left(\frac{x}{P}\right) \times \frac{1}{\beta_0 exp\left(\beta_g log(p_g) + \beta_e log(p_e)\right)} \tag{3.11}$$

Finally, substituting the utility into equation 3.8, I can obtain the expression for the share of expenditure as in 3.12.

$$w_g = a_g + \gamma^*_{ge} log(p_e) + \gamma_{gg} log(p_g) + \beta_g log\left(\frac{w}{P}\right) + \xi_g \tag{3.12}$$

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 3.13. Based on the aggregated stage and the expenditure-share equations, I can derive the price elasticities as indicated in equation 3.14.

$$log(Q_n) = n + \beta log(I_n) + \gamma log(P_n) + Z_n + \epsilon_{nt} \tag{3.13}$$

$$\nu_{ij} = \frac{1}{w_i}\left(\gamma_{ij} - \beta_i w_j\right) + \left(1 + \frac{\beta_i}{w_i}\right)\left(1 + \gamma\right) w_j - 1[i = j] \tag{3.14}$$

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.

### 3.4.4 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 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]

[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.

[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

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.

## 3.5 Results

In this section, I discuss the main results obtained and the policy implications they bring. I start with table 3.4 that presents my main estimates for the turnover elasticity ($\gamma_1$), using equation 3.2. 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

turns out to be more profitable.

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.

### 3.5.1 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 3.4, I present 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]

[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 significantly affect the elasticities.

[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 C.2

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

### 3.5.2 Flex Fuel Vehicles

Table 3.5 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, so I called the next period (2011 to 2015) the "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 3.5 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,

[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.

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 were old cars replaced by FFV, but consumers, in fact, started using the greener option (ethanol) as a substitute for gasoline.

### 3.5.3 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 3.6 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 makes difficult old vehicle replacements for a newer version.

### 3.5.4 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.

$$log(Q_{nt}) = a_n + \beta log(I_{nt}) + \gamma log(P_{nt}) + Z_{nt} + \epsilon_{nt} \tag{3.15}$$

$$w_{gnt} = a_g + \gamma_{ge}^{*} log(p_{ent}) + \gamma_{gg} log(p_{gnt}) + \beta_g log\left(\frac{w_{nt}}{P_{nt}}\right) + Z_{nt} + \xi_g \tag{3.16}$$

Table 3.10 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 the gasoline model is relatively 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

[24] On average, flex-fuel vehicles are also more efficient than gasoline vehicles, presenting better fuel economy as can be seen in figures 3.7 and 3.4.

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, **?** 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 3.11 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 3.11 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 3.1. 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 3.12 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 3.10 but not in the models in table 3.12 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.

## 3.6 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 3.17 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 3.18). 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 3.19). The average intensity of use of a vehicle is calculated as equation 3.20.

$$\begin{gathered} KmTraveled \times EmissionFactor = Pollution \\ (Km/year) \times (g/Km) = (g/year) \end{gathered} \tag{3.17}$$

$$KmTraveled = Fleet \times IntensityOfUse \tag{3.18}$$

$$KmTraveled = \sum_{g,e,d} (FuelVolume \times FuelEconomy) \tag{3.19}$$

$$IntensityOfUse_g = \frac{\sum_{i} (FuelEconomy_{i,g} \times FuelVolume_{i,g})}{Fleet_g} \tag{3.20}$$

Data regarding pollution emission factors is obtained from a series of reports produced by the Brazilian Ministry of Environmental Affairs, MMA, (see MMA (2011*a*)), 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 **?** 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 3.21, 3.22, and 3.23) based on observational data obtained from annual vehicle emission inspections.

For gasoline cars:

$$
\begin{aligned}
IntUse &= 0.6716age^3 - 49.566age^2 + 799.66age + 11266 \\
IntUse &= 6,174 \text{ if the vehicle has over 40 years}
\end{aligned}
\tag{3.21}
$$

For ethanol cars:

$$
\begin{aligned}
IntUse &= -3.292age^3 + 174.31age^2 - 3083.6age + 31628 \\
IntUse &= 8,275 \text{ if the vehicle has over 28 years}
\end{aligned}
\tag{3.22}
$$

For flex-fuel cars:

$$
\begin{aligned}
IntUse &= -24.288age^3 + 426.19age^2 - 2360.4age + 19178 \\
IntUse &= 15,000 \text{ if the vehicle has over 8 years}
\end{aligned}
\tag{3.23}
$$

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

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 3.17. Taking a step back, I used the estimated value for the fleet, data on fuel economy, and based on equation 3.20, I retrieved the required fuel volume that would accommodate an intensity of use according to the estimations from the CETESB.

Figures 3.13 and 3.14 show the estimated volumes for gasoline and ethanol using equation 3.20 against the realization of such fuels. I used equation 3.20 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 were 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 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, another potential factor explaining 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

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

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 updates (see MMA (2011*b*), MMA (2011*a*), 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 (2021).

The counterfactual volume and market shares for gasoline and ethanol were obtained using the fuel demand model (equations 3.15 and 3.16). 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.

[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.

**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

[28]Federal taxes have been used since the beginning of the 2000s as gasoline price instruments to minimize price fluctuations (see figure 3.10). 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 3.9).

around 70% of the total fuel consumed in Brazil in any given year.

Table 3.15 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.

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 3.16 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 $CO_2$ 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 3.17 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 (Rosa and Ribeiro (1998)).

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

Dias De Oliveira, Vaughan and Rykiel (2005) and Rosa and 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 agricultural techniques and advancements in plantations 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 3.18. The first column summarizes the total $CO_2$ equivalent emissions considering all source studies (carbon dioxide, methane, and nitrogen dioxide). The improvement of fuel economy and emission factors has a similar $CO_2$ reduction, of approximately 8%. The introduction of flex-fuel vehicles avoided the emission of 253 billion tons of carbon dioxide, or 21% of the baseline scenario.[32] Having all flex-fuel vehicles consuming only gasoline would represent an increase of 570 billion tons of $CO_2$, or 47% increase. Consuming only ethanol, on the other hand, would avoid the emission of 1557 billion tons, or 128% of the emissions in the baseline.

Price instruments have a strong 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 305 billion of $CO_2$ or 25% of the baseline scenario. One interesting aspect here is the fact that the four years with the price ceiling policy were approximately of the same magnitude as the full impact flex-fuel vehicles had, from 2003 to 2020, in reducing emissions (305 billion vs 253 billion). This result shows how important price policies are with respect to countering greenhouse gas emissions. Policies that drive con-

[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.

[32] This number corresponds to additional 104 billion tons of carbon emissions due to gasoline increased consumption and 149 billion tons due to diminish of ethanol (carbon-neutral) usage

sumers 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.

## 3.7 Policy Discussion: Lessons for Electric Vehicle Adoption and Energy Security

The findings in this chapter on the flexibility offered by multi-fuel technologies offer important insights for Brazil's ongoing transition to electric vehicles (EVs). While EVs promise lower emissions and reduced fossil fuel dependence, their successful deployment depends critically on the resilience and capacity of the electricity supply system. Despite Brazil having over 90 GW of installed capacity, electricity generation remains highly dependent on hydropower, a renewable source that is increasingly vulnerable to climate-related shocks. As illustrated in Figure 3.15, reservoir levels have fluctuated considerably over the past two decades, reaching critically low levels in 2001, 2014, 2015, and 2021. These years saw potential threats of power shortages and prompted government intervention to avoid blackouts. In particular, the 2021 drought led to rationing warnings and record-high thermoelectric generation.

At the same time, as shown in Figure 3.16, Brazil's energy matrix has shifted toward greater reliance on wind and solar. While these are desirable from an environmental standpoint, they are also intermittent and weather-dependent, making grid management more complex.

Another source of concern relates to the fragility of transmission infrastructure. A recent example of this fragility was observed in 2023, when parts of São Paulo experienced a prolonged blackout lasting nearly a week due to strong storms that damaged parts of the transmission towers. Such infrastructure limitations raise concerns about the feasibility of relying on a single energy input –electricity – for a growing share of the vehicle fleet.

This context underscores the value of fuel flexibility. Flex-fuel vehicles offer consumers the ability to switch between ethanol and gasoline, mitigating the risk of price shocks or shortages in any one fuel. Similarly, hybrid or multi-fuel EVs could provide a more secure transitional path, combining the benefits of electrification with resilience mechanisms that safeguard consumers and the broader economy from potential disruptions.

In this light, the lessons from the flex-fuel experience should not be overlooked. A robust EV strategy for Brazil should integrate concerns about energy security, infrastructure reliability, and consumer adaptability. Investments in grid resilience, diversified energy sources, and potentially hybrid vehicle technologies can help avoid over-dependence on a single fuel source and foster a more sustainable and secure transition.

## 3.8 Concluding Remarks

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 the new technology, I focus on measuring the diffusion of flex-fuel vehicles and estimating the price sensitivity of fleet turnover. 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 policymakers 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 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 8% 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 21% of the predicted level of emissions. The scenario with all flex-fuel vehicles consuming ethanol would promote a reduction of 1557 billion tons of $CO_2$, while alternative price scenarios replacing the gasoline price ceiling policy would avoid approximately 305 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.

# Figures and Tables

Table 3.1: 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 3.2: 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 3.3: Effect of Fuel Prices on Used Car Prices

| | All Ages | up to 10 years | above 10 years |
|---|---|---|---|
| Fuel Price $\times$ Quartile 2 | 320.9** | 604.7** | 652.2*** |
| | (159.4) | (258.7) | (136.2) |
| Fuel Price $\times$ Quartile 3 | 1089.6*** | 1885.1*** | 279.4*** |
| | (128.4) | (250.5) | (97.4) |
| Fuel Price $\times$ 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 3.4: Used Vehicle Price Elasticity of Turnover

| | Model 1<br>Main | Model 2<br>IPI tax | Model 3<br>up to 10 years | Model 4<br>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 3.5: Used Vehicle Price Elasticity of Turnover

| | Full Sample | | Excluding 2009, 2012-2014 | |
|---|---|---|---|---|
| | Cars | All Vehicles | Cars | All Vehicles |
| ***Introduction (2003 to 2006)*** | | | | |
| Turnover Elasticity | -0.4205*** | -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 3.6: 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 3.7: Used Vehicle Price Elasticity of Turnover by Usage

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | Main | up to 10 years | above 10 years |
| ***Panel A: Turnover Elasticity - Firm Use*** | | | |
| 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 3.8: 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 3.9: Used Vehicle Price Elasticity of Turnover for Cars

| | Model 1<br>18 to 24 | Model 2<br>25 to 44 | Model 3<br>45 to 64 | Model 4<br>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 $\times$ | 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 3.10: 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 3.15 and 3.16. The elasticities take the form of 3.14. 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 3.11: Fuel Consumption Models by Sub-Period

| | Model 1<br>2002 to 2004 | Model 2<br>2002 to 2010 | Model 3<br>2002 to 2014 | Model 4<br>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 3.15 and 3.16. The elasticities take the form of 3.14. The baseline model used for this exercise was model 2 from table 3.10. 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 3.12: Fuel Consumption Models - Robustness Check

| | Model 1<br><br>OLS | Model 2<br>Triple Policy +<br>Sugar Quality | Model 3<br>Triple Policy +<br>Sugar Price | Model 4<br>Double Policy +<br>Sugar Quality | Model 5<br>Double Policy +<br>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 3.15 and 3.16. The elasticities take the form of 3.14. 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 3.13: Used Vehicle Price Elasticity of Turnover

| | Model 1<br>up to $400k | Model 2<br>No Luxury | Model 3<br>Fuel Increase | Model 4<br>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 3.14: 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 3.15: Pollution Emissions: Actual Emissions and Flex-Fuel Scenarios

| *Period: 2003 to 2020*<br>*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 3.16: Pollution Emissions: All-in Scenarios

| *Period: 2003 to 2020*<br>*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 3.17: Pollution Emissions: Price Scenarios

| *Period: 2003 to 2020*<br>*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 3.18: Total $CO_2$ Emissions and Avoidance

| *Period: 2003 to 2020* *Pollutants in 1,000 tons* | Total $CO_2$ Emitted by Gasoline | Total $CO_2$ Emitted by Ethanol | Total Avoided (1,000 t) | % vs Prediction (Gasoline baseline) |
|---|---|---|---|---|
| Pollution Effectively Emitted | 1,171,873 | 295,939 | - | -2.3% |
| *Baseline Scenario (prediction)* | 1,212,022 | 307,956 | - | 0.0% |
| *Same Emission Factors* | 1,160,592 | 349,113 | -92,587 | -7.6% |
| *Same Fuel Economy* | 1,151,769 | 347,429 | -99,726 | -8.2% |
| *No Flex-Fuel, Same Stats* | 1,316,627 | 158,593 | 253,968 | 21.0% |
| *All-in Gasoline* | 1,554,710 | 79,389 | 571,255 | 47.1% |
| *All-in Ethanol* | 617,344 | 1,269,621 | -1,556,343 | -128.4% |
| *Constant Taxes* | 1,178,219 | 336,921 | -62,768 | -5.2% |
| *US Gasoline Prices* | 1,092,425 | 407,341 | -218,982 | -18.1% |
| *US Gasoline Prices + Constant Taxes* | 1,045,647 | 445,565 | -303,984 | -25.1% |

*Notes:* This table summarizes all simulation scenarios. **Total avoidance** is calculated as the change in gasoline emissions relative to the baseline plus the change in ethanol emissions relative to the baseline (ethanol treated as carbon-neutral). This accounts for the substitution of ethanol for gasoline and the resulting reduction in net carbon emissions. Formally:

$$\text{Total Avoidance} = (\text{Gas}_{\text{scenario}} - \text{Gas}_{\text{baseline}}) + (\text{EtOH}_{\text{baseline}} - \text{EtOH}_{\text{scenario}})$$

where Gas and EtOH are $CO_2$ emissions from gasoline and ethanol, respectively.

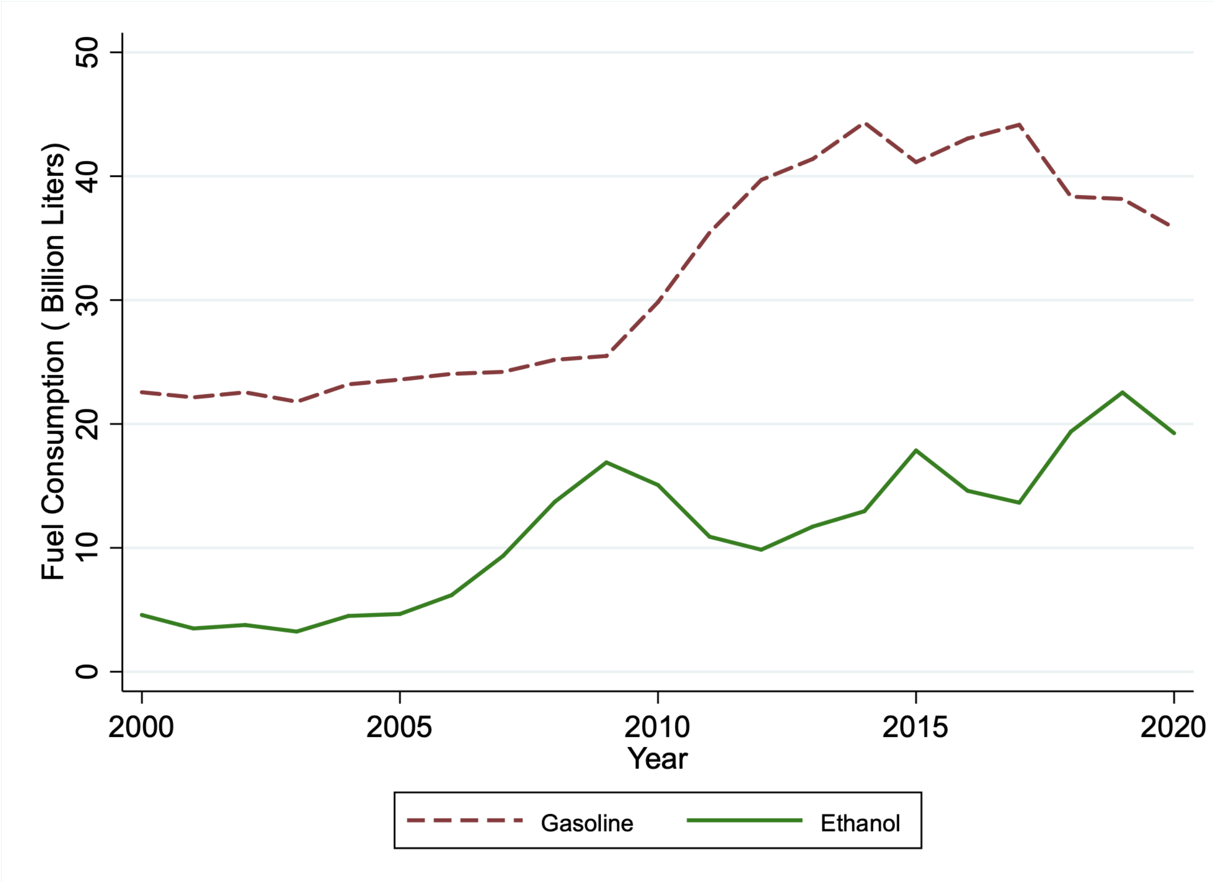


Figure 3.1: Fuel Consumption: Gasoline and Ethanol

*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.

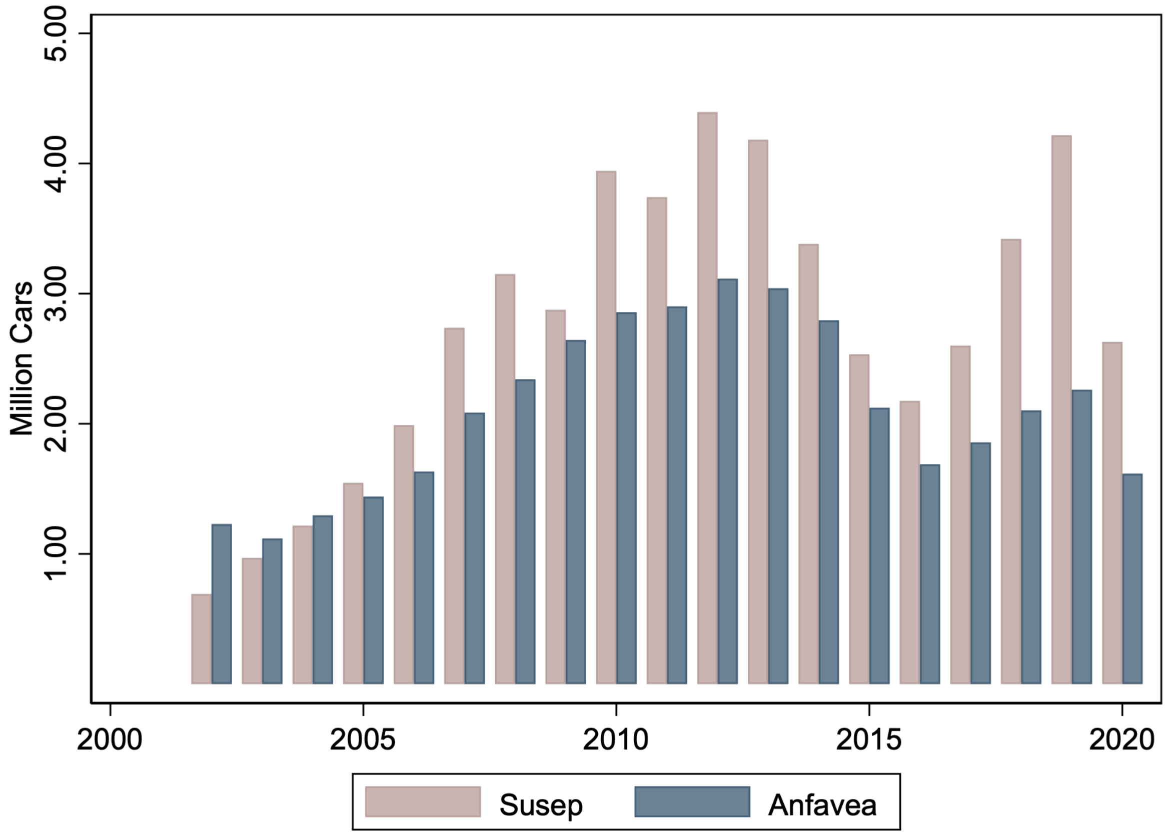


Figure 3.2: Registrations of New Cars: ANFAVEA and SUSEP

*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.

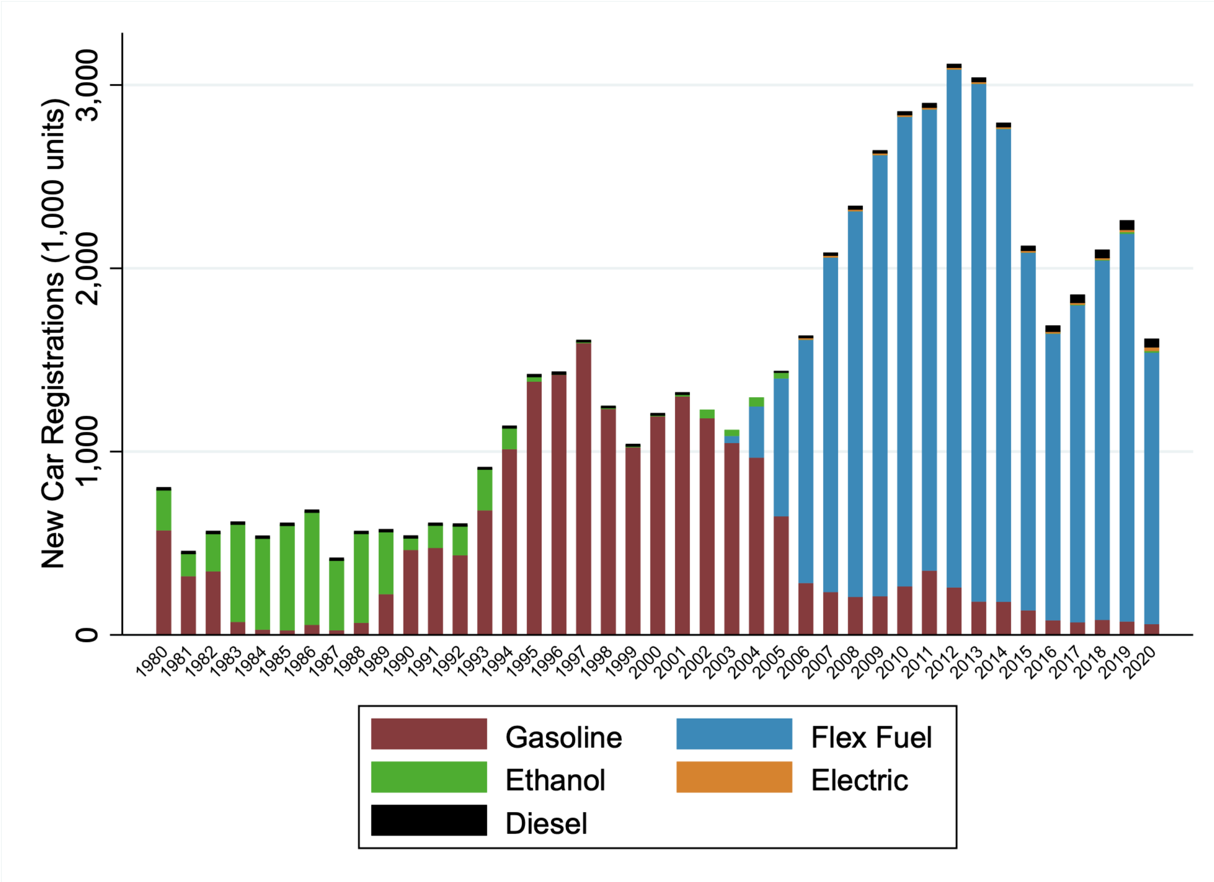


Figure 3.3: Car Registrations by Type of Fuel

*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.

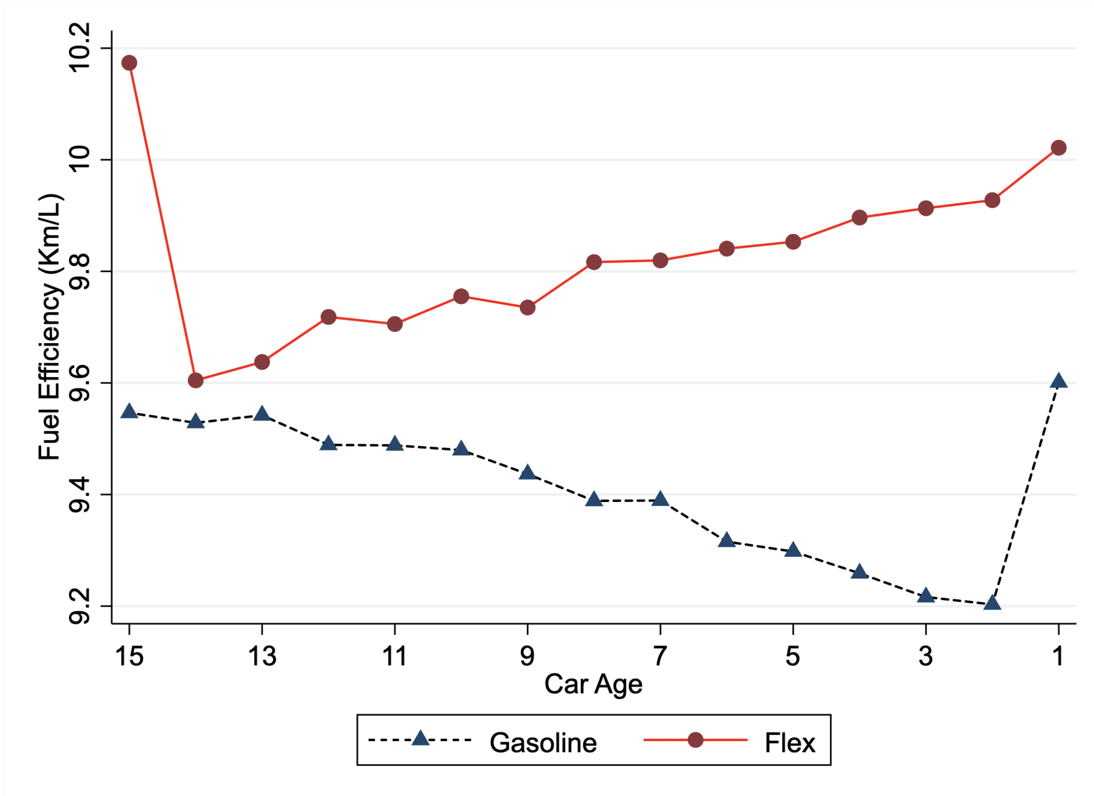


Figure 3.4: Fuel Efficiency of Gasoline and Flex-Fuel Vehicles by Age

*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.

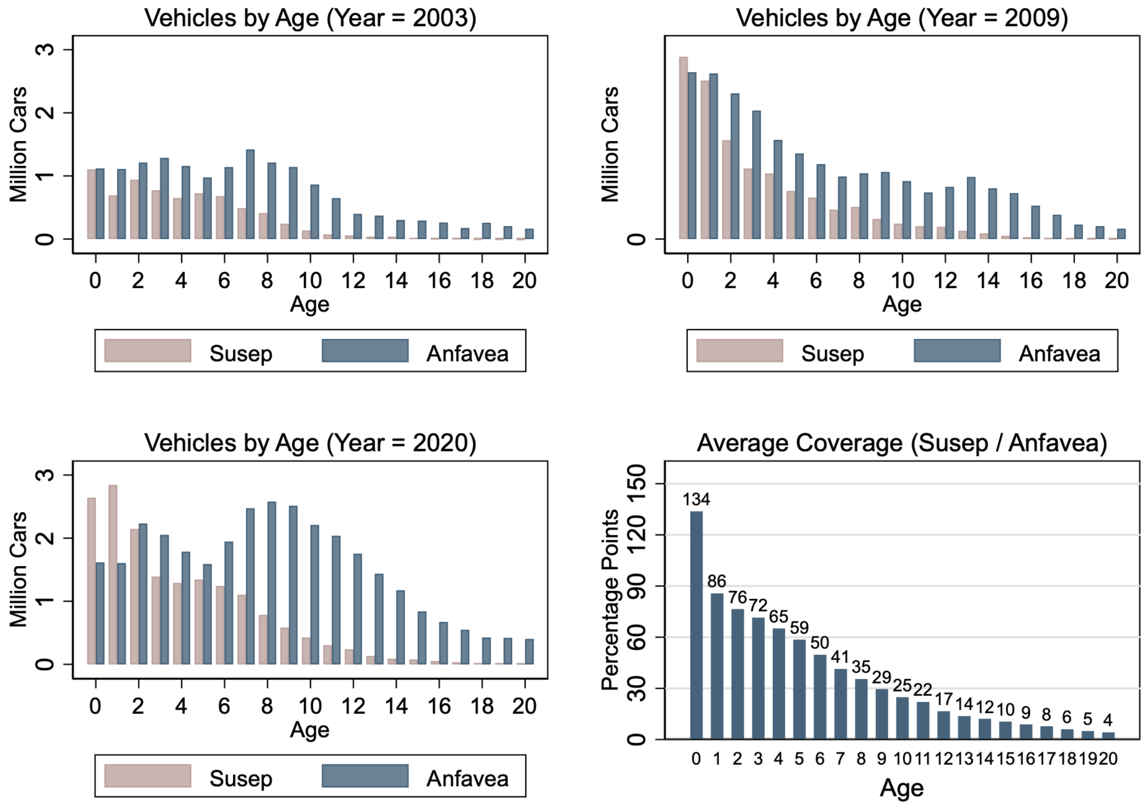


Figure 3.5: Number of Vehicles by Age for Different Years

*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.

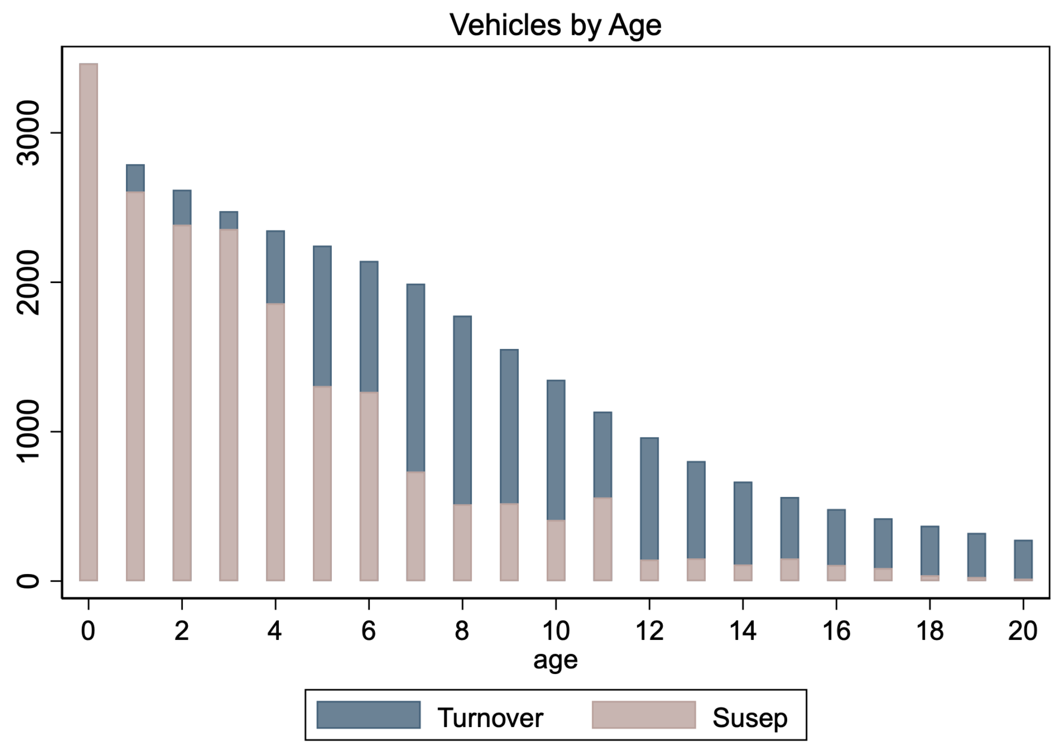


Figure 3.6: Average Turnonver of the Fleet

*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.

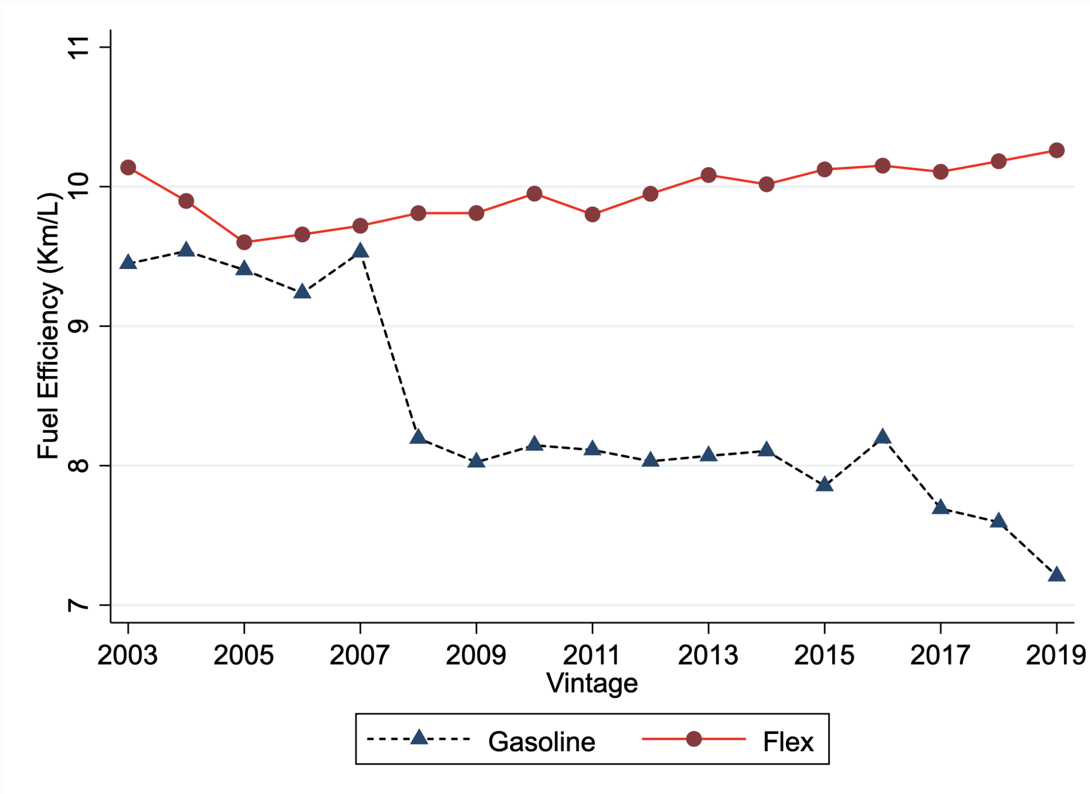


Figure 3.7: Fuel Efficiency of Gasoline and Flex Fuel Vehicles by Vintage

*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.

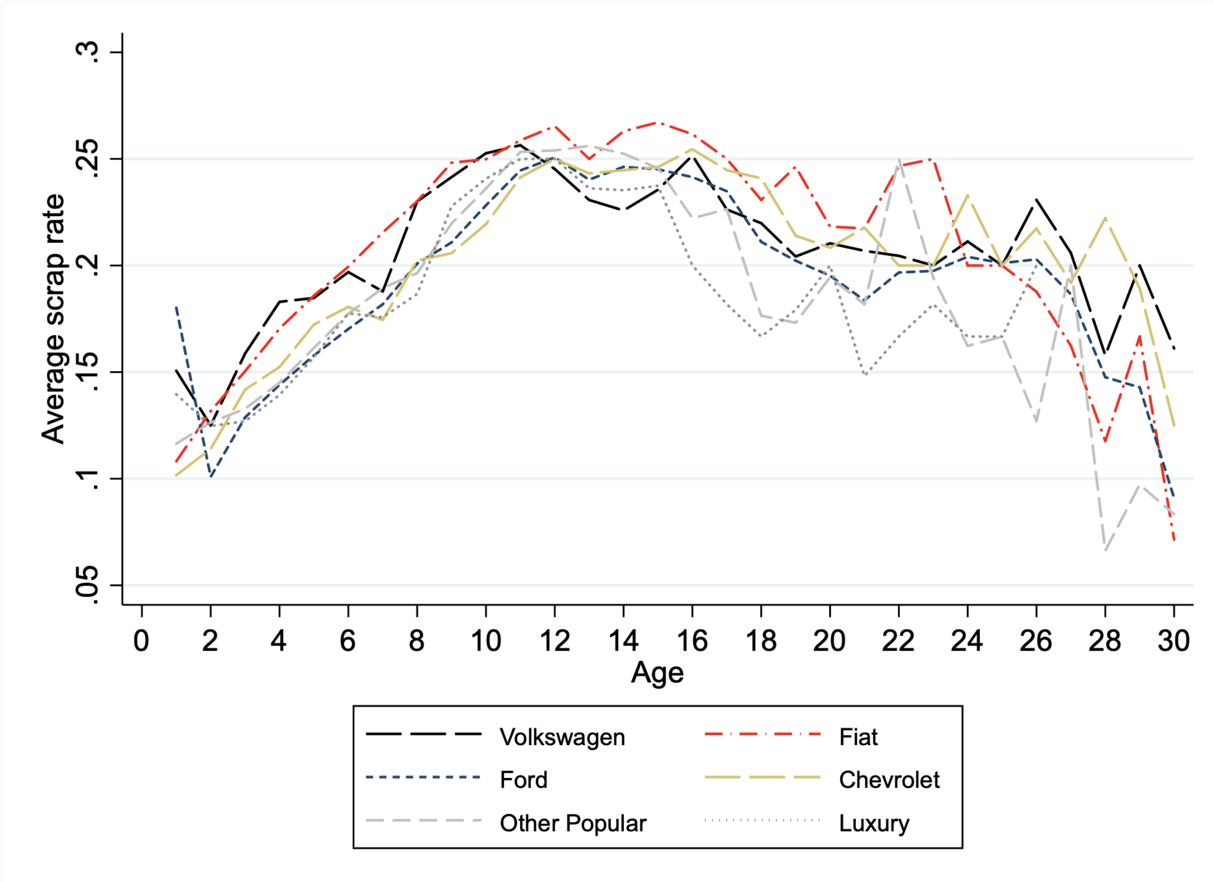


Figure 3.8: Median Turnover Rates by Vehicle Age and Maker

*Notes*: This figure shows the median scrap rates by vehicle age (including replacement rates). 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.

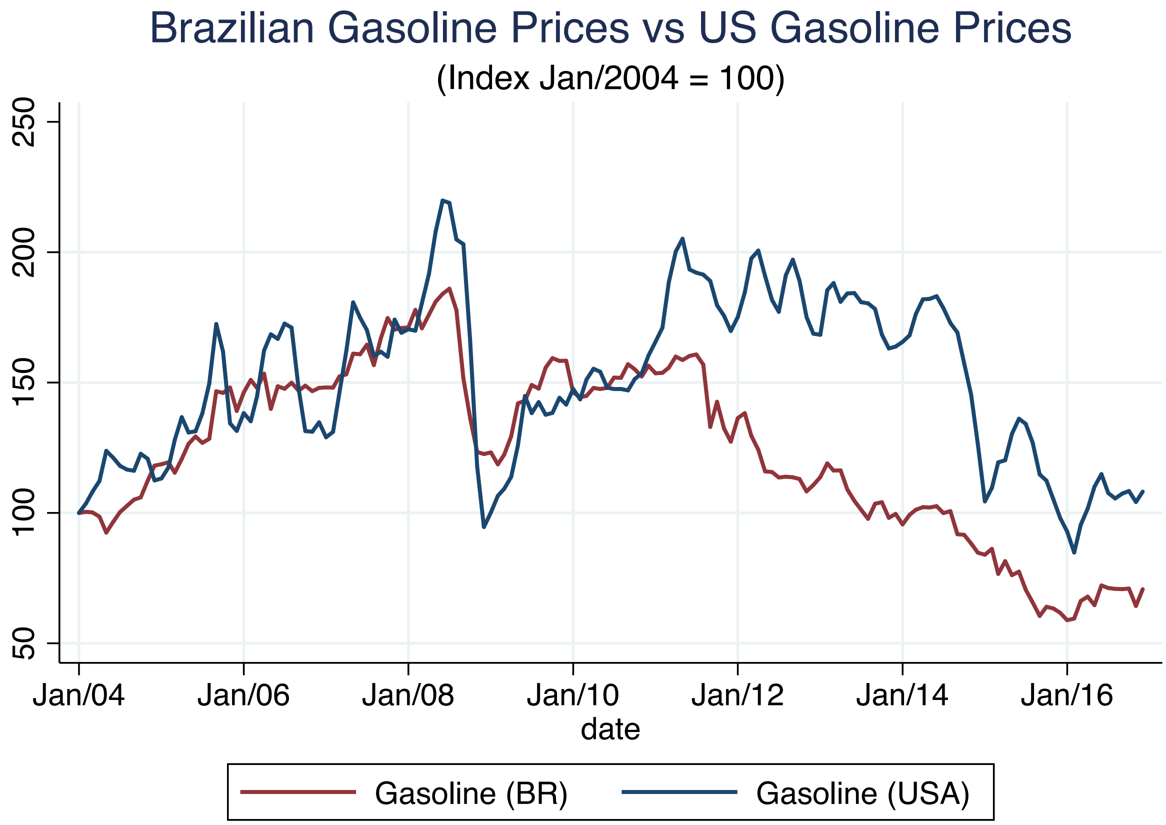


Figure 3.9: Real Gasoline Prices: Brazil and US

*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.

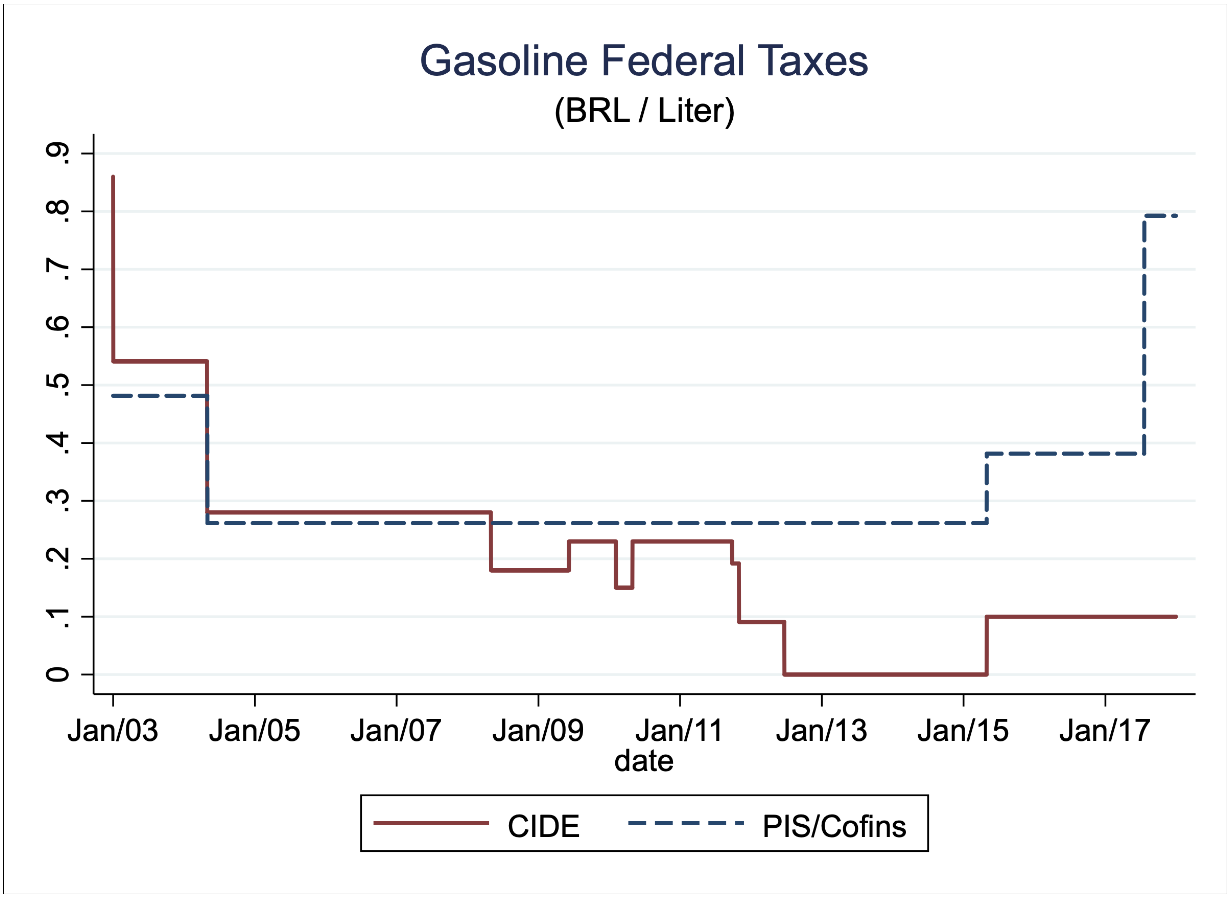


Figure 3.10: Gasoline Federal Taxes in Brazil

*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.

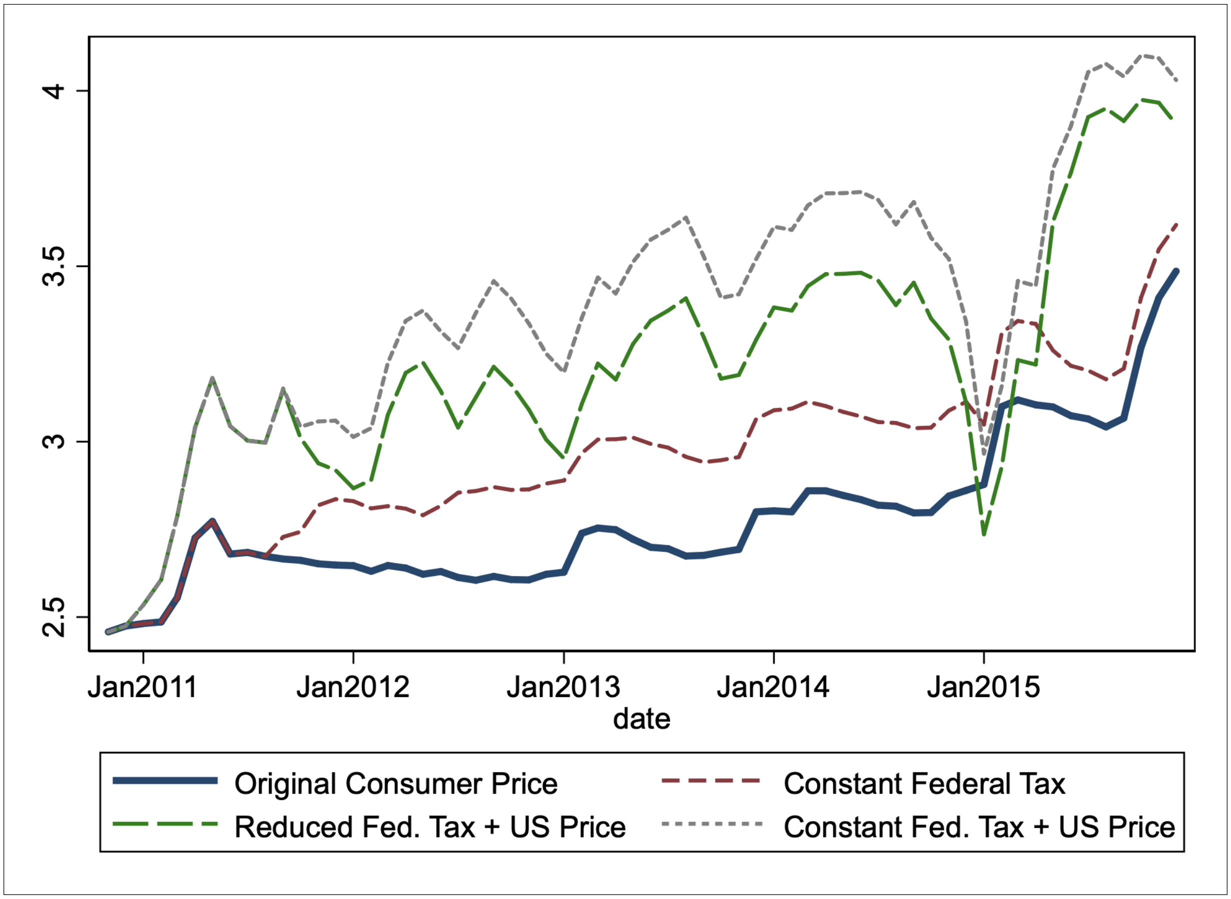


Figure 3.11: Nominal Gasoline Prices - Counterfactual

*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.

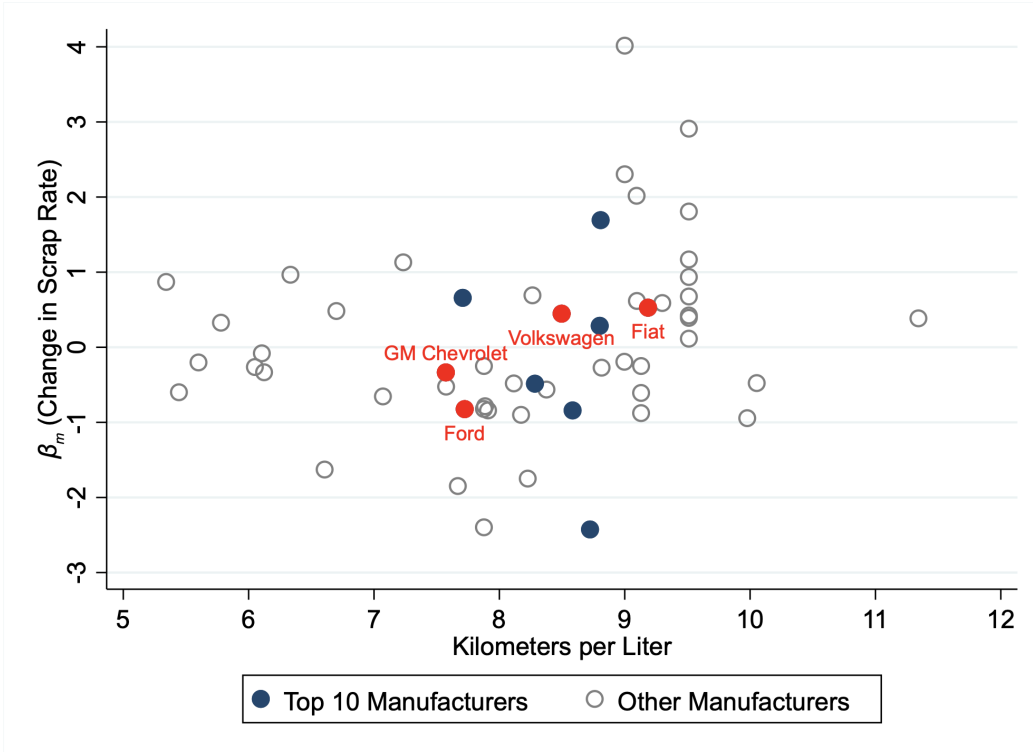


Figure 3.12: Coefficients from the First Stage

*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.

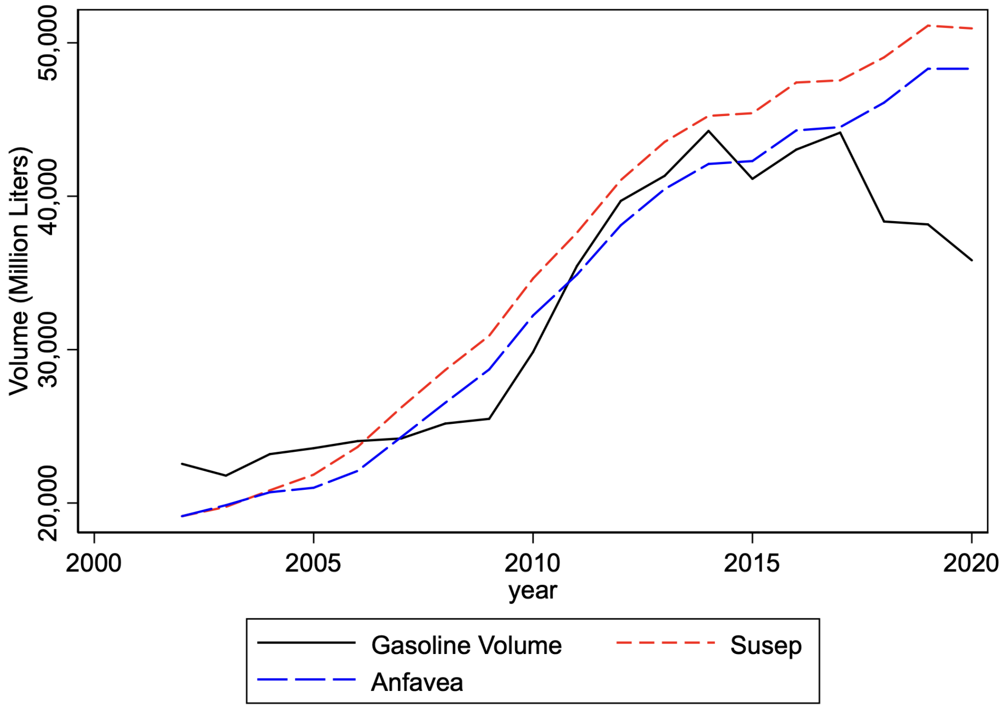


Figure 3.13: Gasoline Volume based on VKT estimates

*Notes*: This figure shows the amount of gasoline necessary to accommodate the average vehicle kilometer traveled according to equation 3.20. Susep estimates are based on the fleet obtained using private insurance information, while Anfavea estimates use Anfavea's new sales registration numbers.

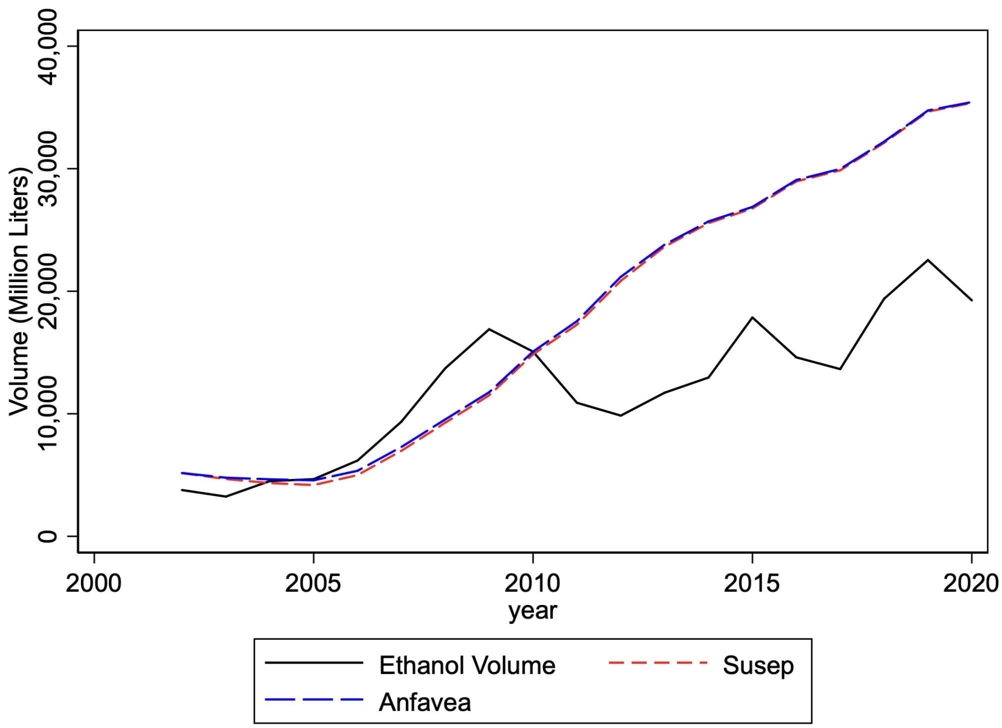


Figure 3.14: Ethanol Volume based on VKT estimates

*Notes*: This figure shows the amount of ethanol necessary to accommodate the average vehicle kilometer traveled according to equation 3.20. Susep estimates are based on the fleet obtained using private insurance information, while Anfavea estimates use Anfavea's new sales registration numbers.

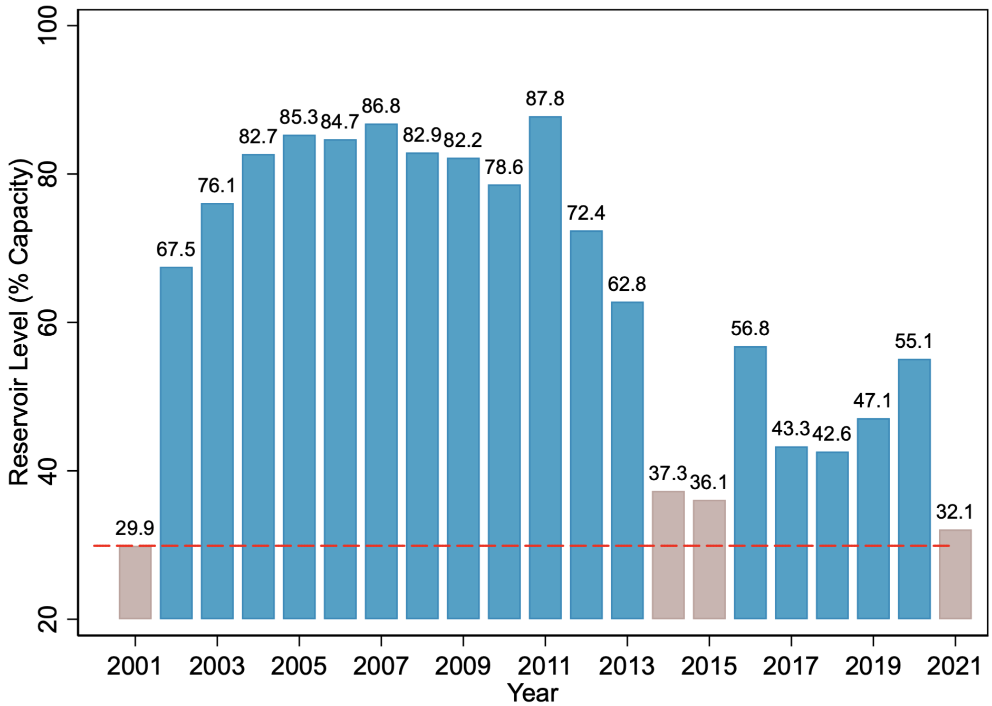


Figure 3.15: Reservoir Levels

*Notes*: This figure shows the evolution of reservoir levels in Brazil. Hydropower remains the most important source of electricity in the country, but it is highly dependent on rainfall to maintain safe operating levels. Between 1998 and 2000, severe droughts led to a critical drop in reservoir levels, culminating in the 2001 energy crisis. In response, the federal government implemented widespread conservation campaigns and demand-side policies, including mandatory energy-efficiency labels on household appliances, public education initiatives, and tax incentives for consumers and industries that reduced electricity usage. While Brazil's reliance on hydropower has decreased over the past 25 years due to diversification of the energy matrix, reservoir levels have once again reached similarly critical lows in recent years.

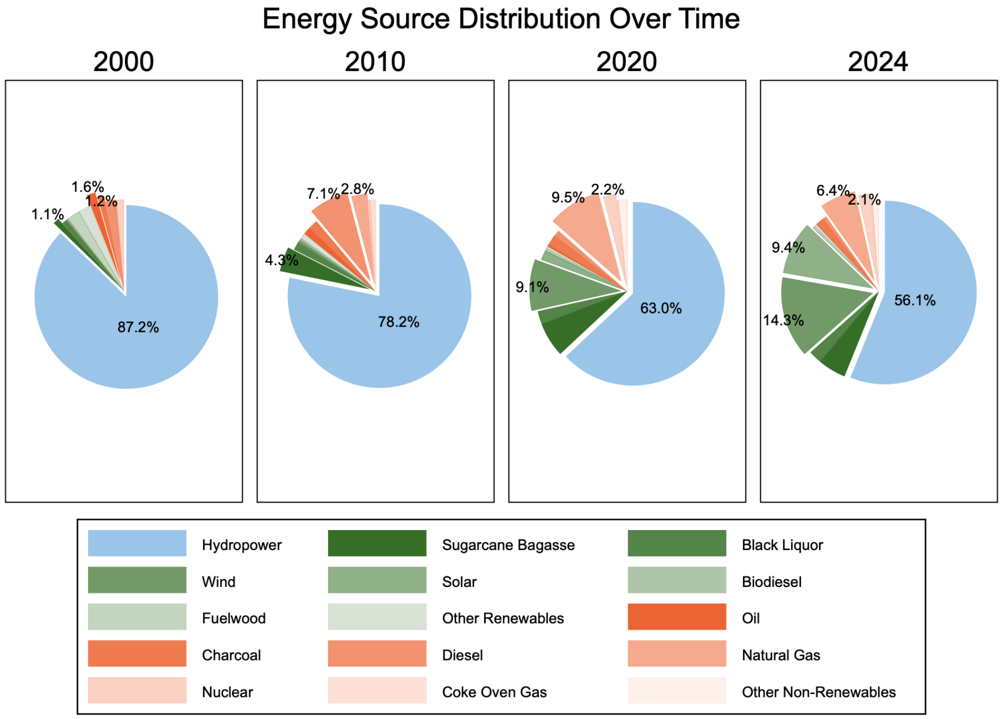


Figure 3.16: Reservoir Levels

*Notes*: This figure illustrates the evolution of Brazil's energy matrix from 2000 to 2024, highlighting a significant shift toward higher diversification in renewable sources. Historically reliant on hydropower, Brazil has expanded its use of alternative renewable production – particularly wind and solar – over the past two decades. The share of wind energy has grown steadily since the early 2010s, while solar energy gained substantial relevance after 2015. Despite this diversification, the matrix still shows considerable dependence on climate-sensitive sources like hydropower. The increasing share of renewables enhances environmental sustainability, but also raises concerns about reliability, especially in periods of drought or low solar/wind output. These dynamics have important implications for energy security and the feasibility of electrifying other sectors, such as transportation.

# Chapter A

# Appendix

## A.1 Appendix to Chapter 1

### A.1.1 Fuel Markets

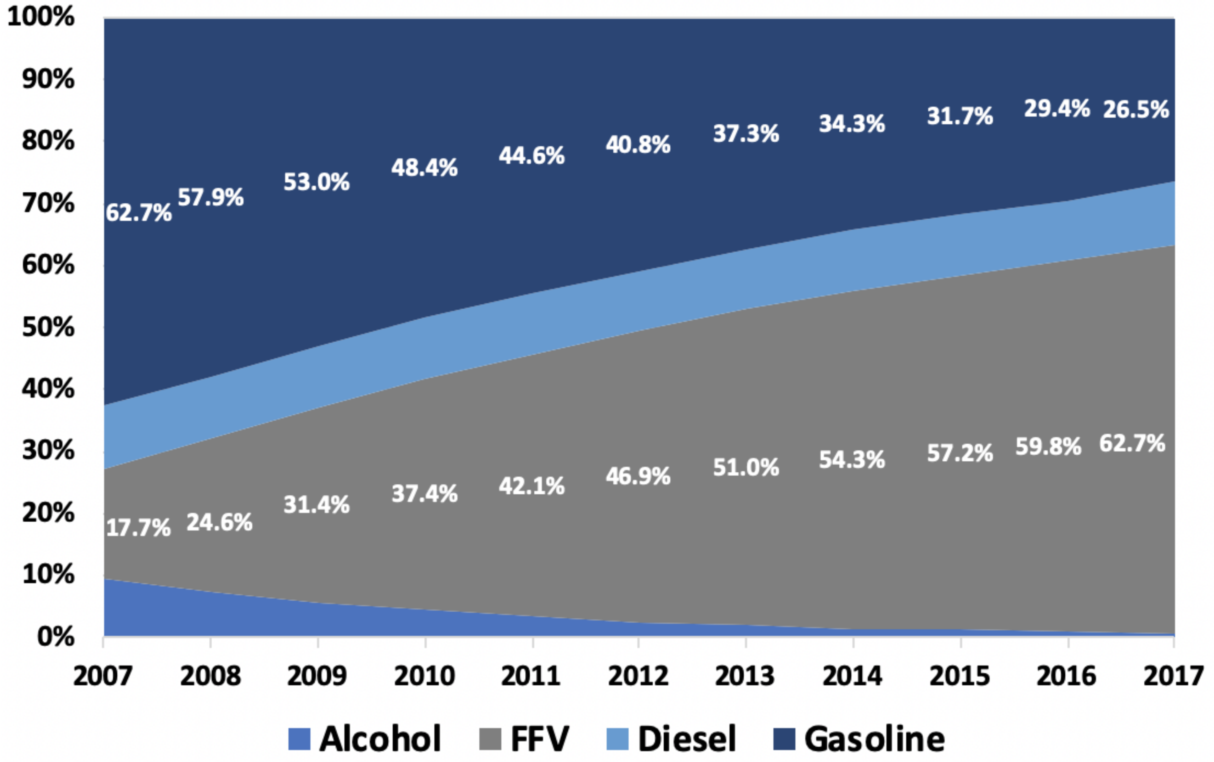


Figure A.1.1: Share of Fleet by Fuel Type

*Notes*: This figure illustrates the evolution of the Brazilian passenger vehicle fleet. Since the sale of diesel passenger cars has been prohibited in Brazil since the 1970s, diesel vehicles are limited to commercial types, such as SUVs and pickup trucks. *Source*: Union of Auto Parts (Sindipeças) and ANFAVEA.

Table A.1.1: Gasoline Demand Model – Balanced Panel

| ***Panel A: Gasoline Demand*** | | | | |
|---|---|---|---|---|
| | OLS: 2005-16 | IV: 2005-16 | IV: 2005-09 | IV: 2010-16 |
| Gasoline Price | -1.0296*** | -1.4140*** | -0.8075** | -2.6075*** |
| | (0.1663) | (0.3046) | (0.3335) | (0.5124) |
| | [-1.3556,-0.7037] | [-2.0111,-0.8169] | [-1.4613,-0.1538] | [-3.6119,-1.6032] |
| Ethanol Price | 0.2271*** | 0.4255*** | 0.2195** | 1.0047*** |
| | (0.0711) | (0.0962) | (0.1029) | (0.1462) |
| | [0.0878,0.3665] | [0.2370,0.6141] | [0.0179,0.4211] | [0.7182,1.2913] |
| N | 21,906 | 21,906 | 8,970 | 12,936 |
| F-Stat | . | 22.42 | 7.55 | 5.20 |
| Gas Vol (Mean & SD) | 9.51 (20.50) | 9.51 (20.50) | 7.42 (17.18) | 11.00 (22.46) |
| Etl Vol (Mean & SD) | 3.64 (11.77) | 3.64 (11.77) | 3.17 (10.60) | 3.97 (12.52) |
| Gas Price (Mean & SD) | 4.00 (0.44) | 4.00 (0.44) | 4.39 (0.35) | 3.72 (0.23) |
| Etl Price (Mean & SD) | 2.82 (0.44) | 2.82 (0.44) | 2.85 (0.53) | 2.79 (0.35) |
| ***Panel B: First Stage for Gasoline Price*** | | | | |
| | | GAS:05-16 | GAS:05-09 | GAS:10-16 |
| Petrobras Gasoline Price | | 0.4499*** | 0.6972*** | 0.2938*** |
| | | (0.0738) | (0.0329) | (0.0975) |
| Sugarcane Quality | | 0.0264*** | 0.0284*** | 0.0410*** |
| | | (0.0093) | (0.0092) | (0.0132) |
| N | | 21,906 | 8,970 | 12,936 |
| ***Panel C: First Stage for Ethanol Price*** | | | | |
| | | ETL:05-16 | ETL:05-09 | ETL:10-16 |
| Petrobras Gasoline Price | | 0.1903 | 0.4078** | 0.1454 |
| | | (0.1151) | (0.1645) | (0.1661) |
| Sugarcane Quality | | 0.2437*** | 0.2638*** | 0.2504*** |
| | | (0.0453) | (0.0679) | (0.0418) |
| N | | 21,906 | 8,970 | 12,936 |

*Notes*: This table shows the results for the gasoline demand under balanced panel data (panel A), and first-stages (panels B and C). Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. The F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by municipality and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.2: Gasoline Demand Model - Instrument Robustness Check

| | | | | |
|---|---|---|---|---|
| ***Panel A: Gasoline Demand*** | | | | |
| | Main Model | Model 2 | Model 3 | Model 4 |
| Gasoline Price | -1.4559*** | -1.3863*** | -1.5116*** | -1.4511*** |
| | (0.3052) | (0.3205) | (0.3368) | (0.3428) |
| Ethanol Price | 0.4402*** | 0.2769** | 0.4464*** | 0.2878** |
| | (0.1026) | (0.1177) | (0.1050) | (0.1169) |
| N | 73,353 | 73,353 | 73,353 | 73,353 |
| F-Stat | 18.03 | 24.44 | 15.75 | 29.03 |
| ***Panel B: First Stage for Gasoline Price*** | | | | |
| | Main Model | Model 2 | Model 3 | Model 4 |
| Petrobras Price (27 states) | 0.4402*** | 0.4275*** | | |
| | (0.0734) | (0.0705) | | |
| Petrobras Price (5 regions) | | | 0.6084*** | 0.5926*** |
| | | | (0.0605) | (0.0584) |
| ATR Value | 0.0199** | | 0.0224*** | |
| | (0.0086) | | (0.0081) | |
| Sugar Export Price | | 0.0265*** | | 0.0246** |
| | | (0.0092) | | (0.0094) |
| N | 73,353 | 73,353 | 73,353 | 73,353 |
| ***Panel C: First Stage for Ethanol Price*** | | | | |
| | Main Model | Model 2 | Model 3 | Model 4 |
| Petrobras Price (27 states) | 0.1455 | 0.0437 | | |
| | (0.1244) | (0.1154) | | |
| Petrobras Price (5 regions) | | | 0.2153 | 0.0689 |
| | | | (0.1392) | (0.1418) |
| Sugarcane Quality | 0.2191*** | | 0.2199*** | |
| | (0.0406) | | (0.0404) | |
| Sugar Export Price | | 0.2299*** | | 0.2295*** |
| | | (0.0303) | | (0.0303) |
| N | 73,353 | 73,353 | 73,353 | 73,353 |

*Notes*: This table shows the robustness check for gasoline demand model using different sets of cost-shift instruments. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. The F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by municipality and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.3: Ethanol Demand Model – Unbalanced Panel

| | | | | |
|---|---|---|---|---|
| ***Panel A: Ethanol Demand*** | | | | |
| | OLS: 2005-15 | IV: 2005-15 | IV: 2005-09 | IV: 2010-15 |
| Gasoline Price | 2.3074*** | 4.5915*** | 1.5070** | 9.8780*** |
| | (0.3486) | (0.9429) | (0.6590) | (2.2997) |
| | [1.6241,2.9907] | [2.7434,6.4396] | [0.2154,2.7985] | [5.3707,14.3852] |
| Ethanol Price | -2.0887*** | -1.9459*** | -1.5823*** | -3.5057*** |
| | (0.1627) | (0.3601) | (0.3279) | (0.5841) |
| | [-2.4077,-1.7698] | [-2.6518,-1.2401] | [-2.2249,-0.9397] | [-4.6505,-2.3608] |
| N | 72,904 | 72,904 | 29,878 | 43,026 |
| F-Stat | | 18.40 | 7.80 | 4.09 |
| Gas Vol (Mean & SD) | 3.74 (11.59) | 3.74 (11.59) | 2.82 (9.59) | 4.40 (12.81) |
| Etl Vol (Mean & SD) | 1.44 (6.55) | 1.44 (6.55) | 1.23 (5.85) | 1.59 (7.02) |
| Gas Price (Mean & SD) | 4.07 (0.46) | 4.07 (0.46) | 4.47 (0.38) | 3.78 (0.25) |
| Etl Price (Mean & SD) | 2.83 (0.64) | 2.83 (0.64) | 2.88 (0.74) | 2.79 (0.56) |
| ***Panel B: First Stage for Gasoline Price*** | | | | |
| | | GAS:05-15 | GAS:05-09 | GAS:10-15 |
| Petrobras Gasoline Price | | 0.4404*** | 0.7073*** | 0.2535** |
| | | (0.0734) | (0.0297) | (0.0975) |
| Sugarcane Quality | | 0.0200** | 0.0232*** | 0.0338** |
| | | (0.0086) | (0.0082) | (0.0132) |
| N | | 72,904 | 29,878 | 43,026 |
| ***Panel C: First Stage for Ethanol Price*** | | | | |
| | | ETL:05-15 | ETL:05-09 | ETL:10-15 |
| Petrobras Gasoline Price | | 0.1456 | 0.4363*** | 0.0424 |
| | | (0.1247) | (0.1627) | (0.1865) |
| Sugarcane Quality | | 0.2206*** | 0.2452*** | 0.2239*** |
| | | (0.0406) | (0.0623) | (0.0409) |
| N | | 72,904 | 29,878 | 43,026 |

*Notes*: This table shows the results for the ethanol demand under unbalanced panel data (panel A), and first-stages (panels B and C). Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. The F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by municipality and month-of-year.

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

Table A.1.4: Ethanol Demand Model – Balanced Panel

| | | | | |
|---|---|---|---|---|
| ***Panel A: Ethanol Demand*** | | | | |
| | OLS: 2005-15 | IV: 2005-15 | IV: 2005-09 | IV: 2010-15 |
| Gasoline Price | 3.2542*** | 4.8573*** | 1.7743*** | 9.3311*** |
| | (0.5073) | (0.9407) | (0.5302) | (1.9761) |
| | [2.2600,4.2483] | [3.0135,6.7011] | [0.7351,2.8135] | [5.4579,13.2042] |
| Ethanol Price | -2.2239*** | -1.9818*** | -1.5070*** | -3.5579*** |
| | (0.2159) | (0.3296) | (0.2660) | (0.5778) |
| | [-2.6470,-1.8007] | [-2.6277,-1.3358] | [-2.0283,-0.9856] | [-4.6904,-2.4254] |
| N | 21,879 | 21,879 | 8,944 | 12,935 |
| F-Stat | | 22.20 | 7.52 | 5.20 |
| Gas Vol (Mean, SD) | 9.51 (20.50) | 9.51 (20.50) | 7.42 (17.18) | 11.00 (22.46) |
| Etl Vol (Mean, SD) | 3.64 (11.77) | 3.64 (11.77) | 3.17 (10.60) | 3.97 (12.52) |
| Gas Price (Mean, SD) | 4.00 (0.44) | 4.00 (0.44) | 4.39 (0.35) | 3.72 (0.23) |
| Etl Price (Mean, SD) | 2.82 (0.44) | 2.82 (0.44) | 2.85 (0.53) | 2.79 (0.35) |
| ***Panel B: First Stage for Gasoline Price*** | | | | |
| | | GAS:05-15 | GAS:05-09 | GAS:10-15 |
| Petrobras Gasoline Price | | 0.4491*** | 0.6965*** | 0.2938*** |
| | | (0.0739) | (0.0331) | (0.0975) |
| Sugarcane Quality | | 0.0264*** | 0.0284*** | 0.0410*** |
| | | (0.0093) | (0.0092) | (0.0132) |
| N | | 21,879 | 8,944 | 12,935 |
| ***Panel C: First Stage for Ethanol Price*** | | | | |
| | | ETL:05-15 | ETL:05-09 | ETL:10-15 |
| Petrobras Gasoline Price | | 0.1896 | 0.4052** | 0.1455 |
| | | (0.1154) | (0.1652) | (0.1661) |
| Sugarcane Quality | | 0.2437*** | 0.2638*** | 0.2504*** |
| | | (0.0454) | (0.0680) | (0.0418) |
| N | | 21,879 | 8,944 | 12,935 |

*Notes*: This table shows the results for the ethanol demand under balanced panel data (panel A), and first-stages (panels B and C). Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. The F statistic is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by municipality and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.5: Simultaneous Demand Models – Balanced Panel

| | OLS: 2005-16 | IV: 2005-16 | IV: 2005-09 | IV: 2010-16 |
|---|---|---|---|---|
| ***Panel A: Cross-Elasticity Restrictions*** | | | | |
| ***Gasoline Demand*** | | | | |
| Gasoline Price | -1.3310*** | -1.7085*** | -0.9390*** | -3.5801*** |
| | (0.0220) | (0.0592) | (0.0615) | (0.1088) |
| Ethanol Price | 0.4386*** | 0.5331*** | 0.2501*** | 1.3070*** |
| | (0.0095) | (0.0267) | (0.0310) | (0.0392) |
| N | 72,904 | 72,904 | 29,878 | 43,026 |
| ***Ethanol Demand*** | | | | |
| | OLS: 2005-16 | IV: 2005-16 | IV: 2005-09 | IV: 2010-16 |
| Gasoline Price | 0.4386*** | 0.5331*** | 0.2501*** | 1.3070*** |
| | (0.0095) | (0.0267) | (0.0310) | (0.0392) |
| Ethanol Price | -1.6106*** | -1.2219*** | -1.2904*** | -1.7580*** |
| | (0.0295) | (0.0871) | (0.1282) | (0.0879) |
| N | 72,904 | 72,904 | 29,878 | 43,026 |
| ***Panel B: No Cross-Elasticity Restrictions*** | | | | |
| ***Gasoline Demand*** | | | | |
| | OLS: 2005-16 | IV: 2005-16 | IV: 2005-09 | IV: 2010-16 |
| Gasoline Price | -1.2489*** | -1.4443*** | -0.8857*** | -2.5411*** |
| | (0.0226) | (0.0606) | (0.0627) | (0.1092) |
| Ethanol Price | 0.4076*** | 0.4317*** | 0.2261*** | 0.9980*** |
| | (0.0097) | (0.0271) | (0.0315) | (0.0387) |
| N | 72,904 | 72,904 | 29,878 | 43,026 |
| ***Ethanol Demand*** | | | | |
| | OLS: 2005-16 | IV: 2005-16 | IV: 2005-09 | IV: 2010-16 |
| Gasoline Price | 1.6654*** | 4.5915*** | 1.5070*** | 9.8780*** |
| | (0.0788) | (0.2139) | (0.2879) | (0.3319) |
| Ethanol Price | -1.8719*** | -1.9459*** | -1.5823*** | -3.5057*** |
| | (0.0339) | (0.0956) | (0.1446) | (0.1176) |
| N | 72,904 | 72,904 | 29,878 | 43,026 |

*Notes*: This table shows the joint estimation of gasoline consumption and ethanol consumption. Panel A shows results under the restricted cross-elasticities assumption, while panel B shows for unrestricted. Controls included: GDP, population, minimum and maximum temperatures, precipitation, city fixed effects, month-of-year fixed effects and year-by-state fixed effects. All standard errors are clustered by municipality.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.6: Gasoline Demand With Aggregated Data

| | | | | |
|---|---|---|---|---|
| ***Panel A: Unbalanced Panel*** | | | | |
| | City-Month OLS | City-Month IV | State-Month OLS | State-Month IV |
| Gasoline Price | -1.2654*** | -1.4559*** | -0.7876*** | -1.2125*** |
| | (0.1184) | (0.3052) | (0.1488) | (0.2753) |
| Ethanol Price | 0.4099*** | 0.4402*** | 0.3998*** | 0.4219*** |
| | (0.0448) | (0.1026) | (0.0641) | (0.1283) |
| N | 73,353 | 73,353 | 3,840 | 3,840 |
| F-Stat | | 18.03 | | 8.72 |
| ***Panel B: Balanced Panel*** | | | | |
| | City-Month OLS | City-Month IV | State-Month OLS | State-Month IV |
| Gasoline Price | -1.2583*** | -1.4140*** | -0.9272*** | -1.2114*** |
| | (0.1257) | (0.3046) | (0.1281) | (0.2811) |
| Ethanol Price | 0.4863*** | 0.4255*** | 0.4685*** | 0.4584*** |
| | (0.0523) | (0.0962) | (0.0575) | (0.1195) |
| N | 22,176 | 21,906 | 3,744 | 3,699 |
| F-Stat | | 22.42 | | 9.71 |

*Notes*: The dependent variable Gasoline Consumption. Panel A shows results for unbalanced panel data, while panel B shows results for a balanced set of municipalities. Columns shows different level of data aggregation. Controls included: GDP, population, minimum and maximum temperatures, precipitation, municipality fixed effects, year fixed effects and year-by-state fixed effects. All standard errors are clustered by municipality.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

### A.1.2 Hospitalization and Pollution Models

Table A.1.7: Pollution Models

| ***Panel A: Pollution and Fuels: PM 2.5 Models*** | | | |
|---|---|---|---|
| | IV 01 | IV 02 | IV 03 |
| Log(Gas vol) | 0.2628*** | | 0.2745*** |
| | (0.0304) | | (0.0350) |
| Log(Etl vol) | | -0.0444** | 0.0261 |
| | | (0.0178) | (0.0221) |
| N | 57,652 | 57,652 | 57,652 |
| F-Stat | 87.76 | 7.47 | 7.43 |

| ***Panel B: Pollution and Fuels: Ozone Models*** | | | |
|---|---|---|---|
| | IV 01 | IV 02 | |
| Log(Gas vol) | -0.0729*** | | -0.0771*** |
| | (0.0062) | | (0.0076) |
| Log(Etl vol) | | 0.0353*** | -0.0074 |
| | | (0.0120) | (0.0056) |
| N | 68,470 | 68,470 | 68,470 |
| F-Stat | 134.10 | 7.00 | 5.34 |

*Notes*: The dependent variable in panel A is PM 2.5, while in panel B is Surface Ozone. Controls included: GDP, population, minimum and maximum temperatures, precipitation, municipality fixed effects, year fixed effects and year-by-state fixed effects. Average PM2.5: 8.68 $\mu g/m^3.AverageOzone$ : $41.79\mu g/m^3.Allstandarderrorsareclusteredbymunicipality.$
$*$p $\leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.8: Hospitalization Models – Ethanol as Control

| | | |
|---|---|---|
| ***Panel A: Hospitalization and Gasoline*** | | |
| | OLS | IV |
| | Log(Hosp Rate) | Log(Hosp Rate) |
| Log(Gas vol) | 0.0054 | 1.2248*** |
| | (0.0374) | (0.1597) |
| N | 66,067 | 66,067 |
| F-Stat | | 387.29 |
| ***Panel B: Pollution and Gasoline*** | | |
| | OLS | IV |
| | Log(PM 2.5) | Log(PM 2.5) |
| Log(Gas vol) | 0.0445*** | 0.2363*** |
| | (0.0101) | (0.0283) |
| N | 61,676 | 61,676 |
| F-Stat | | 104.44 |
| ***Panel C: Hospitalization and Pollution*** | | |
| | OLS | IV |
| | Log(Hosp Rate) | Log(Hosp Rate) |
| Log(PM 2.5) | -0.0005 | 0.2903** |
| | (0.0149) | (0.1137) |
| N | 55,712 | 55,712 |
| F-Stat | | 156.97 |

*Notes*: The dependent variable is infant hospitalization rate due to respiratory diseases (panels A and C), and PM 2.5 (panel B). The average number of hospitalizations per 1 mi population is 215.32. The average PM2.5 from satellite data is $8.6\mu g/m^3$ microgram per cubic meter, ranging from 2.41 to 240.53. Controls included: Ethanol volume, GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population. Fixed effects for municipalities, month-of-year, and year-bu-state included. The F statistic shown is the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.9: Hospitalization Model – Specification Checks

| | IV1 | IV2 | IV3 | IV4 |
|---|---|---|---|---|
| Log(Gas vol) | 1.4415*** | 1.4428*** | 1.4478*** | 1.4550*** |
| | (0.1911) | (0.1907) | (0.1909) | (0.1914) |
| Log(GDP) | | -0.2520*** | -0.2582*** | -0.2443*** |
| | | (0.0744) | (0.0740) | (0.0733) |
| # Beds / 1 mi pop | | | 0.0001*** | 0.0000*** |
| | | | (0.0000) | (0.0000) |
| Log(Population) | | | | -0.3130 |
| | | | | (0.3050) |
| City FE | Y | Y | Y | Y |
| Month-of-Year FE | Y | Y | Y | Y |
| State-by-Year FE | Y | Y | Y | Y |
| Climate Variables | Y | Y | Y | Y |
| N | 67,554 | 67,554 | 67,554 | 67,554 |
| F-Stat | 421.18 | 416.98 | 416.01 | 416.26 |

*Notes*: The dependent variable is infant hospitalization rate due to respiratory diseases. Columns breakdown the analysis highlighting how gasoline consumption impact changes as other controls (GDP, number of hospital beds, and population) are added to the model. Additional controls present in all models are minimum and maximum temperatures, precipitation, and a set of fixed effects listed in the bottom of the table. The F statistic shown refers to the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.10: Hospitalization Models by Age Groups

| | | | | |
|---|---|---|---|---|
| ***Panel A: Hospitalization and Gasoline*** | | | | |
| | OLS: 0 to 1 | IV: 0 to 1 | OLS: 1 to 5 | IV: 1 to 5 |
| | Log(Hosp Rate) | Log(Hosp Rate) | Log(Hosp Rate) | Log(Hosp Rate) |
| Log(Gas vol) | 0.0823*** | 1.2651*** | 0.0451* | 1.6722*** |
| | (0.0254) | (0.2174) | (0.0260) | (0.2053) |
| N | 64,068 | 64,068 | 66,008 | 66,008 |
| F-Stat | | 402.67 | | 369.83 |
| ***Panel B: Pollution and Gasoline*** | | | | |
| | OLS: 0 to 1 | IV: 0 to 1 | OLS: 1 to 5 | IV: 1 to 5 |
| | Log(PM 2.5) | Log(PM 2.5) | Log(PM 2.5) | Log(PM 2.5) |
| Log(Gas vol) | 0.0288*** | 0.2153*** | 0.0288*** | 0.2153*** |
| | (0.0093) | (0.0273) | (0.0093) | (0.0273) |
| N | 63,499 | 63,499 | 63,499 | 63,499 |
| F-Stat | | 68.61 | | 68.61 |
| ***Panel C: Hospitalization and Pollution*** | | | | |
| | OLS: 0 to 1 | IV: 0 to 1 | OLS: 1 to 5 | IV: 1 to 5 |
| | Log(Hosp Rate) | Log(Hosp Rate) | Log(Hosp Rate) | Log(Hosp Rate) |
| Log(PM 2.5) | -0.0186 | -0.0635 | -0.0006 | 0.4852*** |
| | (0.0163) | (0.1232) | (0.0146) | (0.1205) |
| N | 54,415 | 54,415 | 55,899 | 55,899 |
| F-Stat | | 153.43 | | 160.76 |

*Notes*: The dependent variable is infant hospitalization rate due to respiratory diseases (panels A and C), and PM 2.5 (panel B). Columns breakdown the analysis focusing different age brackets. Included controls: GDP, population, minimum and maximum temperatures, precipitation, hospital beds per 1 million population. Panels A and B include fixed effects for year and year-by-state. Panel A includes month-of-year (seasonality) fixed effects while panel C includes month-of-sample. All panels include municipalities fixed effects. The F statistic shown refers to the Kleibergen-Paap rk Wald F statistic associated with the excluded instruments in the first stage. All standard errors are clustered by city and month-of-year.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.1.11: Hospitalization Model – Interactions by Age Group

| *Panel A: Log(Hospitalization Rate) – Children from 0 to 1 year old* | | | | |
|---|---|---|---|---|
| | Main Model | + GDP | + Hosp Beds | + Population |
| Log(Gas vol) | 1.2651*** | 1.0631*** | 0.8533** | 0.6893** |
| | (0.2174) | (0.3085) | (0.3312) | (0.3180) |
| Log(Gas vol) x GDP | | -0.0894* | -0.0711 | -0.1105* |
| | | (0.0528) | (0.0544) | (0.0624) |
| Log(Gas vol) x H. Beds | | | -0.1168** | -0.0996** |
| | | | (0.0461) | (0.0446) |
| Log(Gas vol) x Population | | | | 0.0959 |
| | | | | (0.0618) |
| N | 64,068 | 64,068 | 64,068 | 64,068 |
| *Kleibergen-Paap F-Stat by First Stage Regression* | | | | |
| Gasoline Volume | 402.67 | 193.69 | 125.09 | 94.57 |
| GDP Interaction | | 338.14 | 266.46 | 212.22 |
| Hospital Beds Interaction | | | 138.54 | 109.64 |
| Population Interaction | | | | 230.32 |
| *Panel B: Log(Hospitalization Rate) – Children from 1 to 5 years old* | | | | |
| | Main Model | + GDP | + Hosp Beds | + Population |
| Log(Gas vol) | 1.6722*** | 1.2192*** | 0.7095** | 0.5616 |
| | (0.2053) | (0.3268) | (0.3576) | (0.3475) |
| Log(Gas vol) x pcGDP | | -0.1467** | -0.0981 | -0.1267* |
| | | (0.0606) | (0.0601) | (0.0694) |
| Log(Gas vol) x H. Beds | | | -0.1308** | -0.1157** |
| | | | (0.0508) | (0.0493) |
| Log(Gas vol) x Population | | | | 0.0728 |
| | | | | (0.0697) |
| N | 66,008 | 66,008 | 66,008 | 66,008 |
| *Kleibergen-Paap F-Stat by First Stage Regression* | | | | |
| Gasoline Volume | 369.83 | 179.13 | 111.87 | 84.80 |
| GDP Interaction | | 337.92 | 259.87 | 205.63 |
| Hospital Beds Interaction | | | 136.93 | 108.03 |
| Population Interaction | | | | 224.38 |

*Notes*: The dependent variable is infant hospitalization rate (0-1 years-old in panel A and 1-5 years-old in panel B). First column represents the original IV model. Other columns test interactions of gasoline consumption with GDP, number of hopistal beds, and population, respectively. All standard errors are clustered by city and month-of-year. * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

# A.2 Appendix to Chapter 2

## A.2.1 Price and Margin Regressions

Table A.2.1: Petrobras's Acquisition of Ipiranga Assets - Difference in Difference Models

| ***Panel A: Full period, 12 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | -0.0023*** | 0.0009 | -0.0269* | 0.0012 |
| | (0.0008) | (0.0009) | (0.0140) | (0.0116) |
| N | 51,941 | 137,735 | 34,727 | 86,305 |

| ***Panel B: Time Donut, 10 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | -0.0022** | 0.0010 | -0.0294 | 0.0018 |
| | (0.0010) | (0.0011) | (0.0199) | (0.0146) |
| N | 41,616 | 110,644 | 28,017 | 70,095 |

*Notes*: Difference in Difference Models for post-merger evaluations of the Ipiranga split, with acquisition of their assets from the North, Northeast, and Center-West regions by BR Distribuidora (Petrobas). The dependent variable is the logarithm of retailer prices in columns 2 and 3, and the retailer margin (or markup) in columns 4 and 5. These models represent a stacked difference in difference, where the treatment (merger) occurs in May 2008, and each municipality is treated as a different market. Two sets of control groups are used: columns 2 and 4 compare to the main competitor branded retailer (Shell), while columns 3 and 5 compare to unbranded retailers. Estimations use weekly price data, limited to 12 months before and after the merger. "Time donut" regressions follow Ashenfelter and Hosken (2010), dropping two months surrounding the merger month to account for potential endogeneity in actions during those weeks preceding and following the merger. The models are clustered at the municipality level.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.2.2: Ipiranga's Acquisition of Texaco Assets - Difference in Difference Models

| ***Panel A: Full period, 12 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | -0.0006 | 0.0012 | -0.0375*** | -0.0170 |
| | (0.0009) | (0.0015) | (0.0097) | (0.0129) |
| N | 128,277 | 208,837 | 76,190 | 112,355 |

| ***Panel B: Time Donut, 10 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | 0.0001 | 0.0018 | -0.0392*** | -0.0171 |
| | (0.0012) | (0.0019) | (0.0122) | (0.0165) |
| N | 102,966 | 169,526 | 61,030 | 91,905 |

*Notes*: Difference in Difference Models for post-merger evaluations of the Ipiranga acquisition of Texaco's assets. The acquisition was at the national level, but Ipiranga was not present in the North, Northeast, and Center-West regions, locations where this purchase represented a simple transference of assets between both firms. The models evaluate the regions where both firms were present and where the acquisition would generate an increase in market concentration, i.e., the South and Southeast regions. The dependent variable is the logarithm of retailer prices in columns 2 and 3, and the retailer margin (or markup) in columns 4 and 5. These models represent a stacked difference in difference, where the treatment (merger) occurs in May 2008, and each municipality is treated as a different market. Two sets of control groups are used: columns 2 and 4 compare to the main competitor branded retailer (Shell), while columns 3 and 5 compare to unbranded retailers. Estimations use weekly price data, limited to 12 months before and after the merger. "Time donut" regressions follow Ashenfelter and Hosken (2010), dropping two months surrounding the merger month to account for potential endogeneity in actions during those weeks preceding and following the merger. The models are clustered at the municipality level.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.2.3: Ipiranga's Acquisition of DNP Assets - Difference in Difference Models

**Ipiranga's Acquisition of DNP Assets - Difference in Difference Models**

| ***Panel A: Full period, 12 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | 0.0018 | 0.0005 | 0.0460** | 0.0088 |
| | (0.0021) | (0.0016) | (0.0178) | (0.0063) |
| N | 18,917 | 27,544 | 8,041 | 5,332 |

| ***Panel B: Time Donut, 10 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | 0.0015 | 0.0013 | 0.0731*** | 0.0181** |
| | (0.0017) | (0.0022) | (0.0241) | (0.0084) |
| N | 15,477 | 21,446 | 6,647 | 4,346 |

*Notes*: Difference in Difference Models for post-merger evaluations of the Ipiranga merger with DNP. The merger was localized, since DNP supplied fuels only for states in the North region. The distinctive characteristic of this merger is the widespread market and extensive territories, with a lower concentration and proximity of retailers compared to other regions. The dependent variable is the logarithm of retailer prices in columns 2 and 3, and the retailer margin (or markup) in columns 4 and 5. These models represent a stacked difference in difference, where the treatment (merger) occurs in May 2008, and each municipality is treated as a different market. Two sets of control groups are used: columns 2 and 4 compare to the main competitor branded retailer (Shell), while columns 3 and 5 compare to unbranded retailers. Estimations use weekly price data, limited to 12 months before and after the merger. "Time donut" regressions follow Ashenfelter and Hosken (2010), dropping two months surrounding the merger month to account for potential endogeneity in actions during those weeks preceding and following the merger. The models are clustered at the municipality level.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table A.2.4: Merger of Cosan and Shell - Difference in Difference Models

**Merger of Shell and Cosan - Difference in Difference Models**

| ***Panel A: Full period, 12 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | 0.0004 | -0.0003 | 0.0229*** | -0.0121* |
| | (0.0006) | (0.0006) | (0.0067) | (0.0070) |
| N | 324,177 | 426,094 | 160,949 | 188,363 |

| ***Panel B: Time Donut, 10 months around merger*** | | | | |
|---|---|---|---|---|
| *D.Var.:* | Price | Price | Margin | Margin |
| *Control:* | Main Competitor | Unbranded | Main Competitor | Unbranded |
| Treatment | 0.0009 | -0.0007 | 0.0172** | 0.0012 |
| | (0.0007) | (0.0007) | (0.0075) | (0.0077) |
| N | 258,936 | 337,411 | 130,226 | 151,478 |

*Notes*: Difference in Difference Models for post-merger evaluations of the Cosan merger with Shell. The merger was at the national level, although there was no overlap of operations in the state of Mato Grosso (Center-West) and in some states in the North region (Amazonas, Tocantins, Roraima, and Acre). The dependent variable is the logarithm of retailer prices in columns 2 and 3, and the retailer margin (or markup) in columns 4 and 5. These models represent a stacked difference in difference, where the treatment (merger) occurs in May 2008, and each municipality is treated as a different market. Two sets of control groups are used: columns 2 and 4 compare to the main competitor branded retailer (Shell), while columns 3 and 5 compare to unbranded retailers. Estimations use weekly price data, limited to 12 months before and after the merger. "Time donut" regressions follow Ashenfelter and Hosken (2010), dropping two months surrounding the merger month to account for potential endogeneity in actions during those weeks preceding and following the merger. The models are clustered at the municipality level.

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

# A.3 Appendix to Chapter 3

## A.3.1 Autoseg Database (SUSEP)

Private insurance companies in Brazil must regularly report 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 C.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 C.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 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.

Table C.1: Insurance Data Submitted

Reference year: 2008

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

Source: Autoseg (SUSEP)

*Notes*: This table represents the 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.

### A.3.2 IPI Tax Table

Table C.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 | Tractor |
| Dec/2001 | 4070/2001 | 10.0 | 10.0 | 25.0 | 25.0 | 25.0 | 25.0 | 10.0 | 5.0 | 5.0 |
| Dec/2002 | 4542/2002 | 9.0 | 9.0 | 15.0 | 13.0 | 25.0 | 20.0 | 10.0 | 5.0 | 5.0 |
| Aug/2003 | 4800/2003 | 5.0 | 5.0 | 12.0 | 9.0 | 25.0 | 20.0 | 6.0 | 5.0 | 5.0 |
| Nov/2003 | 4902/2003 | 6.0 | 6.0 | 13.0 | 10.0 | 25.0 | 20.0 | 7.0 | 5.0 | 5.0 |
| May/2004 | 5058/2004 | 7.0 | 7.0 | 13.0 | 11.0 | 25.0 | 18.0 | 8.0 | 5.0 | 5.0 |
| Dec/2008 | 6890/2009 | 0.0 | 0.0 | 6.5 | 5.5 | 25.0 | 18.0 | 1.0 | 0.0 | 0.0 |
| Oct/2009 | 6890/2009 | 1.5 | 0.0 | 8.0 | 6.5 | 25.0 | 18.0 | 1.0 | 0.0 | 0.0 |
| Nov/2009 | 6890/2009 | 3.0 | 0.0 | 9.5 | 7.5 | 25.0 | 18.0 | 1.0 | 0.0 | 0.0 |
| Dec/2009 | 6890/2009 | 5.0 | 3.0 | 11.0 | 7.5 | 25.0 | 18.0 | 1.0 | 0.0 | 0.0 |
| Jan/2010 | 6890/2009 | 7.0 | 3.0 | 13.0 | 7.5 | 25.0 | 18.0 | 4.0 | 0.0 | 0.0 |
| Apr/2010 | 6890/2009 | 7.0 | 7.0 | 13.0 | 11.0 | 25.0 | 18.0 | 4.0 | 0.0 | 0.0 |
| May/2012 | 7725/2012 | 0.0 | 0.0 | 6.5 | 5.5 | 25.0 | 18.0 | 1.0 | 0.0 | 0.0 |
| Jan/2013 | 7725/2012 | 2.0 | 2.0 | 8.0 | 7.0 | 25.0 | 18.0 | 2.0 | 0.0 | 0.0 |
| Jan/2014 | 8168/2013 | 3.0 | 3.0 | 10.0 | 9.0 | 25.0 | 18.0 | 3.0 | 0.0 | 0.0 |
| Jan/2015 | 8168/2013 | 7.0 | 7.0 | 13.0 | 11.0 | 25.0 | 18.0 | 8.0 | 0.0 | 0.0 |
| Mar/2022 | 10979/2022 | 5.7 | 5.7 | 10.6 | 9.0 | 20.4 | 14.7 | 6.5 | 0.0 | 0.0 |
| Abr/2022 | 11055/2022 | 5.7 | 5.7 | 10.6 | 9.0 | 20.4 | 14.7 | 5.2 | 0.0 | 0.0 |
| Aug/2022 | 11055/2022 | 5.3 | 5.3 | 9.8 | 8.3 | 18.8 | 13.5 | 5.2 | 0.0 | 0.0 |

*Notes*: 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.

### A.3.3 Turnover Models

Table C.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 C.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, minibuses, and other light commercial vehicles. Clustered on make-model-(car age) and tax brackets.

Each column represents a different combination of the potential datasets submitted to the governmental agency. Insurance firms must submit twice a year (June and December) a dataset with all vehicle contracts from the past three semesters. This 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 C.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 × | -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 × | -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 × | -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 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, minibuses, and other light commercial vehicles. Buses and trucks are not included in any estimation. Clustered on make-model-(car age) and tax brackets.
* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

### A.3.4 Transportation

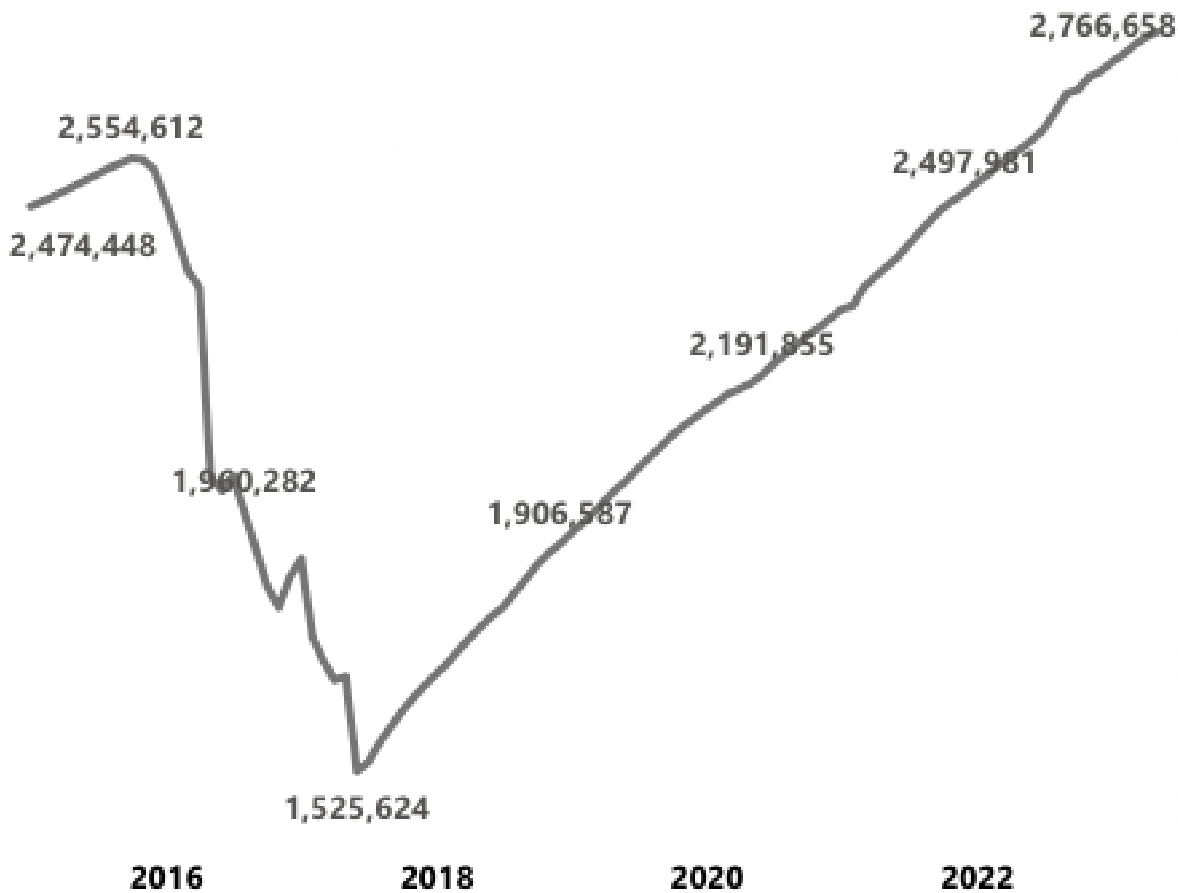


Figure C.1: Mandatory Truck Registration Renewal

*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.

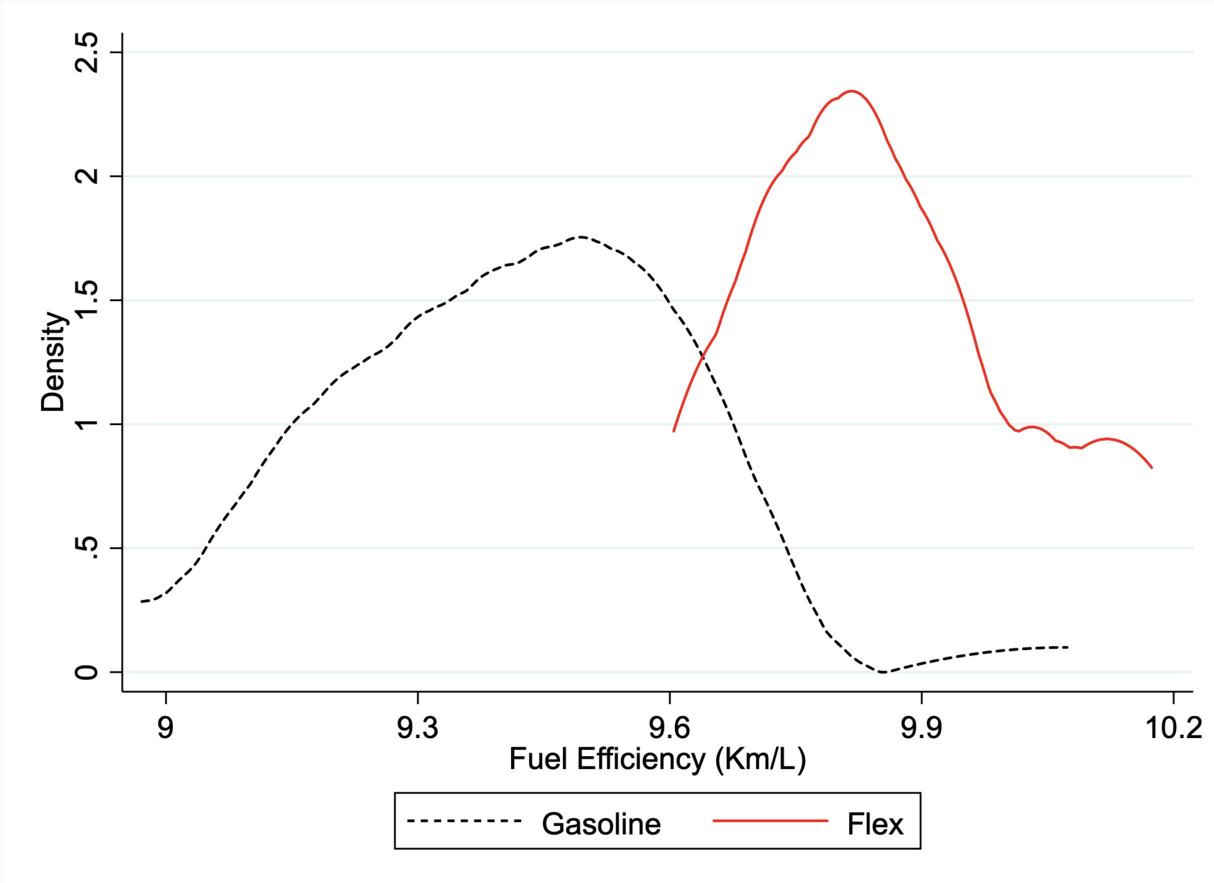


Figure C.2: Fuel Efficiency of Gasoline and Flex Fuel Vehicles - Density

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

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