# Effects of a Gas Prices Holiday on the New Car Market

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**Abstract**

Gas tax holidays have become more popular with US lawmakers and presidential candidates, especially in years of increasing gas prices. This paper uses the Brazilian experience to investigate the environmental effects of artificially repressing gasoline prices below international levels in the period between 2008 and 2013. To compute these environmental effects, it is posed a Random Coefficient Nested Logit to estimate a demand model for new cars in Brazil. From the estimated parameters, a counterfactual scenario in which domestic gasoline prices were aligned with international ones is simulated. The demand model results point to substantial undervaluation of fuel costs, and an important role for the "energy paradox", for the median attention parameter $\gamma$ is about 0.2. That is, only 20% of the present value of an additional BRL in fuel economy is reflected in new car prices. The counterfactuals indicate the reduction in the fuel price gap and the elimination of the "Gas Price Tax Holiday" would imply some realignment towards lower engine displacement models. Additionally, an amount between 89.7 and 130 thousand CO2 tons were emitted in this period due to the artificially low gasoline prices during this period.

**Keywords:** Energy Paradox, Gas Tax Holidays, New Car Demand.

## 1 Introduction

Gas tax holidays have become more popular with US lawmakers and presidential candidates, especially in years of increasing gas prices. Usually such holidays include some sort of temporary repeal of gasoline taxes. Despite appealing to lawmakers, they are at best controversial among economists, with several good reasons to believe they are a very inefficient way to transfer resources to consumers. So far, no one has tried to compute the environmental effects of such holidays.

This paper uses the Brazilian experience to investigate the environmental effects of artificially repressing gasoline prices below international levels in the period between 2008 and 2013. Obvious political dividends come from manipulating fuel prices, and PETROBRAS (the Brazilian state owned monopolist crude oil producer) has suffered in terms of market value.

To compute these environmental effects, it is posed a Random Coefficient Nested Logit as in Grigolon and Verboven (2014) to estimate the parameters of a demand model for new cars in Brazil. It is used a very detailed dataset comprising sales of new cars in all cities with more than 100 thousand inhabitants in Brazil. From the

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estimated parameters, a counterfactual scenario in which domestic gasoline prices were aligned with international ones is simulated, and the effects on sales and fuel consumption are computed. From the counterfactual lifetime fuel consumption it is estimated the additional lifetime emissions from this policy.

Apart from its novelty, the present contribution also connects with several strands of literature. The most important literature it is related is on the environmental effects of policies targeted at the transport sector. Previous relevant contributions are Huse and Lucinda (2014), on the Green Car Rebate in Sweden, Chandra, Gulati and Kandlikar (2010) and Berestenau and Shanjun (2011), more focused on policies directly aimed at increasing adoption of alternative fuel vehicles. Anderson and Sallee (2016) as a helpful survey on the subject.

The second strand of the literature this paper relates to is on the so-called "Energy Paradox", as discussed in Allcott and Wozny (2014), Sallee, West and Fan (2015), as many others[1]. The present paper adds to this literature by bringing estimates for a large emerging market in which the extensive margin – that is, households getting their first automobiles – is still very active. Besides, the behavior of a large middle-income market such as Brazil can also shed some light when much larger countries as India and China reach such income levels.

The present paper is organized in six sections, the first of which is the present introduction. On the following section, it is presented the institutional background in which this policy is presented. Section three is focused on the demand model to be estimated, the Random Coefficient Nested Logit, and section four presents the results for the demand model. Section 5 presents the counterfactual analysis and the sixth section concludes.

## 2 Institutional Background

The Brazilian new car market has strongly changed between 2008 and 2013. Despite not having a marked supply change in terms of available offering in terms of more powerful engines, the demand has moved towards models with higher engine displacement. Figure 1 is a scatterplot of curb weight X fuel economy (km/liter) with a nonparametric regression overlaid to show the technical frontier evolution during this period. Both lines are close together, indicating there seems to be no marked change in the product offerings during the period.

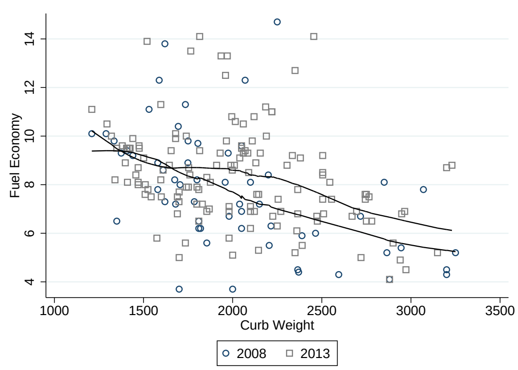



Figure 1: Scatterplot Fuel Consumption X Curb Weight

The next figure is a similar scatterplot, with engine displacement in the X axis instead of curb weight. It also indicates no marked change in the technological frontier during the same period. As in figure 1, every point in figure 2 is a year model pair (2008 and 2013).

[1]Examples are Klier and Linn (2010), Li and Wei (2013), Busse, Knittel and Zettelmeyer (2013), Langer and Miller (2013).

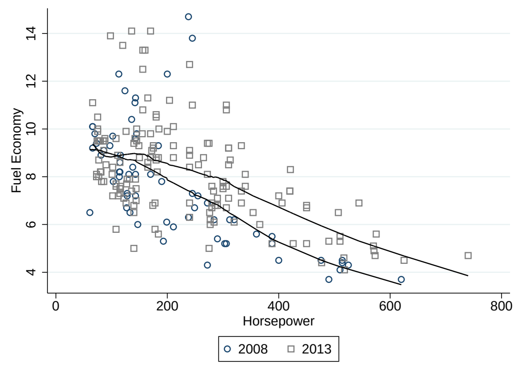



Figure 2: Scatterplot Fuel Consumption X Engine Displacement

Even though there were no supply side changes in the model lineup during this period, there were some marked changes in new car sales composition. Consumers have moved towards engines with higher displacements – with higher consumption levels. Figure 3 has two panels. The first one depicts the sales weighted average fuel consumption for each year in our sample (2008-2013), whereas the second one depicts the unweighted average. The difference is striking, with the second panel being essentially constant (consistent with the evidence in figures 1 and 2) and the first one displaying a decrease in fuel consumption in the latter part of the sample.

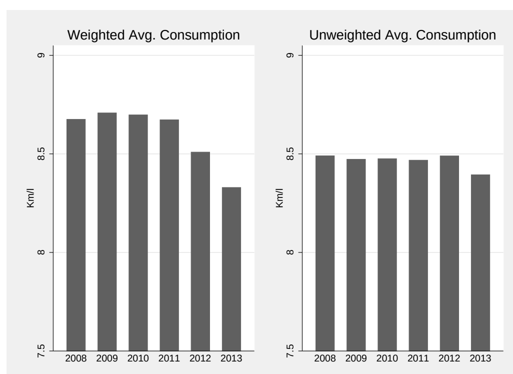



Figure 3: Unweighted and Sales weighted average fuel consumption

The next set of figures gives some clues as to how these changes came into effect. Figure 4 does the same exercise, this time with fuel displacement. The difference is also present there, with the unweighted average essentially a flat line and the weighted average displaying an increase in fuel displacement.

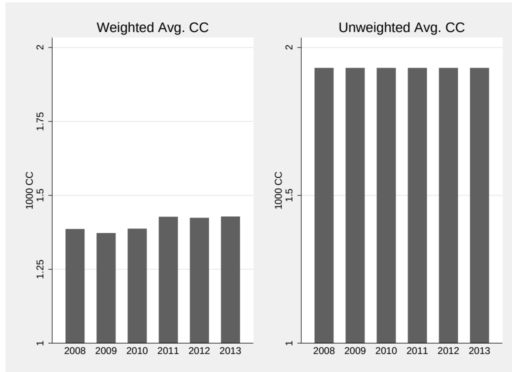



Figure 4: Unweighted and Sales Weighted average fuel displacement

These cars need to have some fuel. Another issue that sets Brazil apart from developed (and most developing) countries is a sizable share of autos that are capable of running on either fuel type, gas or ethanol.

## 2.1 Brazilian Fuel Market

At a typical fuel station in Brazil, there are two different types of fuel pumps. One of them is labeled “gasoline”, which is actually a blend referred to by Petrobras and its regulator as Gasoline type C. The other fuel pump type is labeled “ethanol”, which can be more correctly described as Hydrated Ethanol.

Both types of fuel are provided to fuel stations by fuel distributors. Such distributors, apart from blending the different fuel versions according to octane level, they also make the Gasoline type C blend. This blend is a mix of a pure gasoline (85 octane level), called Gasoline type A, with Anhydrous Ethanol. The mix of fuel types is defined by the Brazilian fuel regulator, ANP [2], and is usually between 20% and 25% of ethanol with the remainder being pure gasoline[3].

According to data for the Brazilian fuel regulator, the distribution sector is both concentrated and vertically integrated. Petrobras supplies 25.4% of all Gasoline type C sold to fuel stations and 17.07% of all Ethanol (both Anhydrous and Hydrated) supplied to fuel stations in 2016. Raízen, the second largest fuel distributor, is also integrated, owning several mills in the main sugarcane growing area. The data is presented on Table 1

| Gasoline | | Ethanol | |
|---|---|---|---|
| Firm | Market Share | Firm | Mkt Share |
| Petrobras | 25.40 | Raízen | 19.10 |
| Raízen | 20.50 | Petrobras | 17.07 |
| Ipiranga | 19.70 | Ipiranga | 16.82 |
| Alesat | 5 .00 | Gran Petro | 7.78 |
| Other | 29.40 | Other | 39.23 |

Table 1: Market Shares in Fuel Distribution - December 2016

Almost all Gasoline A bought by the distributors comes from Petrobras, which owns all 18 oil refineries in Brazil and is responsible for 92.2% of all Gasoline type A sold in 2016. The remainder is imported by independent companies.

[2] Agência Nacional do Petróleo

[3] Evidently there are other technical rules defining the physical properties of the Gasoline Type A, but they are not presented here for the sake of exposition.

Both types of ethanol are produced from crushed sugarcane in the same facilities, which also produce sugar. Mills with distilleries can direct the cane juice to the production of sugar or ethanol, leading to some substitutibility between them. However, technical constraints prevent full specialization. In periods when rainfall is lower, the sugar content of sugarcane is relatively low, and mills would rather produce more ethanol. However, since there are capacity limits to both products and a predefined amount of sugarcane to crush during the harvest, the substitution between sugar and ethanol is between 5 to 10%. The first type of ethanol produced from the distilling of sugarcane juice is the Hydrated ethanol. An additional facility is used to remove water from hydrated ethanol, producing the Anhydrous ethanol.

Despite its legal freedom to set fuel prices, Petrobras follows a price policy of sporadic adjustments that has the stated purpose of avoiding the pass-through of fuel price volatility to Brazilian consumers. In fact, said policy never been considered as transparent. Figures 5 and 6 below show clearly that not only have the gaps been widening since the beginning of 2009. Additionally, important to mention, the losses (especially after 2011) have been boosted by increasing volumes of diesel and gasoline sales.

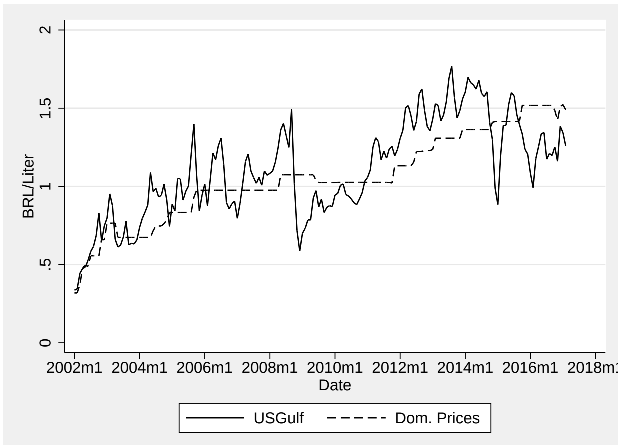



Figure 5: USGulf and Domestic Prices

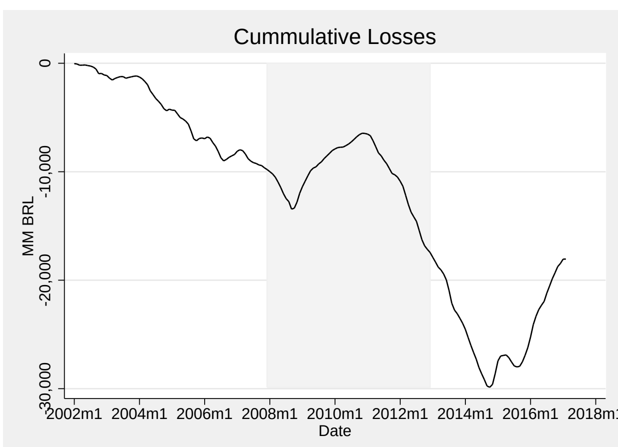



Figure 6: Cummulative Losses to PETROBRAS since 2002

### 2.1.1 Fuel Taxes

There are three main taxes that are levied on the fuel market: the first one is ICMS, a state level tax whose rates are determined independently from the Federal Government and the second one is PIS/COFINS, a federal tax. They are paid by both producers and distributors[4].

The third one is CIDE, a specific federal tax, which the government could . The last one was reduced to zero from 0.28 BRL/liter in 2007 to zero in 2012, and back to 0.1 BRL/liter in 2015. Both types of Ethanol are exempt of this tax.

For PIS/COFINS which only producers pay in the case of gasoline and producers and distributors pay in the case of ethanol, before 2008 both fuels were subject to an *ad valorem* tax, which was changed to a specific tax. In 2013, the specific PIS/COFINS tax was 0.215 BRL/liter for gasoline, 0.03943 BRL/liter for the ethanol at the mill and 0.09857 BRL/liter for ethanol at the distributor.

As for ICMS, state level *ad valorem* taxes are between 25% to 30% for gasoline and between 12% to 30% to ethanol. In the case of the latter, it is important to notice the State of São Paulo – the largest fuel market in the country – has the lowest rate of ICMS, of 12%.

The table 2 shows how the revenues from each fuel type are divided between the Government, fuel producers (in the case of Gasoline Type C, the refiners and the sugar mills) and the downstream distributors and retailers.

| | Gasoline C | Ethanol |
|---|---|---|
| Taxes | 39.30% | 12.00% |
| Producers | 45.00% | 67.70% |
| Distributor and Retail Margins | 15.70% | 20.30% |

Table 2: Composition of Fuel Prices – 2015

## 3 Demand Model

There are $T$ markets, defined as a pair city/year, with $I_t$ consumers in each market $t$. Consumers are supposed to buy a car only in their city of residence. [5] [6]

A car will be defined as a combination of a baseline model $j$ – encompassing a triplet brand, model and body – with engine variant $k$. An engine variant, in turn, will be defined as a combination of engine displacement and fuel type. Every customer in market $t$ must choose between a car – pair $jk$ – or the outside good 0.

This decision implies both an upfront cost, with a purchase price of $p_{jk}$, as well an operating cost, approximated here by fuel costs. Fuel costs will be defined as the product of expected fuel consumption – liter per kilometer, $e_{jk}$ – and expected fuel prices $g_{ks}$, for the whole economic life of the car $S$. The present value of such costs will be defined as $G_{ijk}$:

$$G_{ijk} = E\left[\sum_{s=0}^{S-1}(1-r)^{-s}\beta_m^i e_{jk} g_{ks}\right]$$

[4] There are several arrangements, in the case of ICMS, to the taxes due downstream to be paid upstream, for ease of collection purposes. For the sake of exposition, they are not going to be detailed here, for they are not

[5] This assumption actually describes pretty well the Brazilian new car market, in which a consumer who wants to buy a new car in a different municipality from the one he/she lives in needs to have an authorization from the Traffic Department of his/her city.

[6] For the sake of notation, the subscript $t$ will be omitted whenever its omission does not change interpretation of results.

The term $\beta_m^i$ is the expected annual number of kilometers consumer $i$ is expected to drive and $r$ is the discount rate. As in Grigolon, Reynaert and Verboven (2014), we allow the annual number of kilometers consumer $i$ is expected to drive to be heterogeneous across cars, according to the empirical distribution of mileage of Brazilian cars. We consider this enough to deal with the sorting bias coming from more fuel efficient cars to be purchased by high mileage consumers, as in Bento, Li and Roth (2012).

We assume also expected future fuel prices for a consumer $i$ with an engine type $k$ at a given instant $s$ are equal to the observed fuel prices in time period $s$. Besides being consistent with empirical evidence on consumer behavior in other countries, as in Anderson, Kellogg and Sallee (2013), it is also consistent with the evolution of fuel prices during most of the period in consideration, as seen on the Figure 7:

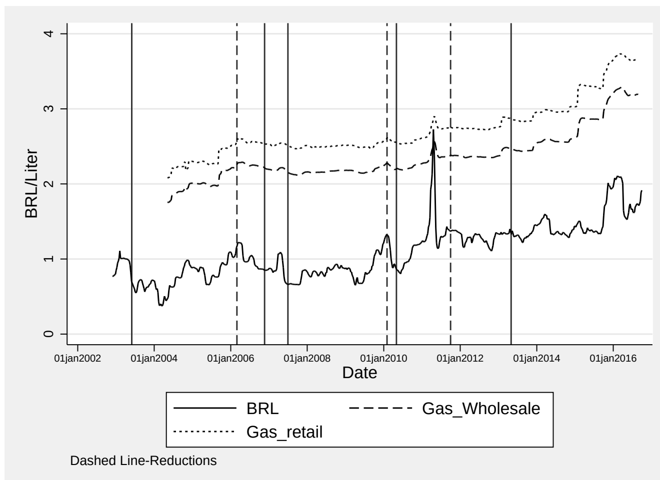



Figure 7: Wholesale and retail fuel prices

These assumption on the heterogeneity on mileage and fuel prices imply $G_{ijk}$ can be simplified as:

$$G_{ijk} = \kappa \beta_i^m e_{jk} g_{ks} \tag{1}$$

in which the $\kappa$ term is the annuity coefficient with converts the annual cost over $S$ periods into a present value. There might be a concern about which fuel to be actually used in the car. To address this issue, Salvo and Huse (2013) note that, despite there are a substantial consumer heterogeneity in the choice between gasoline and ethanol, consumer demand for gasoline might be “sticky”, in a sense that might be required substantial discounts to boost adoption of ethanol. This was far from the case in Brazil.

Figure 8 presents the fuel price parity between fuels during the period. Given the differences in energy content, both fuels are expected to be at parity when the Hydrated Ethanol price is about 70% of Gasoline price. For almost all the period of the dataset, the prices are below this ratio.

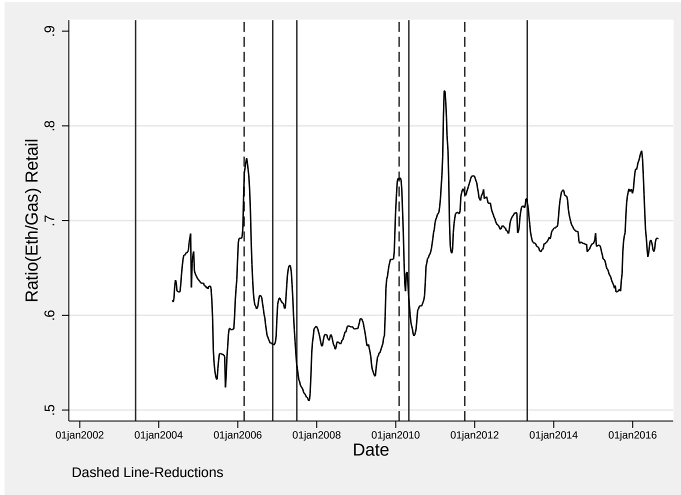



Figure 8: Relative price of Gasoline and Hydrated Ethanol

These assumptions on automobile prices and fuel costs motivate our preferred specification for the conditional indirect utility for consumer $i$ of choosing car model $j$ with engine variant $k$ is as follows:

$$u_{ijk} = x_{jk}\beta^x_{ik} - \alpha_i(p_{jk} + \gamma G_{ijk}) + \xi_{jk} + \varepsilon_{ijk} \tag{2}$$

In which the $\xi_{jk}$ are the unobserved automobile (model and engine) characteristics. The outside good conditional indirect utility is normalized at zero, with a extreme value $\varepsilon_{i0}$. The term $x_{jk}$ is a vector of automobile characteristics with coefficients $\beta^x_{jk}$. Finally, the coefficient $\gamma$ measure the so-called "energy paradox" or, according to the terminology of Allcott and Wozny (2014), the attention parameter. This measures the ability of consumers to trade-off the purchasing price of a new car and the fuel costs. If $\gamma$ is less than one, the consumer is willing to pay less than one BRL for one BRL of present value of fuel cost savings.

Substituting Equation (1) in the conditional indirect function equation, (2), we arrive at an alternative version of the conditional indirect utility function, which makes clear all the relevant parameters to be estimated.

$$u_{ijk} = x_{jk}\beta^x_i - \alpha_i(p_{jk} + t^{jk}) - \alpha_i\gamma\kappa\beta^m_i e_{jk}(g_k + t^G_k) + \xi_{jk} + \varepsilon_{ijk} \tag{3}$$

The additional variables here are the new car taxes, $t^{jk}$ and the fuel taxes $t^G_k$, with the $p_{jk}$ and $g_k$ redefined as prices net of taxes. A final issue with the model implied by the conditional indirect utility in both equations (2) and (3) pertains to the term $\varepsilon_{ijk}$.

More specifically, we will assume the $\varepsilon_{ijk}$ terms are correlated across car models, just as in Grigolon and Verboven (2014), that is:

$$\varepsilon_{ijk} = \zeta_{ig} + (1-\rho)\epsilon_{ijk} \tag{4}$$

In equation (4), $\rho$ is a correlation term between alternatives, $\epsilon_{ijk}$ is a i.i.d. extreme value shock and $\zeta$ has the distribution such as $\varepsilon_{ijk}$ is extreme value. This model requires an assumption from the econometrician regarding the grouping of alternatives into $G$ groups (with generic element $g$, which will be discussed below.

The model is closed by assuming consumer $i$ chooses the automobile $jk$ which yields the largest conditional indirect utility. The parameter vector here can be defined as $\theta_i = (\beta^x_i, \alpha_i, \beta_m, \rho)$ come from a distribution $F_{\theta_i}$.

Under these assumptions, the market shares can be defined as:

$$
\begin{aligned}
s_{jk} &= \int_{\theta_i} \frac{\exp((V_{ijk}/(1-\rho))}{\exp(I_{ig}/(1-\rho))} \frac{\exp(I_{ig})}{\exp I_i} dF_{\theta_i} \\
V_{ijk} &= x_{jk}\beta_i^x - \alpha_i(p_{jk} + t^{jk}) - \alpha_i \gamma \kappa \beta_i^m e_{jk}(g_k + t_k^G) + \xi_{jk} \\
I_{ig} &= (1-\rho) \ln \sum_{jk \in J_g} \exp((V_{ijk}/(1-\rho)) \\
I_i &= \ln \left( 1 + \sum_{g=1}^{G} \exp(I_{ig}) \right)
\end{aligned}
$$

The coefficients will be estimated by the Generalized Method of Moments of Berry, Levinsohn and Pakes (1995), and more specifically for this model, Grigolon and Verboven (2014), with the market share integral approximated by simulation.

# 4 Results

We have a rich dataset from the Brazilian new auto market, obtained from a market research firm[7], which includes data on sales, prices and other product characteristics at a municipality level for every passenger car sold in Brazil from January 2008 to May 2013.

The data cover all Brazilian cities with more than 100,000 inhabitants. For data on sales, the unit of observation is a car variant, defined as a combination of brand/model/engine/fuel type/transmission/body type such as an "Alfa Romeo 147 2000 cc gasoline sedan automatic". In terms of the $jk$ definition and using the previous example, the model would be "Alfa Romeo 147 sedan automatic", whereas the engine would be a "2000 cc gasoline". Initially brands with low sales, such as Ferrari, Aston Martin, Bentley, Jaguar, Lamborghini, Lexus, Maseratti and Rolls-Royce, there was an average of 406 variants in each market, with a minimum of 56 variants and a maximum of 880 variants. The average number of models is 202 models, with a minimum of 34 and a maximum of 343.

Prices are defined as list prices, including all taxes levied on purchase of a new vehicle. Sales are defined as new vehicle registrations, the source of it being the national registration of new cars (RENAVAM - *Registro Nacional de Veículos Automotores*. Even though we have monthly data, the sales data was aggregated by year, from 2008 to 2012. Fuel price data was obtained from the website of the Brazilian regulator of oil and gas sector, ANP (*Agência Nacional do Petróleo*) by municipality, with weekly frequency. We assumed the average price per year of gasoline as the relevant measure of fuel costs, for the reasons discussed in the previous section.

As for information of vehicle kilometers traveled as well as the scrappage curve, intended to give the expected number of lifetime kilometers of a given automobile, they are also from public sources. The scrappage was constructed from the information available at CETESB (2015), which provided scrappage curves from national data. The information on the number of kilometers ran by a given vehicle was computed from Bruni and Bales (2013). They fit a nonlinear regression model with the kilometers per year as a dependent variable and the vehicle age as the independent one, from all the vehicles that were subjected to the annual program of pollution checks in São Paulo city[8]. Both the scrappage curve and the number of kms per year are plotted in Figure 9.

[7] For confidentiality reasons, it is not possible to make public its name.

[8] Their model is $y = 0.6713x^3 - 49466x^2 + 779.66x + 11266$, with $y$ being the yearly amount of km and $x$ the vehicle age.

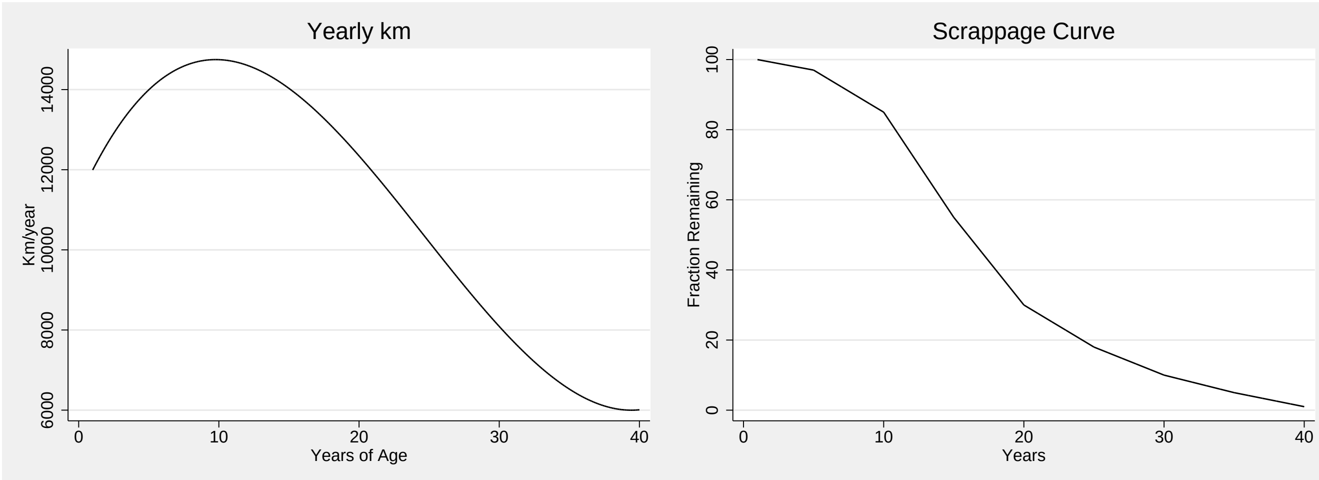



Figure 9: Km/Year and Scrappage Curve

The potential market per city/year, $M_t$, is defined as the city's population multiplied by the probability a household purchases a new car in a given year. The yearly city population estimates are provided by the Brazilian Statistical Office (IBGE)[9], and the probability of a given household purchases a new car is given by the 2008-2009 Budget study (*Pesquisa de Orçamentos Familiares*), also from the Brazilian Statistical Office.

As for the groupings required for the nesting approach for the random coefficient models, we started with the marketing intelligence company classification, which was:

- Large Car
- Luxury Car
- Medium Car – this one was subdivided into two sub-groupings, Medium-large car and Medium-small car
- Sports Car
- MPV
- Station wagon – divided into three sub-groupings, Medium, Large and Luxury
- Small car
- Popular car
- SUV

The original 12 levels were aggregated into eight different nests:

1. Large Cars
2. Luxury Cars
3. Medium Car
4. MPV and Station Wagons
5. Small
6. Popular

[9] They are computed to determine the share of federal taxes to be redistributed to states.

7. SUV

As for the characteristics of these models, the following will be used:

- Transmission – Automatic Transmission
- CV – Engine Power (in cv)
- LITERS – Engine Displacement (in cc)
- TRAC – Four-Wheel Drive not available
- PILO – Automatic Pilot not available
- SOUND – Sound Equipment not available
- VIEL – Electric raising of the windows not available
- ACLU – Luxury finishing not available
- DIRA – Assisted steering wheel not available
- ABS – ABS system not available
- ALAM – Factory installation of alarm system not available
- TRAV – Factory installation of locking system for doors not available
- COPT – Onboard computer not available
- EBD – Electronic Brake Force Distribution system not available
- DIM – Car Area (length between axles multiplied by width) – in sq meters

The discrete characteristics are defined in terms of not having these elements either as a variant of a car model or an separate item to be purchased at the car dealership. Unweighted means of these characteristics are presented in table 3, whereas sales weighted characteristics are in table 4. The role of several of these discrete characteristics is to control for a sizable part of the unobserved characteristics in the demand model, reducing the need for dummies for car models.

Table 3: Unweighted Descriptive Statistics

| | Nests | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Sales | 8.3081 | 6.0429 | 5.5704 | 23.6007 | 86.3230 | 129.3504 | 24.5006 |
| Prices in 1000BRL | 148.3692 | 226.1754 | 283.0643 | 67.5028 | 43.0157 | 37.6079 | 123.8102 |
| Fuel Costs | 3.9084 | 3.5959 | 3.8646 | 4.0548 | 3.7624 | 3.3002 | 3.9594 |
| CV | 208.2488 | 251.2449 | 284.3859 | 121.5739 | 96.4479 | 82.1693 | 187.8827 |
| LITERS | 2.7042 | 2.9331 | 3.3338 | 1.7729 | 1.4061 | 1.1521 | 2.4440 |
| National | 0.0000 | 0.0000 | 0.0431 | 0.8262 | 0.9289 | 0.7713 | 0.3434 |
| Transmission | 1.0000 | 0.9749 | 0.5700 | 0.1921 | 0.0086 | 0.0110 | 0.4419 |
| TRAC | 0.0000 | 0.0740 | 0.1059 | 0.0004 | 0.0000 | 0.0000 | 0.4210 |
| COPT | 0.7695 | 1.0000 | 0.9903 | 0.5102 | 0.4408 | 0.2545 | 0.6143 |
| SOUND | 1.0000 | 1.0000 | 1.0000 | 0.5830 | 0.5752 | 0.5233 | 0.9034 |
| EBD | 1.0000 | 0.9966 | 1.0000 | 0.2154 | 0.1334 | 0.1657 | 0.6531 |
| ACLU | 0.9198 | 0.9997 | 0.9903 | 0.2137 | 0.2559 | 0.3304 | 0.7061 |
| PILO | 1.0000 | 0.8831 | 0.7347 | 0.1197 | 0.1002 | 0.0236 | 0.5149 |
| DIM (sq. mt) | 5.1872 | 5.2041 | 4.7564 | 4.5398 | 4.1514 | 3.8682 | 4.8581 |

Table 4: Sales Weighted Descriptive Statistics

| | Nests | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Prices in 1000BRL | 132.1127 | 189.9388 | 186.9880 | 60.1568 | 37.1400 | 30.4097 | 89.5184 |
| Fuel Costs | 3.7799 | 3.2455 | 3.0451 | 3.9265 | 3.6318 | 3.2000 | 3.7712 |
| CV | 197.4917 | 213.1855 | 226.8751 | 112.6730 | 86.0934 | 74.3440 | 152.4092 |
| LITERS | 2.5803 | 2.4144 | 2.7640 | 1.6656 | 1.2558 | 1.0348 | 2.0617 |
| National | 0.0000 | 0.0000 | 0.0199 | 0.9295 | 0.9592 | 0.9771 | 0.5970 |
| Transmission | 1.0000 | 0.9900 | 0.8240 | 0.1012 | 0.0015 | 0.0005 | 0.2492 |
| TRAC | 0.0000 | 0.0268 | 0.0431 | 0.0000 | 0.0000 | 0.0000 | 0.1990 |
| COPT | 0.8554 | 1.0000 | 0.9951 | 0.5005 | 0.2296 | 0.0449 | 0.4010 |
| SOUND | 1.0000 | 1.0000 | 1.0000 | 0.5106 | 0.6169 | 0.3644 | 0.7217 |
| EBD | 1.0000 | 0.9993 | 1.0000 | 0.1304 | 0.0391 | 0.0169 | 0.4027 |
| ACLU | 0.9468 | 1.0000 | 0.9951 | 0.1234 | 0.1012 | 0.0919 | 0.4261 |
| PILO | 1.0000 | 0.7778 | 0.9001 | 0.0492 | 0.0571 | 0.0017 | 0.3103 |
| DIM | 5.2290 | 5.0928 | 4.7961 | 4.4476 | 4.1153 | 3.9050 | 4.6757 |

Looking at the statistics presented in table 4, one can notice the large differences one can find between groups. Groups 5 (Small) and 6 (Popular), have prices that are a fourth of groups 1(Large) and 2(Luxury). Even between groups 5 and 6 the differences across engine displacement are striking, with the average for group 5 being 21% higher than the average for group 6, with a similar picture for engine power. Engine Displacement and Engine Power are probably important attributes for car model choice, and this will be taken into account in the next section econometric modeling.

As mentioned in the section presenting the model, we have a panel of $T$ markets, understood as combination of city-year. This data panel will be used to estimate the parameters of the demand model specified in equation (3), with a correlation in idiosyncratic demand shocks given by (4).

Observed market shares will be defined as the ratio of observed sales to the potential market, that is:

$$s_{jkt} = \frac{q_{jkt}}{M_t}$$

The equality of observed and model predicted shares is an essential part of the Method of Moments estimation strategy we are going to pursue, similar to Berry, Levinsohn and Pakes (1995) and Grigolon and Verboven (2014). This will require further detail on the model specification.

The taste parameters to be estimated are $\theta = (\beta_i^x, \alpha_i, \kappa\beta_i^m, \rho)$. We will partition the $\theta$ vector in two components during the estimation – one of them, represented by $\bar{\theta}$, represent the mean effects for the characteristics, and the other one, $\theta_i$, represents the random coefficients.

For the second component, $\theta_i$, one component is $\beta_i^m$, which will follow the empirical distribution of mileage and ensures $\gamma\kappa$ are identified. Another component of the random coefficient vector is $\rho$, the parameter governing the correlation pattern of the random idiosyncratic shocks.

As for the coefficients $\beta_i^x$, we chose to adopt random coefficients for only characteristics Cubic Centimeters and Horsepower, since we do not have micro data to identify a lot of random coefficients as in Petrin (2002), and Berry and Haile (2014). For these characteristics it is assumed a normally distributed random coefficients, with covariances equal to zero, so:

$$\beta_i^x = \bar{\beta}^x + \Sigma_x \nu_i^x$$

The terms $\bar{\beta}_i^x$ are to be collected in the vector $\bar{\theta}$, whereas the $\Sigma_x$ will be part of the $\theta_i$ vector. The price coefficient, $\alpha_i$ will be assumed fixed, $\alpha_i = \alpha/Y_t$. The final coefficient vector, $\theta = (\theta_i, \bar{\theta})$, will be thus divided:

- $\theta_i = (\rho, \Sigma_x, \beta_i^m)$
- $\bar{\theta} = (\bar{\beta}^x, \alpha)$

We can rewrite the conditional indirect utility as follows:

$$u_{ijkt} = \bar{\beta}^x x_{jkt} - \alpha \frac{p_{jkt}}{Y_t} + \Sigma_x \nu_i x_{jkt} - \alpha\kappa\gamma\beta_i^m \frac{e_{jkt} g_k}{Y_t} + \xi_{jkt} + \varepsilon_{ijk}$$

Following standard notation in Grigolon and Verboven (2014) and Grigolon, Reynaert and Verboven (2014), we can rewrite the conditional indirect utility as follows:

$$\begin{aligned} u_{ijkt} &= \delta_{jkt} + + \Sigma_x \nu_i x_{jkt} - \alpha\kappa\gamma\beta_i^m \frac{e_{jkt} g_k}{Y_t} + \varepsilon_{ijk} \\ \delta_{jkt} &= \bar{\beta}^x x_{jkt} - \alpha \frac{p_{jkt}}{Y_t} + \xi_{jkt} \end{aligned}$$

## 4.1 Modified Contraction Mapping

As usual in this literature, an essential part of the estimation procedure requires an iterative procedure to find the vector of $\delta_{jkt}$ which makes the estimated market shares match the observed ones. And here we present an innovation from the previous literature, specially Grigolon and Verboven (2014) and Grigolon, Reynaert and Verboven (2014). In the first paper, it is shown the usual contraction mapping strategy of Berry, Levinsohn and Pakes (1995) does have a fixed point.

They propose the following modified contraction mapping:

$$\delta_{jkt}^r = \delta_{jkt}^{r-1} + (1-\rho)(\ln(s_{jkt}) - \ln(s_{jkt}(\delta_{jkt}^{r-1}))) \tag{5}$$

In which the term $s_{jkt}(\delta_{jkt}^{r-1})$ is the predicted share using the $r-1$ iteration vector of mean valuations[10].

However, this modified contraction mapping also poses some problems. As Grigolon and Verboven (2014) themselves pose, and it is easy to notice from inspection of equation (5), this contraction mapping leads to severe problems with execution time as the correlation term $\rho$ approaches 1.

Thus, we used the ideas in Reynaerts, Varadhan and Nash (2012) for dealing with large scale problems, using a Newton-Rapshon approach to find the relevant fixed point:

$$\delta_{jkt}^r = \delta_{jkt}^{r-1} - \mathbf{J}(\boldsymbol{\delta}_{\mathbf{jkt}}^{\mathbf{r-1}})^{\mathbf{-1}}(\ln(s_{jkt}) - \ln(s_{jkt}(\delta_{jkt}^{r-1}))) \tag{6}$$

In which the term $\mathbf{J}(\boldsymbol{\delta}_{\mathbf{jkt}}^{\mathbf{r-1}})^{\mathbf{-1}}$ is the Jacobian matrix of $s_{jkt}(\delta_{jkt})$ evaluated at the $(r-1)$ iteration. From the appendix of Grigolon and Verboven (2014), one can easily find the relevant equations:

[10] It is important to notice there is a typo on the published version of Grigolon and Verboven (2014) paper. The version of the contraction mapping on the paper does not have a fixed point, but the supplementary material – especially the codes – have the correct version.

$$\frac{\partial s_{jkt}}{\partial \delta_{jkt}} = \left(\frac{1}{1-\rho} - \frac{\rho}{1-\rho} s_{jkt|g} - s_{jkt}\right) s_{jkt}$$

$$\frac{\partial s_{jkt}}{\partial \delta_{(jk)'t}} = \left(-\frac{\rho}{1-\rho} s_{(jk)'t|g} - s_{(jk)'t}\right) s_{jkt}, \quad \forall (jk)'t \neq jkt \text{ in the same group } g$$

$$\frac{\partial s_{jkt}}{\partial \delta_{(jk)'t}} = -s_{(jk)'t} s_{jkt}, \quad \forall (jk)'t \neq jkt \text{ in a different group } g$$

The next step on the estimation algorithm is to use GMM from the vector of unobserved product characteristics, $\xi_{jkt}$. We decompose the unobserved product characteristic into $\xi_{jkt} = \xi_t + \xi_b + \tilde{\xi}_{jkt}$, in which the term $\xi_t$ is approximated by a set of market dummies and $\xi_b$ by a set of brand dummies.

The GMM implementation is based on the orthogonality conditions between the $\tilde{\xi}_{jkt}$ and a set of instruments, $E(\tilde{\xi}_{jkt}|z_{jkt})$. The GMM estimates of the $\theta$ vector of parameters is the minimizer of the function:

$$Q(\theta) = \tilde{\xi}(\theta) z \Omega z \tilde{\xi}(\theta)$$

With the $\tilde{\xi}(\theta)$ is constructed from stacking the $\tilde{\xi}_{jkt}$ for all models and markets, and $z$ is defined accordingly for the instrument set. The $\Omega$ matrix is a weighting matrix of the moment conditions.

For the empirical exercise of demand estimation, we are specially focused on identifying some parameters, such as the price sensitivity of demand, which is guided by both $\alpha_i$ and $\rho$, as well as the mileage heterogeneity across consumers, given by $\beta_i$. The effects of engine power and displacement are also important parameters to be identified, since they are directly related to fuel consumption of a given model.

In order to identify the coefficients, we have several sources of identification. The first one is the set of so-called "BLP instruments", which are originally proposed by Berry, Levinsohn and Pakes (1995). They propose as instruments the characteristics of the products, as well as the sums of characteristics of other products of the same firm and the sums of characteristics of the products of other firms.

Besides the "BLP Instruments", we also used a source of identification from changes in one of the taxes on new car sales, presented in table 8. More specifically, we interacted a dummy for 2009 with dummies corresponding to the different engine displacement levels of the tax schedule[11]. We believe this will counteract the fact we have national list prices for car models. Additionally, the fact we have city/year prices for fuels also helps on the identification of the $\beta_i^m$ coefficient.

## 4.2 Results

In order to assess the robustness of results to alternative specifications of the heterogeneity of preferences for fuel consumption, initially two models are considered. The first one is a standard logit model, in which there are no heterogeneity on the fuel cost coefficient and no other coefficient. Besides, we assume there is no nesting structure on preferences.

The second one is a Nested Logit, with no heterogeneity but nesting according to the categorization presented in the previous section. This model will make clear the role of nesting in identifying the fuel coefficients.

The third model is our main Random Coefficient Nested Logit demand model, with heterogeneity in some

[11] We experimented with dummies corresponding to all tax changes, but this one was the strongest set of instruments

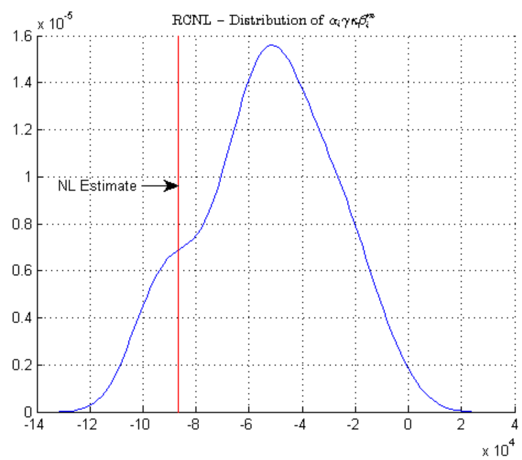
coefficients and heterogeneity in fuel costs given by the empirical distribution of mileage weighted by survival probability. All results are presented in Table 5.

Table 5: Model Coefficients

| | Logit | | Nested Logit | | RCNL | | | |
|---|---|---|---|---|---|---|---|---|
| | Coef | SE | Coef | SE | Mean | SE | Std Dev | SE |
| $\alpha\kappa\gamma\beta_i^m$ | 73886 | 10859 | -86653 | 11780 | | | | |
| CC | 0.36251 | 0.36018 | -1.5731 | 0.36437 | -0.99219 | 2.0304 | 2.00E-13 | 24.064 |
| HP | -0.5046 | 0.01365 | -0.2204 | 0.015865 | -0.37145 | 0.21579 | 0.1653 | 0.17868 |
| Domestic | 0.30194 | 0.011302 | 0.29457 | 0.011304 | 0.23492 | 0.013279 | | |
| Price | -1.4708 | 0.25705 | -2.323 | 0.25819 | -237.48 | 36.471 | | |
| $\rho$ | | | 0.89166 | 0.025363 | 0.93513 | 0.021147 | | |
| $\alpha_i\kappa\gamma$ | | | | | -0.23645 | 0.090377 | | |
| $\kappa\gamma\beta_i^m$ | -50237 | 11689 | 37303 | 6314.8 | | | | |
| $\kappa\gamma$ | | | | | 0.000996 | 0.000519 | | |
| GMM Crit. Fun | 1562.2 | | 326.3 | | 325.02 | | | |
| Number of Obs | 1.66E+05 | | 1.66E+05 | | 1.66E+05 | | | |

**Coefficient Estimates** For the standard logit model, one does find a coefficient for the fuel cost with positive sign, which is against to what we would expect. The coefficients start to have the expected signs on the Nested Logit model, with a negative effect on the price coefficient and negative coefficients for the fuel economy coefficients. Still with respect to the Nested Logit model, the nesting coefficient is 0.85, indicating there is a string preference for models in the same nest. The results are similar to the ones for the Random Coefficient Nested Logit model. The Figure 10 compares the results for the Nested Logit Model with the ones for the Random Coefficient Nested Logit Models.[12]

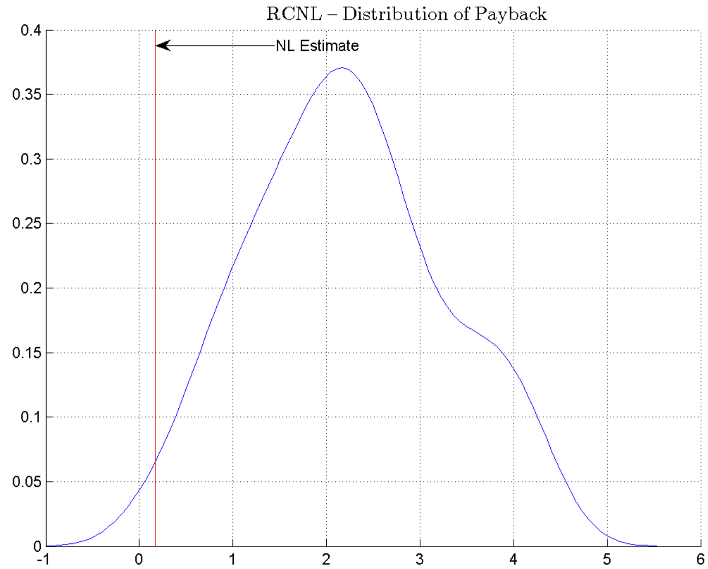
Figure 10: Distribution of Marginal Effects of Fuel Costs




As a comparison, the next figure presents the distribution of the Payback periods for both models – Nested Logit and Random Coefficient Nested Logit in figure 11.

[12]The share weighted mean elasticity is of -6.568, with no price elasticities below unity.

Figure 11: Distribution of Payback Periods in years

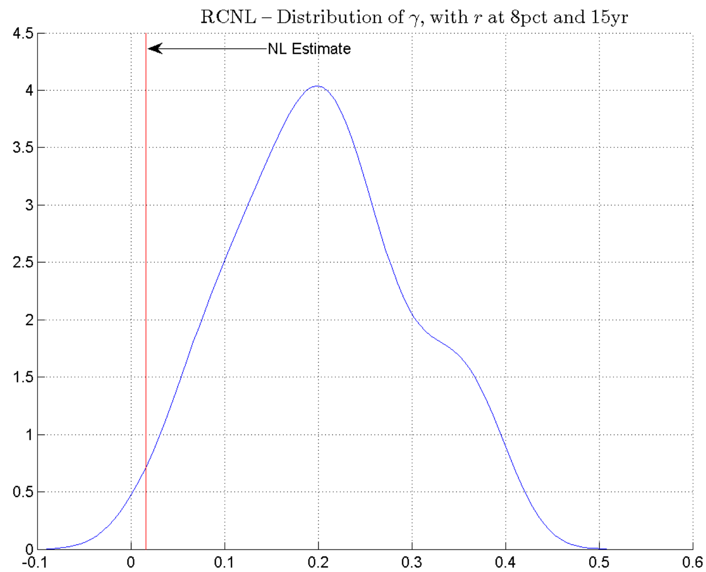



This figure indicates a 3 year payback time for a car, which is consistent with a low income and high interest rate country as Brazil[13]. This also is consistent with the estimates of the Undervaluation parameter which can be constructed by dividing the Payback time of figure 11 with an estimate of expected lifetime of a car and an interest rate.

The results for an interest rate of 8% per year and a lifetime of 15 years are in Figure 11. It is important to notice, though, this result is robust to the criticism posed by Bento, Li and Roth (2012) about consumer heterogeneity and sorting bias.

[13]The main short run interest rate at this time was about 10% per year

Figure 12: Distribution of Undervaluation Parameter in years




The results indicate an important role for the "energy paradox", for the median attention parameter $\gamma$ is about 0.2, that is, only 20% of the present value of an additional BRL in fuel economy is reflected in new car prices. We will consider on the following section what these results entail for policy measures designed to change fuel prices.

# 5 Policy Simulations

In this section, we will investigate an elimination of the artificially low gasoline price in Brazil, getting the domestic price aligned with international levels. Since the gasoline price is only about 31% of the fuel pump price, all adjustments were made taking it into account. We are also supposing firms compete in prices in a multiproduct setting. The new prices are the solutions of the first order condition system for all products in all markets (year+city).

Table 6: Average Fuel Consumption per year

| | **Avg. Consumption km/l** | |
|---|---|---|
| | Baseline | Counterfactual |
| 2008 | 8.639 | 8.650 |
| 2009 | 8.656 | 8.662 |
| 2010 | 8.674 | 8.678 |
| 2011 | 8.671 | 8.697 |
| 2012 | 8.476 | 8.485 |

The results of table 6 indicate the alignment of fuel prices with international levels does change the demand of new cars towards more fuel efficient cars. We also investigate the effects in terms of additional lifetime CO2 tons emitted as a consequence of this policy. For this simulation, we assumed the lifetime mileage distribution combined with the scrappage curve discussed above, as well as two different emission factors per liter of fuel. The first one, 2.214 kg of CO2 per liter of fuel, is the value for gasoline. The other one, 1.526 kg of CO2 per liter of fuel, is the value for hydrated ethanol. Both values are available at Appendix X in CETESB (2015).

Table 7: Additional lifetime 1000 CO2 tons from repressing fuel prices

| | Minimum | Maximum |
|---|---|---|
| 2008 | -17634.5 | -25561.9 |
| 2009 | 10926.02 | 15837.73 |
| 2010 | -43969.3 | -63735.3 |
| 2011 | -44400.7 | -64360.7 |
| 2012 | 5331.51 | 7728.25 |
| Total | -89747 | -130092 |

In Table 7, some changes have different signs because in these years the average price difference of domestic gasoline (type A) prices is positive – that is, the domestic price was above the international one. Even taking it into account, the final result for this period is negative. That is, an amount between 89.7 and 130 thousand CO2 tons were emitted in this period due to the artificially low gasoline prices during this period.

# 6 Conclusion

This paper uses the Brazilian experience to investigate the environmental effects of artificially repressing gasoline prices below international levels, in the period between 2008 and 2013. Obvious political dividends come from manipulating fuel prices, and PETROBRAS (the Brazilian state owned monopolist crude oil producer) has suffered in terms of market value.

To compute these environmental effects, it is posed a Random Coefficient Nested Logit as in Grigolon and Verboven (2014) to estimate the parameters of a demand model for new cars in Brazil. It is used a very detailed dataset comprising sales of new cars in all cities with more than 100 thousand inhabitants in Brazil. From the estimated parameters, a counterfactual scenario in which domestic gasoline prices were aligned with international ones is simulated, and the effects on sales and predicted fuel consumption are computed. From the counterfactual lifetime fuel consumption it is estimated the additional lifetime emissions from this policy.

The demand model results point to substantial undervaluation of fuel costs, and an important role for the "energy paradox", for the median attention parameter $\gamma$ is about 0.2. That is, only 20% of the present value of an additional BRL in fuel economy is reflected in new car prices.

Results from the demand model were used to simulate a counterfactual in which the domestic prices of gasoline were aligned to international levels. The simulation indicates the reduction in the fuel price gap and the elimination of the "Gas Price Tax Holiday" would imply some realignment towards lower engine displacement models. Additionally, an amount between 89.7 and 130 thousand CO2 tons were emitted in this period due to the artificially low gasoline prices during this period.

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# A New car tax rates

more specifically, IPI, ICMS and PIS/COFINS. IPI (in Portuguese, *Imposto sobre Produtos Industrializados* is a national level tax with different rates depending on both fuel types as well as engine displacement in cubic centimeters. PIS/COFINS (in Portuguese, *Programa de Integração Social/Contribuição para o Financiamento da Seguridade Social*) is an additional federal tax originally intended to be used to fund only the Social Security, and it does not change across fuel types nor engine displacement. Finally, ICMS (*Imposto sobre Circulação de Mercadorias e Serviços*) is a state level tax to be defined by each state and presumably discussed in a forum composed of all state government finance ministers, CONFAZ (*Conselho Nacional de Política Fazendária*). During all this period, there were several rounds of changes in tax rates that can be seen in Table 8.

Table 8: Tax Rates for New Vehicles

| Year | Taxes | 1000 cc | from 1000 cc to 2000 cc | | over 2000 cc | | Light Trucks |
|---|---|---|---|---|---|---|---|
| | | | Gasoline | Ethanol/Flex | Gasolina | Ethanol/Flex | |
| 2008 | IPI | 0 | 6,5 | 5,5 | 25 | 18 | 1 |
| | ICMS | 12 | 12 | 12 | 12 | 12 | 12 |
| | PIS/COFINS | 11,69 | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 |
| | % price | 22,2 | 26,4 | 25,8 | 33,1 | 27,3 | 22,6 |
| 2009 | IPI | 5,0 /3,0 | 11 | 7,5 | 25 | 1 | 1 |
| | ICMS | 12 | 12 | 12 | 12 | 12 | 12 |
| | PIS/COFINS | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 |
| | % price | 25,7/24,4 | 29,2 | 27,1 | 36,4 | 33,1 | 22,6 |
| 2010.1 | IPI | 7,0 / 3,0 | 13 | 7,5 | 25 | 18 | 4 |
| | ICMS | 12 | 12 | 12 | 12 | 12 | 12 |
| | PIS/cofins | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 |
| | % price | 27,1/24,4 | 30,4 | 27,1 | 36,4 | 33,1 | 24,7 |
| 2010.2 | IPI | 7 | 13 | 11 | 25 | 18 | 4 |
| | ICMS | 12 | 12 | 12 | 12 | 12 | 12 |
| | PIS/COFINS | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 |
| | % price | 27,1 | 30,4 | 29,2 | 36,4 | 33,1 | 24,7 |
| 2011 on | IPI | 7 | 13 | 11 | 25 | 18 | 4 |
| | ICMS | 12 | 12 | 12 | 12 | 12 | 12 |
| | PIS/COFINS | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 | 11,6 |
| | % price | 27,1 | 30,4 | 29,2 | 36,4 | 33,1 | 24,7 |

Source: Brazilian Car Manufacturer's Association (ANFAVEA).