Pontifícia Universidade Católica do Rio de Janeiro

Thaís Machado de Matos Vilela

Three essays on gasoline and automobile markets in Brazil

Tese de Doutorado

Thesis presented to the Programa de Pós-Graduação em Economia of the Departamento de Economia da PUC-Rio, as partial fulfillment of the requirements for the degree of Doutor.

Advisor: Prof. Leonardo Bandeira Rezende

Rio de Janeiro
March 2015

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Abstract

Vilela, Thaís Machado de Matos; Rezende, Leonardo Bandeira (advisor). **Three essays on gasoline and automobile markets in Brazil**. Rio de Janeiro, 2015. 113 p. PhD Thesis – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

This thesis is comprised of three independent chapters about gasoline and automobile markets in Brazil. In the first two chapters we are interested in the relationship between consumers' behavior and the flex-fuel technology. In the first chapter, we focus on how sensitive Brazilian consumers are to fuel price changes, especially after the introduction of the flex-fuel technology on March 2003. We estimate the own- and cross-price elasticities of gasoline demand taking into account fuel prices endogeneity. We combine two identification strategies – Dynamic Ordinary Least Square and Instrumental Variables. Our results present evidences that the introduction of the flex-fuel technology changed consumers' perception regarding fuel prices fluctuations: consumers became more elastic regarding both gasoline and ethanol after the introduction of the new technology. In the second chapter, we focus on the automotive market. We measure the importance of the flex-fuel technology for consumers when buying a new automobile and we attempt to, through a detailed descriptive analysis, shed some light on the process of introduction of this new automobile characteristic in Brazil. Using only aggregate data, we follow the BLP (1995) approach: we use a discrete-choice model with random coefficients to estimate the demand and the supply parameters. To control for the price endogeneity in the demand curve, we use linear combinations of the automobile characteristics (except for the price) as instruments. The results suggest that the flex-fuel technology is not an important attribute when all the other automobile characteristics are controlled for. This result suggests that the rapid growth in sales is mostly explained by the supply side: automakers' decision to offer only flex-fuel for any other reasons not associated with demand. Finally, in the third chapter, we calculate the economic and environmental costs of government intervention in the gasoline market through its majority position in Petrobras. Based on Microeconomic Theory, we calculate that the deadweight loss resulting from this policy equaled R$ 17 billion from January 2002 to January 2013. When considering separately the effects of this intervention on the emissions of CO_2, on the ethanol market and on the inflation rate, we find that the economic cost increases substantially.

Keywords

Gasoline; ethanol; flex-fuel; cointegration; Instrumental Variables; automobile; BLP; pricing policy; CO_2 emissions.

Resumo

Vilela, Thaís Machado de Matos; Rezende, Leonardo Bandeira (orientador). **Three essays on gasoline and automobile markets in Brazil**. Rio de Janeiro, 2015. 113 p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Esta tese é composta de três capítulos independentes sobre os mercados de gasolina e de automóveis no Brasil. Nos dois primeiros capítulos, estamos interessados na relação entre o comportamento do consumidor e a tecnologia flex-fuel. No primeiro capítulo, analisamos como a introdução da tecnologia flex-fuel a partir de 2003 mudou as elasticidades-preço própria e cruzada da demanda por gasolina no Brasil. Para calcular as elasticidades, combinamos duas estratégias de identificação: Mínimos Quadrados Ordinários Dinâmicos e Variáveis Instrumentais. Os resultados sugerem consumidores mais elásticos às mudanças nos preços dos combustíveis do que estudos anteriores, sugerindo que a introdução da tecnologia flex-fuel mudou o comportamento do consumidor. No segundo capítulo, estudamos o mercado automotivo. Procuramos entender como se deu o processo de introdução da tecnologia flex-fuel e estimamos a importância dessa nova tecnologia para o consumidor. Para tanto, usamos a metodologia proposta em BLP (1995): um modelo de escolha discreta com coeficientes aleatórios para estimar os parâmetros da demanda por e da oferta de automóveis. Para corrigir a endogeneidade dos preços na curva de demanda, usamos combinações lineares das características dos automóveis (exceto preço) como instrumentos. Os resultados sugerem que a tecnologia flex-fuel não é valorizada pelos consumidores quando outras características são controladas. Este resultado sugere que o rápido crescimento das vendas dos automóveis flex-fuel pode ser mais bem explicado pelo lado da oferta. Finalmente, no terceiro capítulo, calculamos os custos econômicos e ambientais da intervenção do Governo Federal através de sua posição majoritária na Petrobras. Com base na Teoria Microeconômica, calculamos o peso morto gerado por tal política governamental. Encontramos um custo total de R$ 17 bilhões entre janeiro de 2002 e janeiro de 2013. Ao analisarmos separadamente os impactos ambientais – emissões de CO_2 – e os efeitos sobre o consumo de álcool hidratado e sobre a inflação, verificamos que o custo econômico aumenta substancialmente.

Palavras-chave

Gasolina; álcool combustível; flex-fuel; cointegração; Variáveis Instrumentais; automóvel; BLP; política de preços; emissões de CO_2.

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1
Did flex-fuel technology change the price elasticities of fuel consumption? A new approach for estimating gasoline demand in Brazil

1.1
Introduction

Since March 2003, automakers in Brazil produce automobiles designed to run on gasoline, ethanol or any mixture of both fuels. The well-developed[1] ethanol distribution network in Brazil allows consumers to find gasoline and ethanol in any filling station, allowing them to choose between both fuels according to fuel prices and their preferences. Understanding how consumers respond to changes in prices of both fuels is important for developing and evaluating energy and environmental policies, and for decreasing the unpredictability of fuel demand for producers.

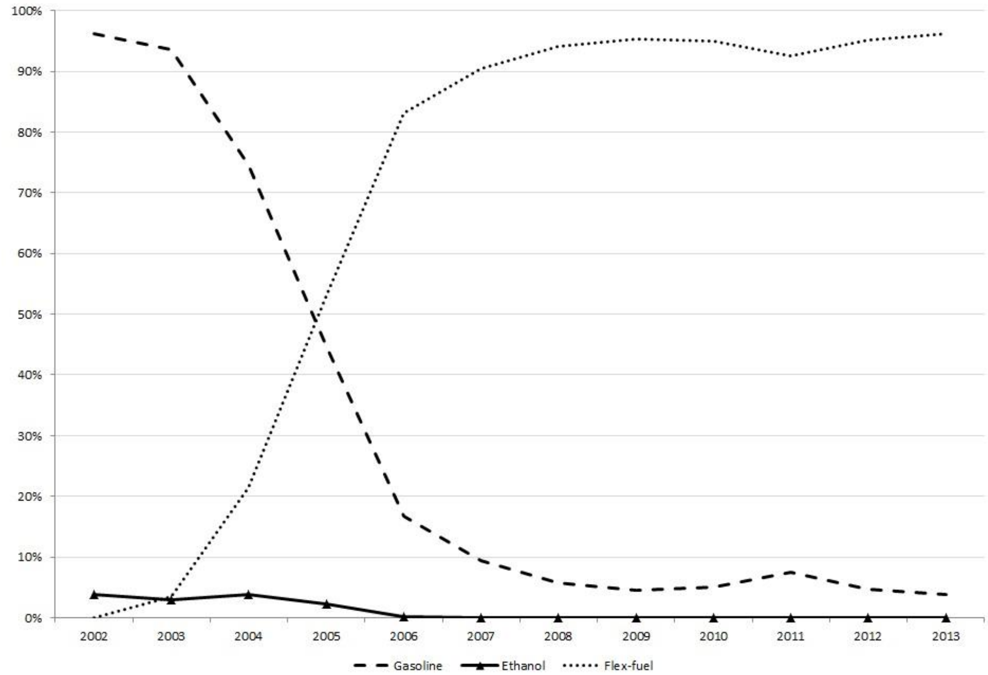
In this chapter, we answer the following question: did flex-fuel technology change the long run own- and cross-price elasticities of gasoline demand? There is a widely-accepted standpoint that the introduction of the flex-fuel technology represented a structural change in the gasoline markets, and that the price of ethanol became an important variable to explain changes in the demand for gasoline (ANP, 2013). By estimating the own- and cross-price elasticities for different periods and comparing the results we are able to test both hypotheses.

As shown in Figure 1.1, flex-fuel automobiles represented over 90 percent of total sales only four years after the introduction of the new technology. To estimate the impact of the flex-fuel technology in the gasoline market, we divide our sample into two equal time periods. We interpret the period from December 2002 to December 2007 as the introduction phase and the one from January 2008 to January 2013 as the consolidation phase. Ideally, one would use more data from the period before the introduction of the new technology, but data before December 2002 is unavailable for some key variables. This limitation can

[1] All gas stations in Brazil sell gasoline and ethanol.

possibly mean that the results are lower bounds on the effect of the new technology, since flex-fuel automobiles already compose part of the fleet in the first period.

Figure 1.1
New automobile licensing by fuel type



Source: Anfavea, statistical yearbook 2014.

We follow the Engle and Granger Two-Step procedure to estimate long run elasticities and shorter-term dynamics. The first step is the identification of the long run demand for gasoline. Different from most papers in the demand for fuel literature, especially those which use Brazilian data, we take into account that gasoline and ethanol are potential endogenous variables in the gasoline demand and supply equations. To correctly identify the estimated equation as a demand equation, we rely on two different identification strategies. Endogeneity in the non-stationary variables is controlled using Dynamic Ordinary Least Squares (DOLS), while an Instrumental Variables (IV) approach is used for the others.

In the second step of the Engle and Granger procedure, we go one step further from what is commonly done in the fuel demand literature and calculate the response of gasoline demand to shocks in the prices of gasoline and ethanol. To estimate the Impulse Response Functions (IRF), we use a non-recursive identification strategy to be sure that we are estimating the parameters of the demand equation. We impose some restrictions on the contemporaneous relationships between the variables in our model, while also including another instrument for gasoline demand based on Brazilian regulation.

We have four main results. First, controlling for price endogeneity matters. Consistent with the endogeneity hypothesis, we find higher long run own- and cross-price elasticities of gasoline demand (in absolute values) than previous papers. Second, the own price elasticity increases in absolute value from the initial period to the final one. Third, the long run cross-price elasticity of gasoline demand in the consolidation period is substantially higher than and statistically different from the cross-price elasticity found for the introduction period. These shifts in consumers' behavior corroborates with the view that the introduction of the flex-fuel technology represented an important change in the gasoline market. Fourth, in the second step of the Engle and Granger procedure, we find that transitory shocks in the prices of gasoline and ethanol lead to permanent changes in the demand for gasoline.

The remainder of this chapter is organized as follows. Section 1.2 sets the background by describing previous studies that estimate price elasticity of gasoline demand. Section 1.3 describes the data. Section 1.4 presents the model and the identification strategy. Sections 1.5 and 1.6 presents the results and additional robustness checks, respectively. Section 1.7 concludes the chapter.

1.2
Price elasticities in other empirical studies

Since the first crude oil shock, in 1973, there has been a growing literature on automobile fuel market. Most studies are interested in the demand-side fuel market and most have been done using United States data. Although many studies differ methodologically, the main controversial aspect concerns the exogeneity hypothesis about fuel prices.

Almost all papers assume that fuel prices are exogenous variables in the fuel demand equation. There is a well-accepted standpoint that fuel prices – mainly, gasoline price – are largely determined by the international crude oil price. This hypothesis, however, may be too strong, and ignoring the potential fuel price endogeneity may leads to estimates that are downward bias. To control for fuel price endogeneity, the identification strategy most used is IV. Finding valid and strong instruments for fuel prices, however, has been a challenge.

Ramsey et al (1975) and Dahl (1979) use the price of other crude oil-related products, such as kerosene and heavy fuel oil, as instrument for the price of gasoline in the United States. However, it is likely that these prices are correlated with gasoline demand shocks via shocks in the international crude oil market. If this is true, then the orthogonality condition is not satisfied and both prices are not valid as instruments for the price of gasoline.

In Yatchew and No (2001) and Manzan and Zerom (2008), regional dummies are used as instruments for the price of gasoline. However, if the regional dummies are capturing, for example, the level of development in each state, then the dummies are probably correlated with the gasoline demand within that state. In this case, the exclusion restriction is violated.

Burke and Nishitateno (2011), Scott (2012) and Coyle et al (2012) use, respectively, proven crude oil reserves, disruptions in crude oil production and the crude oil price in the international crude oil market as instruments for the price of gasoline. The validity of each variable as instrument depends on its non-correlation with gasoline demand shocks.

In an attempt to find better instruments, Scott (2012) also uses federal and state gasoline taxes (excluding *ad valorem* taxes) as instruments for the price of gasoline. According to the author, tax level is a major source of price variation in both time and state dimensions in the United States and it should not be gasoline demand-driven.

Instead of using the gasoline taxes level, Davis and Killian (2011) use inflation-adjusted change in the log of the tax per gallon as instrument for the price of gasoline. The hypothesis is that even though tax legislation may respond to current prices, the implementation of tax changes typically occurs with a lag, making it reasonable to believe that changes in tax rates are uncorrelated with unobserved changes in the demand for gasoline in the United States.

In the search of a stronger instrument for the gasoline price in the United States, Liu (2011) argues that if almost all variation in the price of gasoline is explained by changes in the international crude oil market, then the price of gasoline across the states must be correlated. Therefore, Liu (2011) uses the average gasoline price by state – excluding the adjacent states – as instrument for the price of gasoline in each state. Once more, the validity of this identification strategy depends on the non-correlation among the gasoline demand shocks in each state.

Liu (2011) finds similar results for gasoline price elasticity estimates when ignoring price endogeneity. Different from other papers, Liu (2011) argues that the gasoline price is endogenous only to a minor extent and, therefore, the bias size could be ignored.

With less ambiguity, most papers in the demand for fuel literature that use Brazilian data assume that fuel prices are exogenous variables in the fuel demand equation. There is a widely accepted standpoint that fuel prices in Brazil are determined by the federal government and do not respond to changes in the fuel market conditions – or if it does, it is to a minor extent.

Because of several changes in the Brazilian fuel market from 1975 to 2003, the estimates of fuel prices elasticities differ considerably from one study to another. Overall, almost all papers that use more recent data set indicate that since the introduction of the flex-fuel technology on March 2003, consumers' sensitivity to fuel prices variation has changed (Nappo (2007), Silva et al (2009) and Santos (2013)).

Nappo (2007) explicitly estimates the effect of the flex-fuel technology in the long run price elasticities of gasoline demand in Brazil. To capture the change in consumers' response to fuel prices variation, Nappo (2007) uses an interaction between a dummy variable – equal to 1 after March 2003 and 0 otherwise – and the gasoline price. According to Nappo (2007), because of the presence of multicollinearity between gasoline and ethanol prices, ethanol price is excluded from the main regression equation.[2]

Taking out the ethanol price from the model, however, introduces an omitted variable bias. Ethanol price is positively correlated with gasoline demand and with the other independent variables. Thus, the omission of the ethanol price introduces an upward bias in Nappo (2007). On the other hand, as with other studies, Nappo (2007) does not take into account fuel prices endogeneity, leading

[2] We find that the correlation between the price of gasoline and the price of ethanol is 0.49. We use the state-level average price (inflation adjusted) for Brazil to calculate this correlation. As there is no perfect (or close to perfect) collinearity, we do not exclude the price of ethanol from our regressions

to a downward bias. Thus, in this case, it is hard to determine the final direction of the bias.

As with Nappo (2007), our interest lies in the probable consumers' behavior change after the introduction of the flex-fuel automobiles in Brazil. However, to obtain better estimates of the long run own- and cross-price elasticities of gasoline demand, we take into account the potential fuel price endogeneity in the gasoline demand curve. We have no knowledge of a study that, using Brazilian data, controls for both gasoline and ethanol prices endogeneity.

Within this context, this paper contributes to the literature by developing a new identification strategy. We combine a cointegration technique – DOLS – and IV approach to control for fuel prices endogeneity. Also, in the second stage of Engle and Granger's methodology, we estimate a full system error correction model instead of a single-equation model, which is more common in the demand for fuel literature. To identify the error correction model, we use a non-recursive strategy. This approach allows us to draw IRF to assess the relevance of shocks in the prices of gasoline and ethanol on the gasoline market.

1.3
Data

1.3.1
Data set

In this study, we use data from different sources. From the National Petroleum, Natural Gas and Biofuel Agency (ANP, acronym in Portuguese), we get data on gasoline consumption and on gasoline and ethanol prices sold in filling stations over different Brazilian states. ANP provides state-level averages of both consumption and price data. To get constant prices, we use the official Extended Consumer Price Index (IPCA) from the Brazilian Institute of Geography and Statistics (IBGE). Prices are converted to January 2013 Brazilian Reais.

From the National Traffic Department (DENATRAN), we get data on automobile fleet for each state. A monthly income measure is not available for all Brazilian states. We follow the literature and use electric power consumption as a proxy for income. The data on electric power consumption is collected by Eletrobras. Although the data is available monthly, it is at the regional level. So, to account for the dependence within regions, we use cluster-robust standard errors.

The use of electric power consumption as an income proxy is not ideal because of the regional variation dimension. As a robustness exercise, we use other proxies to income. From the Central Bank of Brazil we get data on the number of banking agencies, the amount of bank deposits and the amount of bank loans. The results do not change significantly (Additional robustness check Section) from the primary result.

As instrument for the ethanol price we use an interaction between the state tax known as State Tax on Circulation of Good and Services (ICMS) and a supply shifter variable, the Total Recoverable Sugar (TRS) price. The ICMS is collected from the Brazilian Legislation while the TRS price is obtained from the Producers Council of Sugarcane, Sugar and Ethanol of the state of São Paulo (CONSECANA/SP). The TRS price is available only for São Paulo, the biggest sugarcane, sugar and ethanol producer in Brazil. The interaction between both variables allows us to have variation in both state and time dimensions.

When estimating the full error correction model, we also use an instrument for the gasoline price. Similarly to the ethanol price, we use an interaction between the ICMS over gasoline and the federal gasoline tax CIDE, Contribution for Intervention in the Economic Domain. The interaction between both taxes is based on the composition of the gasoline price. The composition structure is given by ANP.

The idea is to use the variation that the federal and the state tax generate over the refinery price – the price of gasoline A. According to ANP, the price of the gasoline A – gasoline without the addition of anhydrous ethanol – is defined as the realization price (by the refiners) plus the federal taxes such as CIDE. The state tax, $ICMS_g$, is imposed over this sum. Due to tax replacement (*substituição tributária* in Portuguese), there is an additional step to get the refinery final price. However, as we are interested on the variation generate by taxes on the producer price with the ICMS over gasoline that the producer pays, there is no need for this final step. In detail, we have:

1. A = realization price by the refiners (FOB price without any taxes)
2. B = CIDE
3. C = Other federal taxes
4. Price without ICMS (D) = A + B + C
5. Fraction of the ICMS that the refiners must pay (E) = $\frac{D}{1-ICMS_g}$ - D
6. Price with ICMS = D + E = $\frac{A+B+C}{1-ICMS_g}$

Therefore, the instrument for the gasoline price is: $\frac{CIDE}{1-ICMS_g}$. This instrument attends exclusion and inclusion conditions.

For most variables, we have data from July 2001 to January 2013. However, the automobile fleet data is available from December 2002. Therefore, the data set used in this study covers the period from December 2002 to January 2013. In total we have 3,294 observations. Table 1.1 presents the description of the database.

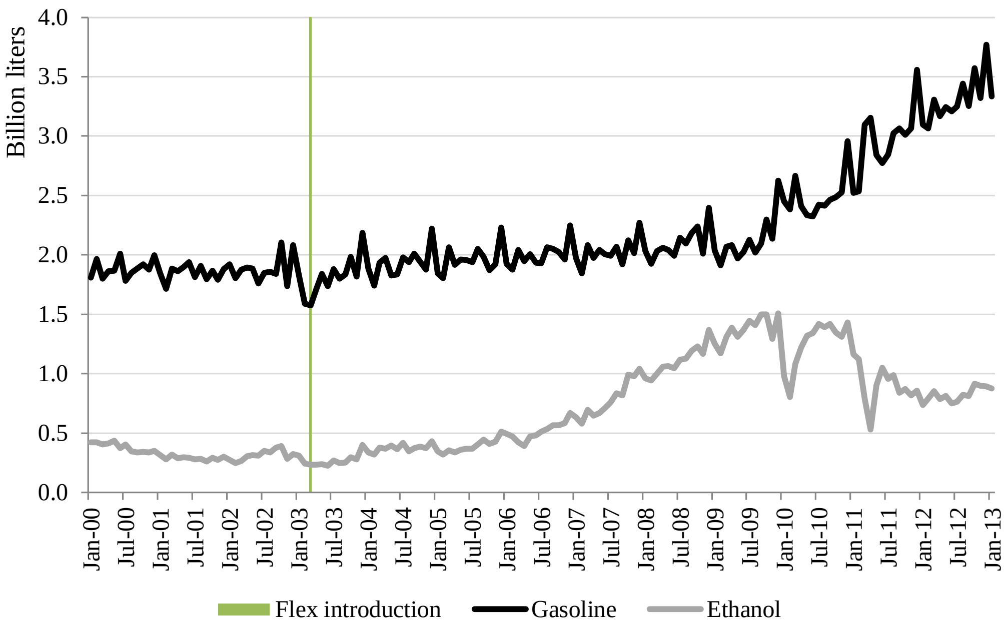
Table 1.1
Database description

Variables	Cross-section level	Source
Gasoline consumption (million liters)	State	ANP
Gasoline price (R$/liter)	State	ANP
Ethanol price (R$/liter)	State	ANP
Electric power consumption (GWh)	Regional	Eletrobras
Automobile fleet (unity)	State	Denatran
CIDE - gasoline (R$/liter)	Federal	Brazil. legislation
ICMS – gasoline (%)	State	Brazil. legislation
ICMS – ethanol (%)	State	Brazil. legislation
TRS price (R$/liter)	São Paulo	Consecana/SP

1.3.2
The gasoline market

During this ten-year study, the consumption of gasoline increased approximately 60%. From a low of 2.1 billion liters on December 2002 to a high equal to 3.3 billion liters on January 2013. Figure 1.2 shows, however, that the upward trend does not completely characterized the consumption of gasoline during this period. While the consumption of gasoline was almost flat – it grew 0.6% per month – from December 2002 to December 2009, it followed a sharp increase since January 2010.

Figure 1.2
Fuel consumption in Brazil



According to ANP (2013), the consumption of gasoline increased less than the GDP growth from 2003 to 2009 (Table 1.2). It is a standpoint among analysts (ANP, 2013) that the slow growth is due to the introduction of the flex-fuel technology on March 2003. Indeed, since 2003, the consumption of ethanol increased significantly. From a low of 236 million liters on March 2003 to a high equal to 1.5 billion liters on December 2009.

Table 1.2
Annual GDP variation and gasoline consumption variation

Year	GDP	Gasoline	Ethanol
2002	2.7%	1.8%	8.3%
2003	1.2%	-3.6%	-14.4%
2004	5.7%	6.3%	39.1%
2005	3.2%	1.6%	3.4%
2006	4.0%	1.9%	32.6%
2007	6.1%	1.3%	51.4%
2008	5.2%	3.5%	41.9%
2009	-0.3%	0.9%	23.9%

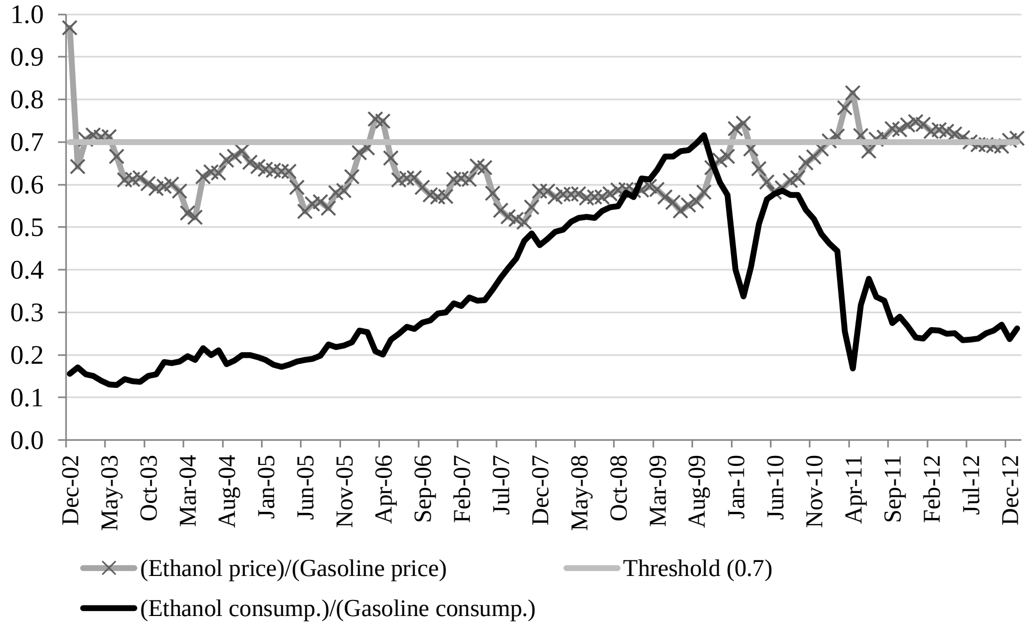
Source: ANP (2013)

Figure 1.3 shows the empirical relationship between the relative consumption – the consumption of ethanol as a proportion of the gasoline consumption – and the relative price – the ratio between the ethanol price and the price of gasoline. In the first period of our sample, as shown before, the consumption of ethanol increased substantially more than the consumption of gasoline. It is not evident, however, the relationship between the relative consumption and price during this first period. Although the consumption of ethanol is increasing, it is still low compared to the consumption of gasoline which may explain the apparently low correlation between both variables in Figure 1.3. In the final period of our sample, however, this situation seems to change.

Figure 1.3 shows a clear inverse relationship between the relative consumption and relative prices: whenever the relative price increases, the relative consumption decreases. This empirical evidence corroborates with the widely accepted standpoint that both prices (gasoline and ethanol) are important to explain changes in the fuel consumption.

It is also worth mentioning that from 2010 to January 2013, the relative prices were above the 70% threshold. Within this scenario, it is more economically advantageous to use gasoline. Figure 1.3 present evidences that consumers respond to this “rule of thumb” by changing from ethanol to gasoline. Once more, this evidence corroborates with the assumption that the price of ethanol became an important variable to explain variations in the demand for gasoline.

Figure 1.3
Relative consumption and relative price (%)



Source: ANP

1.4

Methodology

First, to estimate the long run own- and cross-price elasticities of gasoline demand in Brazil, we estimate the long run equilibrium relationship.[3] In this first step, we assume that there is no dynamic interaction between the variables in our model, i.e., changes in the gasoline price, for example, are not followed by changes in other independent variables. Within this context, we divide our sample and estimate the fuel price elasticities for each span of time to capture the effect of the flex-fuel technology on consumers' behavior.

Second, given that a cointegrating relationship exists, we specify and estimate the error correction model. Different from most papers that use Brazilian data, we estimate the full error correction model instead of estimating only the gasoline demand equation, allowing us to compute impulse response functions.

[3] We test for a cointegration relationship between the variables of interest using our demand model. We accepted the hypothesis that the variables are cointegrated and, based on economic theory, we assume that this cointegration regression represents the long run equilibrium relationship.

1.4.1 Model specification

We assume that the gasoline market is characterized by the following demand and supply equations:

$$Q_g = f_g^d(\text{gasoline price}, \text{ethanol price}, \text{income}, \text{automobile fleet})$$
$$Q_g = f_g^s(\text{gasoline price}, \text{production costs}, \text{shipping cost}, \text{federal and state taxes}, \text{markup})$$

The presence of the markup in the supply equation allows price to respond to demand fluctuations. We assume that, in the long run, demand pressure does not alter production and shipping costs and, therefore, both costs are exogenous to aggregate demand shocks.

Regarding the federal and state taxes, we believe that fuel tax changes in Brazil were implemented as a result of political decision making rather than response to market changes. As pointed out in Davis and Killian (2011), even within a context where tax legislation respond to current prices, the implementation of tax changes typically occurs with a lag. Thus, it is reasonable to believe that changes in tax rates are uncorrelated with current aggregate gasoline demand shocks.

As we are interested in the demand for gasoline, we must complete the description of our model by describing the ethanol supply, income and the automobile fleet. We characterize the supply of ethanol in the same way as the supply of gasoline:

$$Q_e = f_e^s(\text{ethanol price}, \text{production costs}, \text{shipping cost}, \text{federal and state taxes}, \text{markup})$$

We assume that income is exogenous to gasoline market changes and that the automobile fleet is a function of income and the prices of gasoline and ethanol. It is likely that other variables are important to explain the automobile fleet trend over the years and the differences across states. But, if these other variables do not affect gasoline demand by any other channel than automobile fleet, then we do not need to consider them explicitly here.

$$\text{Automobile fleet} = f_{automobile}(\text{gasoline price, ethanol price, income})$$

1.4.1.1
Single cointegrating vector

As it is usual in the demand for fuel literature which uses Brazilian data, we assume a parametric log-log model to describe the demand for gasoline (Eq.1).

$$\ln(Q_g)_{it} = \alpha_i + \gamma_{m(t)} + \beta_1 \ln(P_g)_{it} + \beta_2 \ln(P_e)_{it} + \beta_3 \ln(Income)_{it} + \beta_4 \ln(Fleet)_{it} + \varepsilon_{it} \quad (1)$$

where α_i are the state fixed effects; $\gamma_{m(t)}$ are the month fixed effects; $(Q_g)_{it}$ is the demand for gasoline in state i and month-year t; $(P_g)_{it}$ and $(P_e)_{it}$ are the gasoline and ethanol prices; $Income_{it}$ is the income in the state i and month-year t; and $Fleet_{it}$ is the automobile fleet in state i and month-year t.

The β coefficients in Eq. 1 are interpreted as long run elasticities of gasoline demand. In this study, our interest lies in estimating β_1 and β_2. The procedure used here to estimate the price elasticities follows, initially, the standard procedure in this literature. First, we check the stationarity of every variable in our model.

Panel unit root tests[4] indicate that, except for the ethanol price, variables are non-stationary. Although we do not have all variables integrated of order one (I(1)), we may still have a cointegration relationship between them (Lutkepohl (2007)). Therefore, we assume that we have one equilibrium relationship described by Eq.1.[5]

To control for non-stationary variables endogeneity – and for possible serial correlation –, we use a cointegration technique, DOLS. This approach is similar to the control function approach.

To better explain, suppose we have a vector with all the I(1) variables in our model, i.e., $X_{it} = (P_{g_{it}}, Income_{it}, Fleet_{it})$. As they are I(1), we assume that $X_{it} = X_{it-1} + u_{it} \Rightarrow u_{it} = \Delta X_{it}$, where $\mathrm{E}[X'_{it} \cdot \Delta X_{it}] = 0$ and $\mathrm{E}[\varepsilon_{it} \cdot \Delta X_{it}] \neq 0$.

[4] The tests were done using the software Eviews 7. We consider a model with constant. The panel unit root tests used were: Levin, Lin and Chu; Im,Pesaran and Shin; ADF-Fisher and PP-Fisher.
[5] Kao and Pedroni panel cointegration tests corroborate with this hypothesis (Eviews 7).

Following the standard control function approach, to control for the gasoline price endogeneity we would run the linear projection of ε_{it} on ΔX_{it} and substitute the error term in Equation 1: $\varepsilon_{it} = \delta \Delta X_{it} + e_{it}$ where, by construction, e_{it} is not correlated to ΔX_{it}.

In the DOLS approach, instead of introducing only ΔX_{it} in Eq.1, we also introduce $\delta(L)\Delta X_{it}$, where $\delta(L) = \sum_{k=-K}^{K} \delta_k L^k$. This method is equivalent to use as instrument for the price of gasoline the lags and leads of the price of gasoline.

$$\ln\left(Q_g\right)_{it} = \propto_i + \gamma_t + \beta_2 \ln(P_e)_{it} + \beta' X_{it} + \textstyle\sum_{k=-K}^{K} \delta_k \, \Delta X_{it-k} + e_{it}, \text{ where } \beta = (\beta_1, \beta_3, \beta_4) \quad \text{Eq.2}$$

Although we have control for the gasoline price endogeneity in Eq. 2, we still have to control for ethanol price in the gasoline demand equation. Because of its stationarity, we use the IV approach.

The instrument used here is the interaction between the state tax (ICMS) and the Total Recoverable Sugar (TRS) price. Both, as previously mentioned, are exogenous to gasoline demand shocks. The TRS price composition[6] assures us that TRS price affects gasoline demand only via ethanol price,[7] thus satisfying the exclusion condition.

$$\text{TRS price} = f_{TRS}\left(\text{Index}_{cane}, P_e^{domestic}, P_e^{international}, P_{sugar}^{domestic}, P_{sugar}^{international}\right)$$

Where Index_{cane} is an index for the quantity and quality of sucrose in sugarcane; $P_e^{domestic}$ and $P_e^{international}$ is, respectively, the domestic and international price of ethanol; and $P_{sugar}^{domestic}$ is the domestic price of sugar and $P_{sugar}^{international}$ is the international price of sugar. Although ethanol price affects TRS price, we need only a strong correlation between both variables. It is not our goal, in this study, to obtain a causal relationship between the ethanol price and the TRS price.

We estimate Eq. 2 using a simple IV regression. The coefficients are interpreted as the long run elasticities of gasoline demand.

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[6] The composition of the TRS price is defined by CONSECANA/SP and can be found in http://www.unicana.com.br/?pagina=consecana.

[7] In the first stage of the IV approach, we test the correlation between the TRS price and the price of ethanol.

1.4.1.2
Full system error correction model

In this subsection, we describe our strategy to estimate the error correction model. Instead of estimating only the gasoline demand curve – as it is mostly done in the fuel demand literature – we estimate one equation for each variable in our model. This procedure allows us to capture the potential short run dynamic interactions between the variables and to draw impulse response functions.

To be able to uniquely determine the impulse responses, we need to identify the aggregate shocks. Different from the single regression model, to control for gasoline and ethanol prices endogeneity we use solely the Instrumental Variables approach.

From the gasoline price function, we choose to use as instrument an interaction between the federal tax, known as CIDE, and the state tax, ICMS. CIDE is the acronym in Portuguese for Contribution for Intervention in the Economic Domain. We interact both taxes so we can have variation in both state and time dimensions.

Finally, to deal with the panel structure of our data set, we follow Holz-Eakin, Newey, and Rosen (1988) and rewrite our variables as vectors, i.e.:

$$Y_t = (Y'_{1t}, Y'_{2t}, Y'_{3t}, \dots, Y'_{27t})'$$

where $Y_t = \left(Q'_{gt}, P'_{gt}, P'_{et}, Income'_t, Fleet'_t, Z'_{1t}, Z'_{2t}\right)'$, Z_1 is the instrument for the ethanol price and Z_2 is the instrument for the gasoline price.

The model – the complete set of equations – is described as:

$$\Delta Y_t = cD_t + \rho \hat{e}_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \vartheta_t \qquad \text{Eq. 3}$$

where D_t refers to the deterministic terms – in this case, fixed effects –, p is the optimal order of the VAR model, and $\hat{e}_{t-1}$ is the long run equilibrium deviation estimated in the first stage (Eq. 2). As mentioned before, we assume that the equilibrium relationship between the model variables is unique and, therefore, $\hat{e}_{t-1}$ is the same for all the equations.

To select the order of the VAR, we use the Bayesian Information Criterion. We test for p equal up to 10. According to the results, the optimal order is 2. Therefore, we write the model as:

$$AY_t = cD_t + \Lambda_1 Y_{t-1} + \Lambda_2 Y_{t-2} + \varpi_t \qquad \text{Eq. 4}$$

To identify the VAR model, we use a non-recursive identification strategy, the A-Model. Based on the contemporaneous relationships among the model variables, we set some elements of the matrix A to zero.

$$\begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} & 0 & 0 \\ a_{21} & 1 & a_{23} & 0 & 0 & a_{26} & a_{27} \\ 0 & a_{32} & 1 & a_{34} & a_{35} & a_{36} & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & a_{52} & a_{53} & a_{54} & 1 & 0 & 0 \\ 0 & 0 & a_{63} & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \ln(C_g) \\ \ln(p_g) \\ \ln(P_e) \\ \ln(Income) \\ \ln(Fleet) \\ \ln(Z_1) \\ \ln(Z_2) \end{bmatrix}$$

We use variation from Z_1 and Z_2 to generate exogenous variation in fuel prices and to identify the demand for gasoline curve. Therefore, the restrictions impose on the demand curve (in the first line) are the exclusion restrictions. From the second and the third line, one may note that the channels through which Z_1 and Z_2 affect gasoline demand are the price of gasoline and the price of ethanol.

It is worth mentioning that we are identifying neither the ethanol demand nor the ethanol supply. The third line – and thus the third equation of our dynamic model – describes the equilibrium relationship in the ethanol market. We are assuming that the ethanol market is related to the gasoline market only via the gasoline price.

The restrictions imposed on matrix A satisfy both the order and the rank conditions. First, regarding the order restriction, to solve uniquely for A we need a total of $\frac{K(K+1)}{2}$ restrictions, where K is the number of variables in our model. In this case, 7. Because we choose the diagonal elements of A to be unity, we are left to a total of $\frac{K(K-1)}{2}$ restrictions, i.e., 21 restrictions. The restrictions we imposed on A sum 26, so more than enough to identify the remaining parameters.

Second, to verify the rank condition, we follow Lutkepohl (2007) and calculate the rank of the following matrix:

$$\begin{bmatrix} -2D_K^{+}(\Sigma_u A^{-1}) & D_K^{+}(A^{-1}\otimes A^{-1})D_K^{+} \\ C_A & 0 \\ 0 & C_\sigma \end{bmatrix}$$

Where Σ_u is the covariance matrix of the reduced form; D_k is a $K^2 \times \frac{1}{2}K(K+1)$ duplication matrix; $D_K^{+} := (D_K' D_K)^{-1} D'_k$; C_A is a $\frac{1}{2}K(K+1) \times K^2$ selection matrix that selects the elements of $vec(A)$; C_σ is a $\frac{1}{2}K(K-1) \times \frac{1}{2}K(K+1)$ selection matrix that selects the elements of $vech(A)$ below the main diagonal.

Once we have the matrix rank, we check if it equals to $K^2 + \frac{1}{2}K(K+1)$. If yes, then the model is uniquely – and globally[8] – identified and we are able to compute the gasoline demand impulse response to fuel prices shocks.

1.5 Results

Table 1.3 shows that the interaction between the TRS price and the ICMS is a strong instrument for the ethanol price. Both instrument and the price of ethanol are strongly correlated and the F-statistic of the first stage equals 88.58.

Table 1.4 shows that controlling for gasoline and ethanol prices endogeneity leads to larger estimates than OLS. When taking into account price endogeneity, the coefficients of interest increase, approximately, by 0.3 percentage points in magnitude. A 1% increase in gasoline price, *ceteris paribus*, reduces gasoline demand by 1.68% while a 1% increase in ethanol price, *ceteris paribus*, is associated with an increase of 0.80% in gasoline demand. Therefore, the long run own- and cross-price elasticities of gasoline demand presented in

[8] Although the rank condition is a necessary and sufficient condition for local identification, setting the diagonal elements of A equal to 1 guarantee that the solution is global (Lutkepohl (2007)).

Table 1.4 are consistent with the hypothesis that the OLS estimates are downward biased.

Also in Table 1.4, we find that income and automobile fleet estimates are not statistically different from zero.[9] This result is contrary to the expected. One explanation for this is the likely high correlation between income and automobile fleet that do not allow estimating both precisely. As a robustness check, we omit one of those variables and re-estimate the long run equilibrium relationship. The results are presented in the third and fourth columns of Table 1.4.

Table 1.3
First-stage results: OLS estimates of TRS price on ethanol price

	Dependent variable: ethanol price
Ethanol instrument	0.578***
	(0.061)
Gasoline price	0.622***
	(0.101)
Income	-0.074
	(0.135)
Automobile fleet	-0.055
	(0.050)
Lags and leads?	Yes
State and month dummies included?	Yes
No. of Obs.	3,051
F-statistic [p-value]	88.58 [0.001]
R^2	0.805

Notes: Wild cluster bootstrap standard errors at the regional level are presented in parentheses. The number of observations is less than 3,753 – the total number of observations – because of the availability of dataset on automobile fleet and the lags and leads introduced in the regression for controlling gasoline price endogeneity.

The results found from omitting either income or automobile fleet are consistent with our explanation. When omitting one of these variables, the other becomes statistically significant. Nonetheless, the omission of one of those variables introduces an omitted variable bias in the model. Both income and automobile fleet are positively correlated with gasoline demand and the remaining regressors. Within this context, the fuel price elasticities presented in the third and fourth columns are, as expected, overestimate.

[9] There is a consensus in the automobile and fuel literature that a good point estimate for the fleet elasticity is 1, i.e., the gasoline demand grows in proportion to fleet increase. In Brazil, however, this standpoint may not be true because of the flex-fuel technology and, consequently, the existence of ethanol as a close alternative to gasoline.

Table 1.4
Second-stage results: DOLS and IV estimates of fuel prices on gasoline demand

	Dependent variable: gasoline demand			
	OLS	DOLS and IV		
	(1)	(2)	(3)	(4)
Gasoline price	-1.346***	-1.683***	-1.977***	-2.259***
	(0.178)	(0.233)	(0.397)	(0.230)
Ethanol price	0.393***	0.804***	0.947***	1.083***
	(0.118)	(0.174)	(0.147)	(0.138)
Income	0.829**	0.587		0.702***
	(0.413)	(0.621)		(0.166)
Automobile fleet	0.159	0.249	0.457***	
	(0.131)	(0.206)	(0.106)	
Lags and leads?	No	Yes	Yes	Yes
State and month dummies included?	Yes	Yes	Yes	Yes
No. of Obs.	3,294	3,051	3,051	3,672

Notes: Wild cluster bootstrap standard errors at the regional level are presented in parentheses. The number of observations differs between columns because of the omission or not of the automobile dataset and the lags and leads introduced in the regression for controlling gasoline price endogeneity.

In Table 1.5 we present the long run own- and cross-price elasticity of gasoline demand considering different time periods. Instead of introducing a dummy variable – and its interaction – to represent the introduction of the flex-fuel technology in Brazil, we divide our sample into two equal periods. Because of the availability of our data, the introduction of a dummy variable would not allow us to estimate precisely the own- and the cross-price elasticities of gasoline demand before March 2003.

The two time periods consider in this study are: (i) December 2002 to December 2007; and (ii) January 2008 to January 2013. We interpret the first period as the period of introduction of the flex-fuel technology and the second period as the consolidation one.

Table 1.5 shows that the long run own- and cross-price elasticities of gasoline demand have increased – in absolute terms – over time, suggesting that since the introduction of flex-fuel automobiles in the Brazilian automotive market, consumers became more sensitive to fuel price changes. For the initial period, the long run own-price elasticity of gasoline demand equals -0.71. An increase of 1% in gasoline price reduces gasoline demand in 0.71%. This estimate is slightly higher to gasoline price elasticities estimated for other countries, such as the

United States, and found in meta-analysis studies, such as Espey (1998) and Havranek et al (2012). Besides, for the initial period, the cross-price elasticity of gasoline demand equals approximately 0.2. A 1% increase in the price of ethanol is associated with a 0.2% increase in gasoline demand *ceteris paribus*.

Also in Table 1.5, the results found for the final period of our sample suggest that, once the flex-fuel technology is consolidated in the Brazilian automotive market, the relationship between gasoline and ethanol changed as well as consumers' sensitivity to fuel price variation. A 1% increase in the price of gasoline reduces gasoline demand in 0.89% while a 1% increase in the price of ethanol is associated with a 0.43% increase in gasoline demand *ceteris paribus*.

A comparison of the results found using different subsamples should, however, be done with care. One may argue that although we control for seasonality, other confounding factors may still be present leading to bias estimates. Ideally, to capture common changes over time, such as common aggregate shocks, instead of introducing month fixed effects, we would like to introduce time fixed effect. However, introducing more than 100 dummies in our model leads to variation loss and non-statistically different from zero estimates.

We interpret the results shown in Table 1.5 as a suggestion that something has changed over the years in the Brazilian fuel market and likely the explanation for this change is the large presence of flex-fuel automobiles in the automotive market. This interpretation is corroborated by other studies such as Assunção, Pessoa and Rezende (2013). Using a different approach, they show that as the market-share of flex-fuel automobiles increases, the competition between gasoline and ethanol also increases.

Table 1.5
Second-stage results: DOLS and IV estimates of fuel prices on gasoline demand for different time periods

	Dependent variable: gasoline demand	
	12.2002 – 12.2007	01.2008 – 01.2013
Gasoline price	-0.713***	-0.888***
	(0.086)	(0.171)
Ethanol price	0.196***	0.429***
	(0.034)	(0.137)
Income	0.795***	0.485***
	(0.205)	(0.165)
Automobile fleet	0.014	0.863***
	(0.019)	(0.189)
Lags and leads?	Yes	Yes
State and month dummies included?	Yes	Yes
No. of Obs.	1,620	1,620

Notes: Wild cluster bootstrap standard errors at the regional level are presented in parentheses. The number of observations differs from the total (1.647) because of the introduction of the leads and lags in the gasoline demand equation.

Tables 1.3 to 1.5 show the long run relationships between our variables of interest. The coefficients are interpreted as the percentage change in gasoline demand from a 1% increase in one of the independent variables while holding the other constant. Now, to compute the short run own- and cross-price elasticity of gasoline demand and the gasoline demand response to shocks in fuel prices, we estimate the error correction model. Outside the equilibrium context, there is dynamic interaction between the variables used in the model.

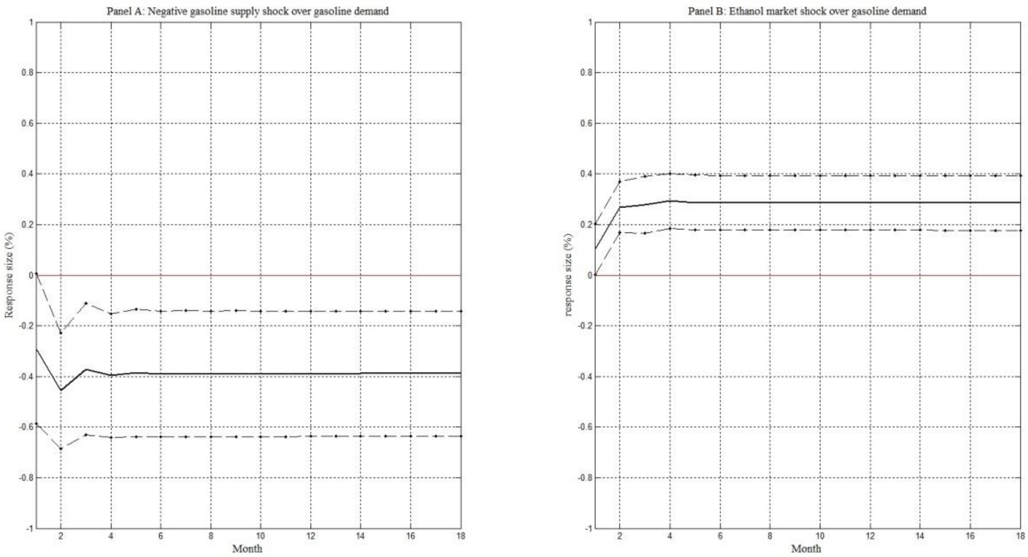
To trace out the marginal effect of an exogenous shock in fuel prices on gasoline demand over time, we estimate impulse response functions using the structural VAR.

Figure 1.4 shows the gasoline demand response to a transitory negative gasoline supply shock (Panel A) and to a transitory shock in the ethanol market (Panel B).[10] Because the system is not stable, the effect of a 1% increase in the price of gasoline and in the price of ethanol is permanent. Panel A shows that a 1% increase in the price of gasoline reduces gasoline demand permanently in about 0.4%. According to our findings, the immediate response to this increase is not statistically significant, but the long run effect is. Panel B shows that a 1% increase in the ethanol price increases gasoline demand in, approximately, 0.3%.

[10] Both shocks are unit shocks.

This effect is statistically significant considering the 95% confidence interval. These findings are important for the design and implementation of public policies.

Figure 1.4
Gasoline demand response to transitory shocks in the gasoline supply (Panel A) and in the ethanol market (Panel B)



Notes: Wild cluster 95% bootstrap confidence interval with Rademacher weight and 2,000 simulations (Cameron, Gelbach and Miller (2008))

1.6

Additional Robustness Checks

1.6.1

Heterogeneity

To capture non-observed heterogeneity across Brazilian states, we follow the traditional approach and estimate a fixed effect model. In this case, the intercepts are allowed to vary across states, but the long run response coefficients are constrained to be the same. Due to budget or solvency constraints, arbitrage conditions and common technologies, it is reasonable to assume long-run homogeneity elasticities across states (Pesaran, Shin and Smith (1997)). However, within the context of cointegrated panel, one may argue that pooled regression leads to inconsistent parameters estimation of the mean effect (Pesaran and Smith (1995)).

The most unconstrained procedure to estimate the average long run effects of fuel prices over gasoline demand is the Mean Group Estimator. This procedure consists in estimating separate regressions for each state. We assume that for each state there is a single cointegration relationship and that the cointegrated vector may vary across states. To compare with our long run estimative, we average the estimated coefficients over states.

The long run own- and cross-price elasticities are estimated using Eq. 2. The identification strategy used in this robustness exercise is the same as before. We combine DOLS with IV to obtain the elasticities. As we now allow states to behave differently, the optimal number of the lags and the leads of the first-differences introduced in the model differ across states.

The result shows that allowing heterogeneity among the Brazilian states does not change the mean effect of a 1% price change over gasoline demand. Despite some heterogeneity between the long run elasticities, we find that the mean effect of a 1% increase in gasoline price over gasoline demand is -1.43%. This value is close to the one we found initially assuming observed homogeneity in the long run. Regarding the cross price elasticity, we find that the mean effect of 1% increase in the price of ethanol is associated with 0.68% increase in gasoline demand.

1.6.2
Income proxies

Although the use of electric power consumption as a proxy for income is widely accepted, one may argue that its use here is inappropriate because of the different cross-section dimension. While gasoline demand, fuel prices and automobile fleet vary across states, electric power consumption varies at the regional level.

To assess the robustness of our primary results, we use some alternative income proxy variables. From the Central Bank of Brazil, we get data on the number of bank agencies and the amount of bank deposits and loans in each state.

Table 1.6 shows that our results are robust to these alternative income measures. Except for the estimates in Column 3, the results in Columns 2 and 4 show that the long run own- and cross-price elasticities are within 1 standard deviation from our primary results.

Table 1.6
The elasticity of gasoline demand using different income proxies

	Dependent variable: gasoline demand			
	DOLS and IV			
	(1)	(2)	(3)	(4)
Gasoline price	-1.683***	-1.567***	-2.156***	-1.529***
	(0.233)	(0.199)	(0.413)	(0.254)
Ethanol price	0.804***	0.725***	0.981***	0.747***
	(0.174)	(0.175)	(0.201)	(0.216)
Electric power consumption	0.587			
	(0.621)			
No. of bank agencies		0.670***		
		(0.229)		
Bank deposits			-0.025	
			(0.011)	
Bank loans				0.190***
				(0.094)
Automobile fleet	0.249	0.265	0.301	0.130
	(0.206)	(0.167)	(0.137)	(0.105)
Leads and lags?	Yes	Yes	Yes	Yes
State and month dummies?	Yes	Yes	Yes	Yes
No. of observation	3,051	3,051	2,441	3,267

Notes: Wild cluster bootstrap standard errors at the state level are presented in parentheses. The number of observations differs between columns because of the lags and leads introduced in the regression for controlling gasoline price endogeneity.

1.6.3
Different identification strategy

Although the power of panel unit root tests is bigger than time series unit root tests, one may argue that they have still low power against the alternative hypothesis that the series is stationary. If this is the case, then it may be that the ethanol price is not stationary. In a context where all our variables are non-stationary, we could use DOLS as our identification strategy.

In this case, using DOLS allows us to control for the price of gasoline and the price of ethanol endogeneity and also to control for the potential autocorrelation. The results are presented in Table 1.7. Column 2 shows that, although smaller in magnitude, gasoline price is robust to this identification strategy. The coefficient associate with the ethanol price, however, decreases almost 2 standard deviations from our primary results which may suggest that the downward bias is still present. Not controlling for the ethanol price endogeneity may also explain the decrease (in absolute terms) in the gasoline price.

To better validate our main identification strategy, we would like the standard deviations to be larger in Column 2. However, the introduction of the lags and leads of the ethanol price first-differences decreases the error variance and allows us to estimate the coefficients more precisely. Such result, however, should not be view as a fail of our identification strategy since it does not control for ethanol price endogeneity.

Table 1.7
The elasticity of gasoline demand using different identification strategies

	Dependent variable: gasoline demand	
	DOLS and IV	DOLS
	(1)	(2)
Gasoline price	-1.683***	-1.396***
	(0.233)	(0.180)
Ethanol price	0.804***	0.426***
	(0.174)	(0.137)
Electric power consumption	0.587	0.784
	(0.621)	(0.454)
Automobile fleet	0.249	0.195
	(0.206)	(0.146)
Leads and lags?	Yes	Yes
State and month dummies?	Yes	Yes
No. of observation	3,051	3,294

Notes: Wild cluster bootstrap standard errors at the regional level are presented in parentheses.

1.6.4

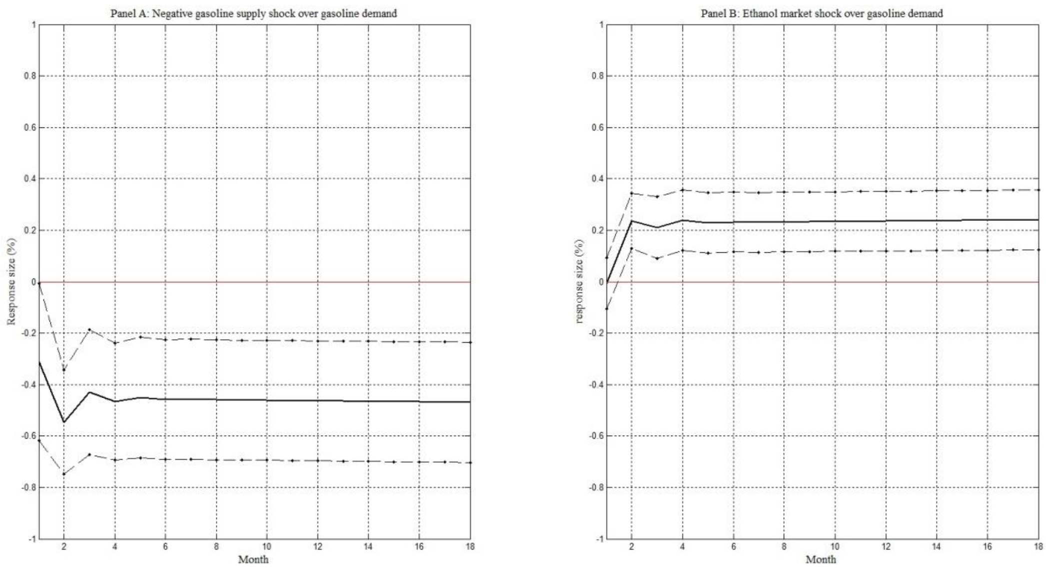
Gasoline instrument: a version without the CIDE

The federal tax CIDE is used by the Brazilian government as an instrument to diminish the impact of changes in the price of gasoline sold by Petrobras to distributors. Since June 2012, the value of the CIDE has been zero, which means that from June 2012 to January 2013, we do not use variation from CIDE to explain variations in the retail price of gasoline. To control for the gasoline price endogeneity in this period we are using the changes in the state tax ICMS.

In this subsection, we estimate the Impulse Response Functions using only variation between states to control for the price of gasoline endogeneity. For many states, however, the state tax ICMS did not vary from December 2002 to January 2013. Within this context, the model will not be identified for all Brazilian states.[11] In this sense, the comparison between both results – with and without the CIDE – is not straightforward.

Figure 1.5 shows that when we do not use the federal tax CIDE as an instrument, the effect of a transitory shock in the price of gasoline on the demand for gasoline is slightly larger than the one we found earlier. On the other hand, the permanent effect of a 1% increase in the price of ethanol is lower than the one we found previously. These differences might be explained by the elimination of the federal tax CIDE as an instrument and/or the fact that instead of using all the 27 states, we are using information about only 11 states to identify our model.

Figure 1.5
Gasoline demand response to transitory shocks in the gasoline supply (Panel A) and in the ethanol market (Panel B) – without CIDE as instrument



Notes: Wild cluster 95% bootstrap confidence interval with Rademacher weight and 2,000 simulations (Cameron, Gelbach and Miller (2008))

[11] The model will be identified for the following Brazilian states: Ceará, Espírito Santo, Goiás, Minas Gerais, Pará, Paraíba, Pernambuco, Piauí, Paraná, Roraima, Sergipe.

1.6.5
Natural gas price

The use of natural gas as a fuel alternative in Brazil is common among cabs and other vehicles used to transport passengers. Although natural gas price is usually less than gasoline and ethanol prices, its use is not straightforward as ethanol. Technical changes in the automobile have to be made, so it can be filled with natural gas and gasoline. This initial adaptation cost, however, is expensive (more than R$ 1,000) so, to be worth the change, one has to drive more than the average.

Natural gas market has not grown much since its introduction in the 90s and different from the relationship between gasoline and ethanol, the consumers of natural gas appears to be more captive. Nevertheless, in a scenario where the Brazilian federal government promotes more fuel alternatives to reduce urban pollution and to achieve greater energy independence, the natural gas may play an important role.

Within this context, knowing how consumers react to changes in natural gas price is important. In this subsection, we estimate the long run natural gas price elasticity using Eq. 2. Unit root tests show that the price of natural gas is non-stationary. The identification strategy used here to estimate fuel price elasticities is, as before, a combination between DOLS and IV. In this case, we use DOLS to control for gasoline and natural gas price endogeneity.

Before going to the results, it is worth mentioning that, different from the ethanol distribution net, natural gas is not available in every Brazilian state[12] and even when it is available, it is not in all filling stations. Thus, when we take into account the price of natural gas, our sample size reduces from 3,294 to 1,464.

Table 1.8 shows that the introduction of natural gas price leads to unexpected results. While ethanol price is robust to the introduction of natural gas price, the marginal effect of gasoline price on gasoline demand reduces, in absolute terms, more than 2 standard deviations. Besides, the direction of the

[12]Natural gas as an alternative fuel is available in 3 Brazilian regions: Northeast (Alagoas, Bahia, Ceará, Paraíba, Pernambuco, Rio Grande do Norte and Sergipe); Southeast (Espírito Santo, Minas Gerais, Rio de Janeiro and São Paulo); and South (Paraná).

income – although it is not statistically significant – is contrary to what we would expect to find initially.

All in all, the results in Column 2 should be analyzed with caution. The introduction of natural gas price reduces not only the sample size, but also the number of clusters and the number of observations within each cluster. If the number of observations within cluster is sufficiently small, then the coefficients are not precisely estimated. Besides, according to Cameron and Miller (2013), "with small clusters the asymptotics have not kicked in". In this case, the cluster variance is downward bias. Indeed, the results found suggest a smaller standard error than our primary results. Therefore, we do not believe this result invalidates our main findings.

Table 1.8
Fuel price elasticities of gasoline demand including natural gas as a fuel alternative

	Dependent variable: gasoline demand	
	DOLS and IV	
	(1)	(2)
Gasoline price	-1.683***	-1.175***
	(0.233)	(0.157)
Ethanol price	0.804***	0.662***
	(0.174)	(0.153)
Gas natural price		-0.350**
		(0.151)
Electric power consumption	0.587	-1.223
	(0.621)	(0.642)
Automobile fleet	0.249	1.346***
	(0.206)	(0.281)
Leads and lags?	Yes	Yes
State and month dummies?	Yes	Yes
No. of observation	3,051	1,356

Notes: Wild cluster bootstrap standard errors at the regional level are presented in parentheses. The number of observations differs between columns because of the introduction of the price of natural gas in the model that reduces the sample size to 1,464 and also because of the lags and leads.

1.7 Conclusion

Different from most papers that use Brazilian data sets, we estimate the long run own- and cross-price elasticities of gasoline demand taking into account that both gasoline and ethanol are potentially endogenous variables in the gasoline demand curve. To identify the effect of 1% increase in fuel prices on gasoline demand while holding all other variables in the model constant, we use a new identification strategy. We combine DOLS and IV. The results show that Brazilian consumers are more elastic to fuel price changes than earlier studies suggest.

Dividing our sample into two equal periods and re-estimating our model, we find evidence that the introduction of the flex-fuel technology on March 2003 changed consumers' sensitivity to fuel price variations. In the introduction phase, we find that the long run own-price elasticity of gasoline demand is close to long run own-price elasticities estimates found for other countries and that changes in the price of ethanol explain a small part of the changes in the gasoline demand. This scenario changes after consumers learn about this new technology: once flex-fuel technology is consolidated in the Brazilian automotive market, the long run own- and cross-price elasticities of gasoline demand increase (in absolute value) substantially.

To understand how gasoline demand responds to price changes outside the equilibrium context, we calculate impulse response functions using a structural VAR. To identify the shocks, we use a non-recursive strategy – the A-Model – and impose contemporaneous restrictions among the variables in our model. We find that transitory shocks lead to permanent effects on gasoline demand. A unit gasoline price shock, for example, implies in a permanent decrease of 0.4% in the demand for gasoline. Tracing out the marginal effect of fuel price shocks on gasoline demand is important for the design, implementation and social welfare analysis of public policies.

All in all, this paper contributes for the fuel demand literature in different aspects. First, we use a new identification strategy combining two different techniques to compute the long run own- and cross- price elasticities. Second, we estimate the impact of the flex-fuel technology on consumers' sensitivity regarding fuel price changes. Third, we estimate the full system error correction model instead of estimating only the gasoline demand equation. Forth, based on the structural VAR, we draw impulse response functions, which, from our knowledge, have not been done in the Brazilian context.

2

Does flex-fuel technology matter for automobile demand? A structural analysis using a random coefficients discrete choice model

2.1 Introduction

Since its introduction, the sales of flex-fuel automobiles increased from 48,178 in 2003 to 2,529,743 in 2010, corresponding to market shares of new sales of 3% and 95% respectively. In the first chapter of this thesis, we showed that the flex-fuel technology changed consumers’ perception regarding fuel prices fluctuations, resulting in important changes in the fuel market in Brazil. In this chapter, we focus on the automotive market. We attempt to measure the importance of the new technology for consumers when buying a new automobile and, through a detailed descriptive analysis, shed some light on the process of introduction of the flex-fuel technology in Brazil.

To measure the importance of the flex-fuel technology we follow the discrete choice differentiated products literature of Berry (1994), and Berry, Levinsohn, and Pakes (1995) (henceforth BLP). We use a random coefficient utility model to estimate the parameters of the demand using solely market-level data. This model is ideal for estimating demand for large systems of differentiated products while capturing heterogeneous preferences and controlling for unobservable product characteristics. We based our analysis on Brazilian auto data between the years 2002 and 2010.

To our knowledge, two papers have measured the benefits of the flex-fuel technology in Brazil: Lucinda (2010) and De Souza, Petterini and Miro (2010). Lucinda (2010) is closest to our study regarding the main question: the benefits of the flex-fuel technology. Using the approach presented in BLP (1995) and a counterfactual analysis, he finds that the welfare gain from the introduction of the flex-fuel technology was about R$ 1,000 per family on May 2005.[13] We differ from Lucinda (2010) mainly by treating the flex-fuel technology as an automobile

[13] Under the assumption of Bertrand competition. Under perfect competition, the welfare gain was approximately R$ 1,200 per family.

attribute in our demand model. This approach allows the estimation of the mean preference toward flex-fuel automobiles, as well as the standard deviation. The monetary value of the new technology is obtained by comparing the estimates with the effect of price on consumer's utility.

De Souza, Petterini and Miro (2010) also treat the flex-fuel technology as a characteristic, but the importance of the flex-fuel technology is, actually, a secondary result in their paper.[14] To obtain the parameters of demand, they use the BLP (1995) methodology and consider that the flex-fuel technology is an observable characteristic. They find that the average consumers like flex-fuel, but, from the estimation of the random coefficients, they find that some consumers prefer gasoline-powered automobile.

Contrary to Lucinda (2010) and De Souza, Petterini and Miro (2010), the estimation of the demand parameters from our full model suggests that the flex-fuel technology is not important for consumers when all the other automobile characteristics are controlled for. This finding may indicate that the rapid growth in sales is the result of automakers' decision to offer only flex-fuel for any other reasons not associated with demand.

From the descriptive statistical analysis, we find that the introduction of the flex-fuel technology was not exogenous to other automobile characteristics. Our data analysis shows that the new technology was first introduced on economy and compact automobiles instead of luxury ones.[15] Different from other attributes – more related to comfort and efficiency –, the flex-fuel technology is mainly associated with fuel prices, i.e., the possibility to use the fuel (gasoline or ethanol) with the lowest price.

The remainder of this chapter is organized as follows. In Section 2.2, we present a brief literature review. In Section 2.3, we describe the data and do a detailed descriptive analysis. In Section 2.4, we describe the demand model and the estimation procedure. In Section 2.5, we present the results and some robustness check. And, in Section 2.6, we conclude the chapter.

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[14] They are mainly interested in measuring the burden of taxes on automobile sales for consumers and suppliers.

[15] It is expected that innovations occur first on sophisticated automobiles before becoming standard equipment.

2.2
Discrete choice models and the automobile industry

The simultaneity estimation of demand and supply curves within an oligopoly context was first attempt in Bresnahan (1987) to understand and explain the below average quality-adjusted price in 1955 in the automobile industry in the United States. Since then, the methodology used has been improved toward more realistic and precise estimation.

The BLP (1995) seminal paper develops a framework to estimate the demand and the supply parameters in oligopoly markets with differentiated products using only market-level and aggregate consumer-level data. To obtain more plausible substitution patterns, they allow for interaction between consumer preferences and product characteristics. They apply their technique to the automobile market in the United States from 1971 to 1990. The estimated parameters are consistent with what was expected initially by the authors.

Since this seminal paper, the BLP framework has been used mostly to analyze the welfare effects of the introduction of new technology. Petrin (2002), for example, estimates the change in consumer welfare from the introduction of the minivan in the United States from 1981 to 1993. Besides market-level data on sales and characteristics, he uses information on purchaser aggregate from the Consumer Expenditure Survey, such as income level and family size. This extra information allows him to relate the average demographics of consumers to the characteristics of the products they purchase and, although he does not have consumer-level data, this information allows him to better identify taste heterogeneity. Combining market-level data with micro moments improve precision of the estimates when compared with the traditional BLP approach.

To estimate the welfare effects from the introduction of the minivan, Petrin (2002) uses the parameter estimates and conducts a counterfactual analysis by removing the minivan from consumers' choice set. In the BLP approach, however, it is assumed a product-level idiosyncratic taste shock, so consumer's welfare diminishes as the number of new product decreases. Petrin (2002) finds that the minivan generated substantial benefits by offering a better alternative to station wagons – the concurrent version – and by increasing price competition.

Similar to Petrin (2002), Lucinda (2010) estimates the welfare gains from the introduction of flex-fuel automobiles in Brazil using market-level data. Lucinda (2010) uses the BLP methodology to estimate the parameters of the automobile demand. Different from our paper, Lucinda (2010) does not consider flex-fuel technology as an automobile characteristic. Besides price, he estimates the average and the standard deviation regarding engine displacement, number of valves, number of cylinders, and a dummy variable for four wheel drive. To increase the efficiency of the estimation procedure – as suggested in BLP (1995) – Lucinda (2010) also uses some individual characteristics, such as family income.

To estimate the demand for automobiles in Brazil, Lucinda (2010) uses two models. In the first model he interacts income level and income squared with price while, in the second model, he introduces the price squared. The results found for the price coefficient are robust to these different specifications. He finds that an increase of R$ 1,000 in price decreases the marginal utility in about 0.05. To compute the welfare change resulting from the introduction of flex-fuel automobiles, Lucinda (2010) follows Petrin (2002) and does a counterfactual analyze by removing flex-fuel automobiles from the consumer's choice set and allowing households to re-sort to the next best alternative. Both models lead to similar results. For Model 1, for example, the flex-fuel technology represents a gain to consumer of R$ 1,275 in a perfect competition context and of R$ 1,093 in a Bertrand context.

Interested in examining the welfare effects of the hybrid vehicles innovation in the United States, Furlong (2011) follows a similar approach to Petrin (2002). Using the BLP approach and micro moments, Furlong (2011) estimates the demand and the supply for all vehicles in the United States from 2000 to 2008. Then, trough counterfactual exercises, Furlong (2011) quantify consumer welfare from hybrid vehicles entering in the auto market. Furlong (2011) follows the methodology present in Hausman and Leonard (2002) and decomposes compensating variation into price and product variety effects. Regarding the demand estimations, his results suggest that the average household dislikes hybrid vehicles, but, from the interaction of hybrid vehicles with time, it appears that the average household is changing his preference towards hybrid vehicles. Furlong (2011) also finds that the introduction of hybrid vehicles leads to a total welfare gain of $ 14.7 billion from 2000 to 2008. Most of these gains result from an increase in the product variety.

Within the Brazilian context, besides Lucinda (2010) study, discrete choice models have been used also to analyze the effects of public policies in oligopoly markets. Ferraz, Fiuza and Motta (2001), for example, estimate the demand and supply parameters in the automobile industry in Brazil from 1993 to 1997 to analyze the impact of a new environmental regulation. Through a counterfactual exercise, they find that the implementation of a new environmental policy leads to the adoption of more green technologies.

Similarly, De Souza, Petterini and Miro (2010) estimate the demand and the supply parameters to analyze Brazilian tax policy on automobile sales. Regarding the demand estimation, different from Lucinda (2010) and similar to our paper, they estimate the flex-fuel parameter in the demand equation. According to their results, the average consumer likes flex-fuel automobiles, but a fraction of the consumers in their model still prefers gasoline-powered automobiles. The interpretation of the magnitude of the results found, however, is not that straightforward due to the functional form used for the price.

Also, in a more recent paper, Dubé, Fox and Su (2012) show that loose tolerance for the inner loop leads to incorrect parameters estimates – not even local minimum – and failure in the Generalized Method of Moments optimization procedure. De Souza, Petterini and Miro (2010) choose 10^{-5} as the tolerance level for the inner loop and 10^{-5} for the outer loop. This choice for the tolerance levels, even using gradient, may cause the optimization routine to terminate early and – if convergence is achieved – produces incorrect point estimates that do not satisfy the first order condition for a local minimizer (Dubé, Fox and Su (2012)).

In this study, we follow Dubé, Fox and Su (2012) and choose a more conservative tolerance level. For the inner loop we use 10^{-14} while for the outer loop we use 10^{-6}. These tolerances levels ensure that convergence in the outer loop optimization routine is reliable and robust.

2.3
Data

2.3.1
Data set

The data set used in this study combines data from two different sources. From the National Association of Motor Vehicle Manufactures (ANFAVEA, acronym in Portuguese), we obtain data on automobile sales and product characteristics such as fuel and automobile origin (domestic or import). From the Brazilian magazine *Quatro Rodas*– specialized in automotive vehicles – we collect data on automobile retail prices and other attributes such as engine displacement, horsepower and dummy variables for whether the automobile has air conditioning, electric or hydraulic power steering, power windows, power door lock, automatic transmission, air bag, and ABS brakes as standard equipment. To match both data sets, we use the characteristics of the base model, i.e. the sub-model with the plainest set of characteristics.[16]

Our database includes information on almost all models marketed from 2002 through 2010.[17]As shown in Table 2.1, our sample captures 79% or more of the total automobile sales in Brazil, except in one year. The distribution of automobiles by fuel type is also close to the true distribution.

[16] The level of aggregation of *Quatro Rodas*'s data set is finer than the ANFAVEA's data set. While on *Quatro Rodas* we get information by sub-model, ANFAVEA aggregates sales across many sub-models with different sets of characteristics and prices.
[17] The matching is not always possible.

Table 2.1
Ratio between our sample and ANFAVEA's data set (%)

	Automobile market	Flex-fuel automobile market
2002	93	
2003	86	
2004	94	66
2005	72	70
2006	79	78
2007	81	82
2008	83	84
2009	88	90
2010	85	87

Note: To obtain the sample-ANFAVEA ratio, we use the new automobile registrations in Brazil (reported by ANFAVEA) as proxy for automobiles sales.

Since automobile models enter and exit the sample over the nine-year study, the number of automobile models in each year changes but, in total, we have 870 observations. Although we have monthly data set available from both sources, we set the data set as annual because of the low month-to-month variation regarding automobile retail prices and characteristics.

For the annual automobile sales, we sum the sales of each month from January to December. For the automobile characteristics, we use the data set available for January of each year. Since monthly changes in model characteristics are not common, we believe this choice does not lead to any biases in general. One possible exception is the year of 2003 – the year of introduction of the flex-fuel technology.

The first automobile with the flex-fuel technology was introduced in the Brazilian automotive market on March 2003, and it appeared in the *Quatro Rodas* magazine in the May issue. So, by using the January issue, we may introduce a potential measurement error which may leads to an attenuation bias in the estimates of the effect of the flex-fuel technology on automobile sales. By comparing the share of flex-fuel automobiles in total sales of new automobiles from ANFAVEA registers with the corresponding number in our annualized database, the discrepancy between both data sets is relevant for 2003 and, arguably, for 2004 (Table 2.2).

Table 2.2
Share of flex-fuel in total sales of new automobiles (%)

	ANFAVEA	Our sample
2002	0	0
2003	3	0
2004	22	16
2005	53	52
2006	83	83
2007	91	92
2008	94	95
2009	95	98
2010	95	98

Table 2.3 provides some summary descriptive statistics. From this Table, some trends can be highlighted. Average sales increased from a low of 1,134 in 2002 to 2,235 in 2010. This increase is associated with a downward trend in inflation adjusted prices since 2005. To deflate automobile prices we use the Extended Consumer Price Index provided by the Brazilian Institute of Geography and Statistics (IBGE, acronym in Portuguese). For imported cars, we also use the exchange rate provided by the Central Bank of Brazil. All prices are in 2010 Brazilian *Real*.

Table 2.3 shows that price (in real terms) fall substantially through 2008 to 2010. This average retail price drop may be explained by the Brazilian government policy of reducing the Tax on Industrialized Products (IPI, in Portuguese). The IPI reduction was 100% for automobiles with 1.0 liter powered engine – in the Brazilian market, the less powerful and most common automobiles –, and 50% for automobiles with cylinder capacity between 1.0 and 2.0 liters. It is likely that this price reduction boosted automobile demand.

Regarding the flex-fuel technology trend, Table 2.3 shows that the ratio between flex-fuel and total automobiles[18] increased significantly since the flex-fuel introduction, from 16% to 98%. This upward trend may demonstrate not only consumers' preference toward automobiles with this technology, but also automakers' decision to produce only flex-fuel automobiles.

Table 2.3 also shows some descriptive statistics relative to other automobile characteristics. While only 8% of automobiles in Brazil had air conditioning as standard equipment in 2002, in 2010 the percentage increased to

[18] Sale of new automobiles.

26%. This trend indicates a more general one toward more extensive standard equipment. Also, it may suggest that more advanced equipment, such as ABS brakes, are becoming more accessible for most consumers. However, one must be careful when interpreting the second part of Table 2.3. It is probably true that for some characteristics, such as air conditioning, most automobiles are sold with this equipment. Therefore, we might have measurement errors in our database regarding, for example, air conditioning, power window and power door locks. As a result, using these variables could lead to a downward bias.

2.3.2
Understanding the introduction of the flex-fuel technology

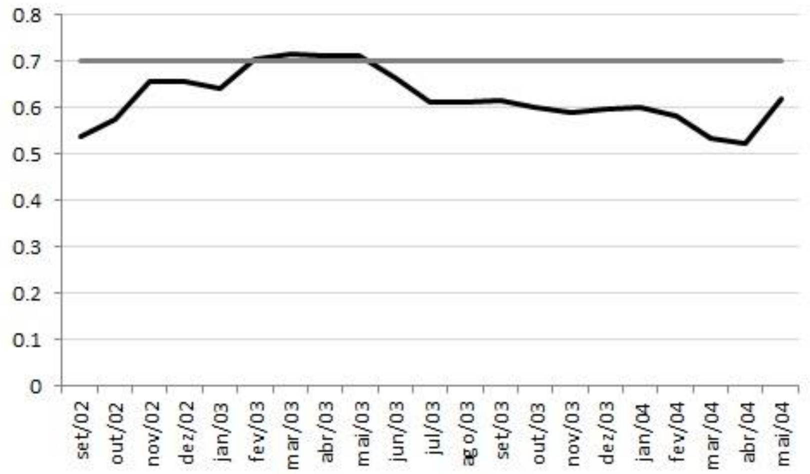
Flex-fuel automobiles were introduced by Volkswagen on March 24, 2003. The first automobile with this technology to be sold in Brazil was a new version of the *Gol Total Power* 1.6, named *Gol Total Flex* 1.6. Previously, *Gol Total Power* already had two versions: one with gasoline engine and another with ethanol engine. All the three automobiles had similar standard equipment. Regarding their performance, the *Gol Flex*, when fueled with 100% gasoline (ethanol), had a similar performance – concerning fuel consumption per kilometer traveled – to *Gol Total Power* with gasoline (ethanol) engine.[19] Because of the new technology, the retail price of the *Gol Total Flex* 1.6 was higher than its counterparts, but the initial price difference – R$ 950,00 – was less than optional extras such as pearlescent paint. The *Gol Total Flex* was an immediate success, with sales equal to 17,936, i.e., 11% of the total sales of *Gol Total* 1.6, in its first year.

The rapid acceptance of the *Gol Total Flex* by Brazilian consumers may be explained by the ratio between ethanol and gasoline prices. Based on fuel efficiency, fueling with ethanol is economic advantageous if its price is at least 70% of gasoline price.[20] From Figure 2.1, the efficiency ratio is less than 70% only a few months after *Gol Flex* was launched which may explain the upward trend regarding the sales of *Gol Total Flex.*

[19] The tests were done by the *Quatro Rodas* magazine.

[20] The ethanol-gasoline price relation of 70% represents an average and, accordingly to the National Institute of Metrology, Quality and Technology (INMETRO, acronym in Portuguese) it may varies from 69% to 72% depending on the engine.

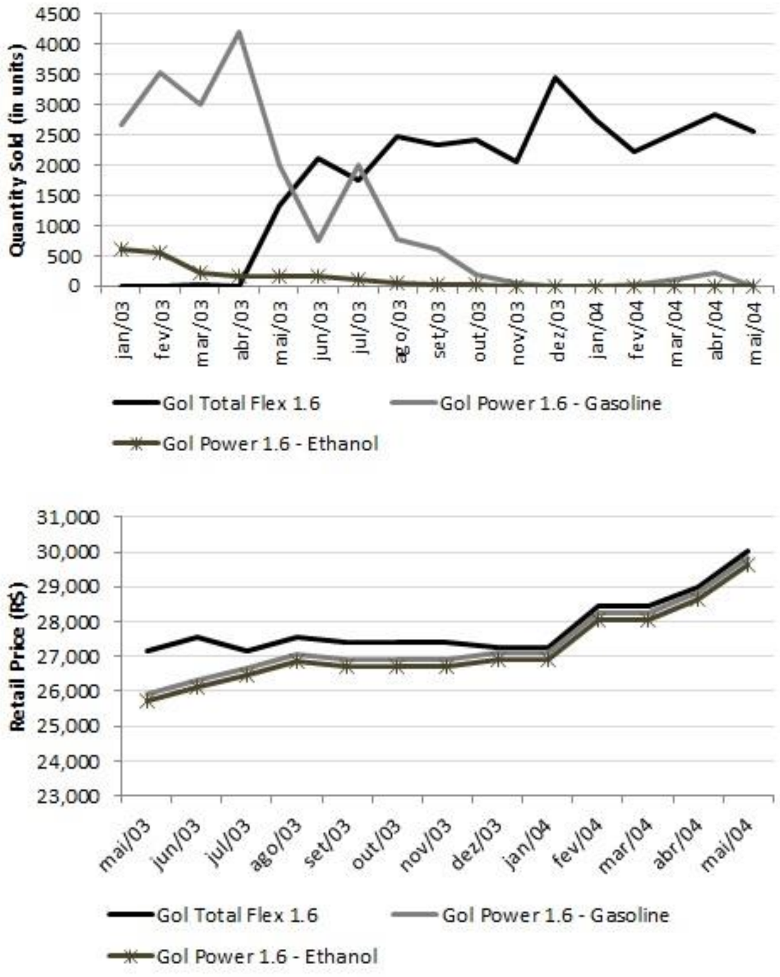
Figure 2.1
Ratio between the price of ethanol and the price of gasoline



Source: National Agency of Petroleum, Natural Gas and Biofuels (ANP).

Figure 2.2 shows the initial evolution regarding the quantity sold and the retail price of the three versions of *Gol Total* 1.6. Given that the product characteristics were similar, it appears that consumers prefer to buy flex-fuel automobiles over gasoline and ethanol powered engine. Regarding the prices, as the flex-fuel technology becomes cheaper, the difference between prices decreases.

Figure 2.2
***Gol Power* 1.6 - the first automobile with the flex-fuel technology sold in Brazil**

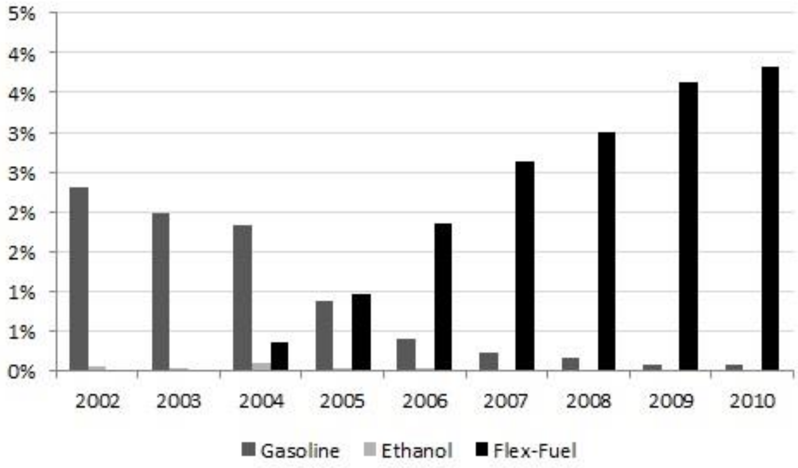


Source: *Quatro Rodas* magazine.

Other automakers quickly responded, introducing their own versions of flex-fuel automobiles. In May/June 2003, Chevrolet introduced the flex-fuel version of the *Corsa* 1.8 and in July, of the same year, Fiat introduced the *Palio Flex* 1.3. So, although Volkswagen was the first automaker to sell flex-fuel automobiles, it did not own the flex-fuel technology. Consequently, Volkswagen did not dominate the market of flex-fuel automobiles. The new technology was well known by all the major players (Volkswagen, Chevrolet, Fiat and Ford) at the time flex-fuel automobiles were introduced in the Brazilian automotive market. If it was not for uncertainties regarding regulation measures, flex-fuel automobiles should have been introduced earlier in Brazil.[21]

Figure 2.3 shows that as soon as the flex-fuel technology was introduced in the Brazilian automotive market, it has quickly gained market-share.[22] This figure also shows that, over the nine-year study, there was a substitution between gasoline-powered toward flex-fuel automobiles.

Figure 2.3
Market-shares by fuel type



Notes: To obtain total market-share by fuel for each year, we sum the market-shares of each model according to fuel type. The market-share of each model is computed as the ratio of its sales (from our database) to the potential market. Following BLP (1995), we consider that the potential market equals the number of household. This information is provided by the IBGE.

The substitution pattern, however, was not the same for all automobile models. In Figure 2.4, we use monthly data from ANFAVEA (from March 2003 through March 2004) to assess what was the percentage of flex-fuel automobiles in total sales for some models right after the introduction of the new fuel option. We normalize the data on which the automobiles were introduced to better visualize the different trajectories. For some models, such as *Gol*, *Corsa* (Chevrolet), and *Palio* (Fiat), the substitution between gasoline and flex-fuel took longer than for other automobile models, such as *Meriva* (Chevrolet) and *Fox* (Volkswagen).

[21] An important regulatory measure came on August 2002 when the Federal Government decided that the flex-fuel system should have the same tax rate - IPI - as ethanol engine.

[22] To compute the market-share we use the number of households as the potential market. This data set is provided by the Brazilian Institute of Geography and Statistics (IBGE, acronym in Portuguese).

In Figure 2.5, we use the data set from the *Quatro Rodas* magazine to investigate how prices of the new flex-fuel option compared with that of the gasoline version. We are not able to construct a series of monthly price for each automobile model as we have done in Figure 2.4 because the prices for many models are not available consistently (i.e. monthly) in the magazine. So, for each year, we consider automobile models for which both versions exist (flex-fuel and gasoline engine) and have the prices available. We can have different automobiles in each year, but we have the same automobile models for the flex-fuel automobiles set and for the gasoline engine set. For each year, we take an average of each set and use it to calculate the ratio between the price of flex-fuel automobiles and the price of gasoline-powered automobiles. Figure 2.5 presents evidence that when flex-fuel automobiles were introduced in the Brazilian market, they were more expensive than their gasoline-powered versions. This situation reverse as the flex-fuel technology becomes cheaper and as the gasoline versions become more sophisticated and, thereby, more expensive.[23]

Indeed, Figure 2.6 shows that gasoline-fueled engine automobiles became, over the years, more associated with more sophisticated automobiles– most of them imported – which may help explain the rise in prices in real terms.[24] This general trend is confirmed when we compare the other product characteristics. While flex-fuel automobiles followed a similar trend to the Brazilian automotive market, the observed trend regarding gasoline engine automobiles attributes indicates an expansion of almost all characteristics considered in this study as standard equipment (Table 2.4).

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[23] Ideally we would like to compare exactly the same automobile models except for the flex-fuel technology. From our database, however, this kind of comparison is not possible. The automobile models differ regarding other characteristics besides the flex-fuel.

[24] The circles represent the size of each market, flex-fuel and gasoline automobiles.

Table 2.3
Descriptive statistics - average between models per year

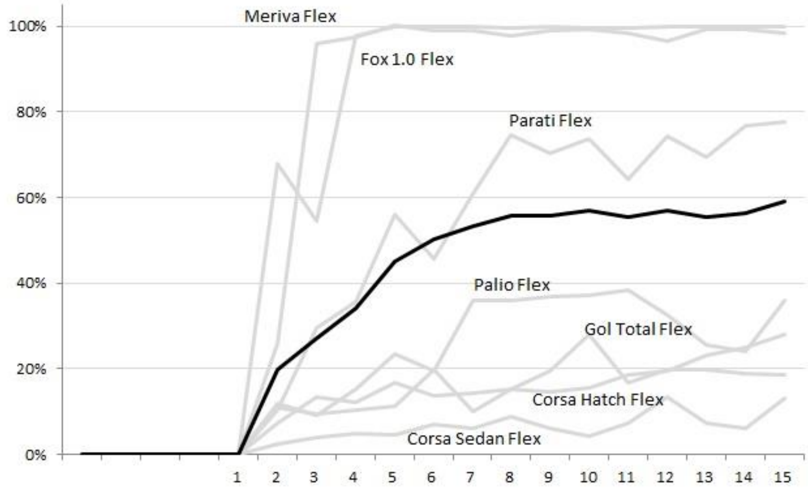
	Quantity (in thousands)	Inflation Adjusted Price (in R$ 1,000)	Flex	Domestic	Engine Displacement	Horsepower
2002	1,134.69	34.47		0.98	1.20	73.14
2003	1,008.87	31.29		0.99	1.21	74.82
2004	1,179.85	32.80	0.16	0.99	1.19	76.41
2005	980.16	39.91	0.52	0.97	1.33	84.06
2006	1,222.25	38.62	0.83	0.97	1.20	79.23
2007	1,597.48	37.81	0.92	0.96	1.21	79.62
2008	1,818.57	38.78	0.95	0.94	1.25	82.19
2009	2,178.41	35.15	0.98	0.96	1.22	82.25
2010	2,235.39	34.36	0.98	0.89	1.23	85.95

Notes: Except for the first column, the entry in each column is market-share weighted mean; Prices are in 2010 Brazilian Real.

	Air Conditioning	Electric or hydraulic power steering	Power window	Power door locks	Automatic transmission	Air bag	ABS
2002	0.08	0.26	0.17	0.16	0.00	0.10	0.02
2003	0.12	0.39	0.20	0.20	0.01	0.05	0.02
2004	0.13	0.28	0.14	0.13	0.00	0.10	0.01
2005	0.21	0.31	0.21	0.19	0.01	0.11	0.03
2006	0.21	0.28	0.19	0.19	0.01	0.09	0.06
2007	0.21	0.29	0.19	0.19	0.02	0.10	0.07
2008	0.22	0.32	0.23	0.23	0.01	0.14	0.10
2009	0.24	0.34	0.25	0.29	0.01	0.13	0.07
2010	0.26	0.34	0.29	0.33	0.01	0.15	0.06

Note: The entry in each column is market-share weighted mean.

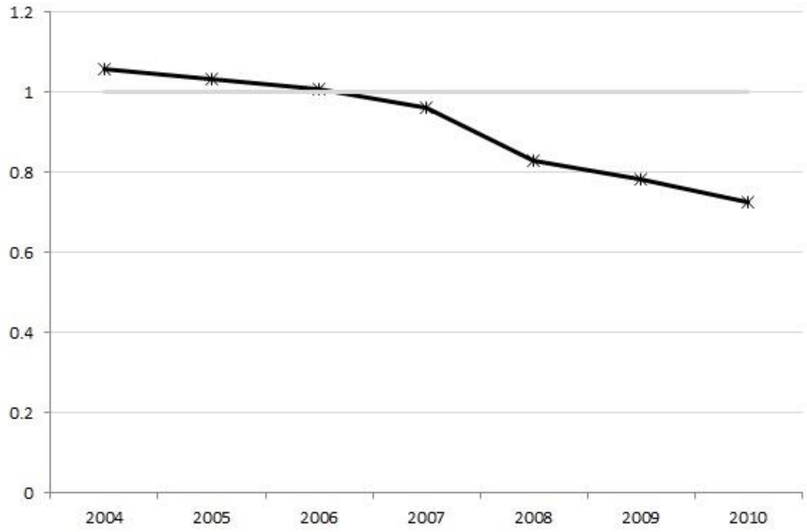
Figure 2.4
Share of flex-fuel automobiles relative to total automobile sales - by model



Months since introduction

Note: we use the data set from ANFAVEA. We use monthly data from March 2003 through March 2004.

Figure 2.5
Ratio between the price of flex-fuel automobiles and the price of gasoline engine automobiles



Note: we use annual data. Using the data set from the *Quatro Rodas* magazine we are not able to construct a series of monthly price for each automobile model as we have done in Panel A. So, for each year, we consider automobile models that have both versions, flex-fuel and gasoline engine, and for which we have the price of both version. We can have different automobiles in each year, but we have the same automobile models for the flex-fuel automobiles set and for the gasoline engine set. For each year, we take an average of each set and use it to calculate the ratio between the price of flex-fuel automobiles and the price of gasoline-powered automobiles.

Figure 2.6
Descriptive statistics by fuel type

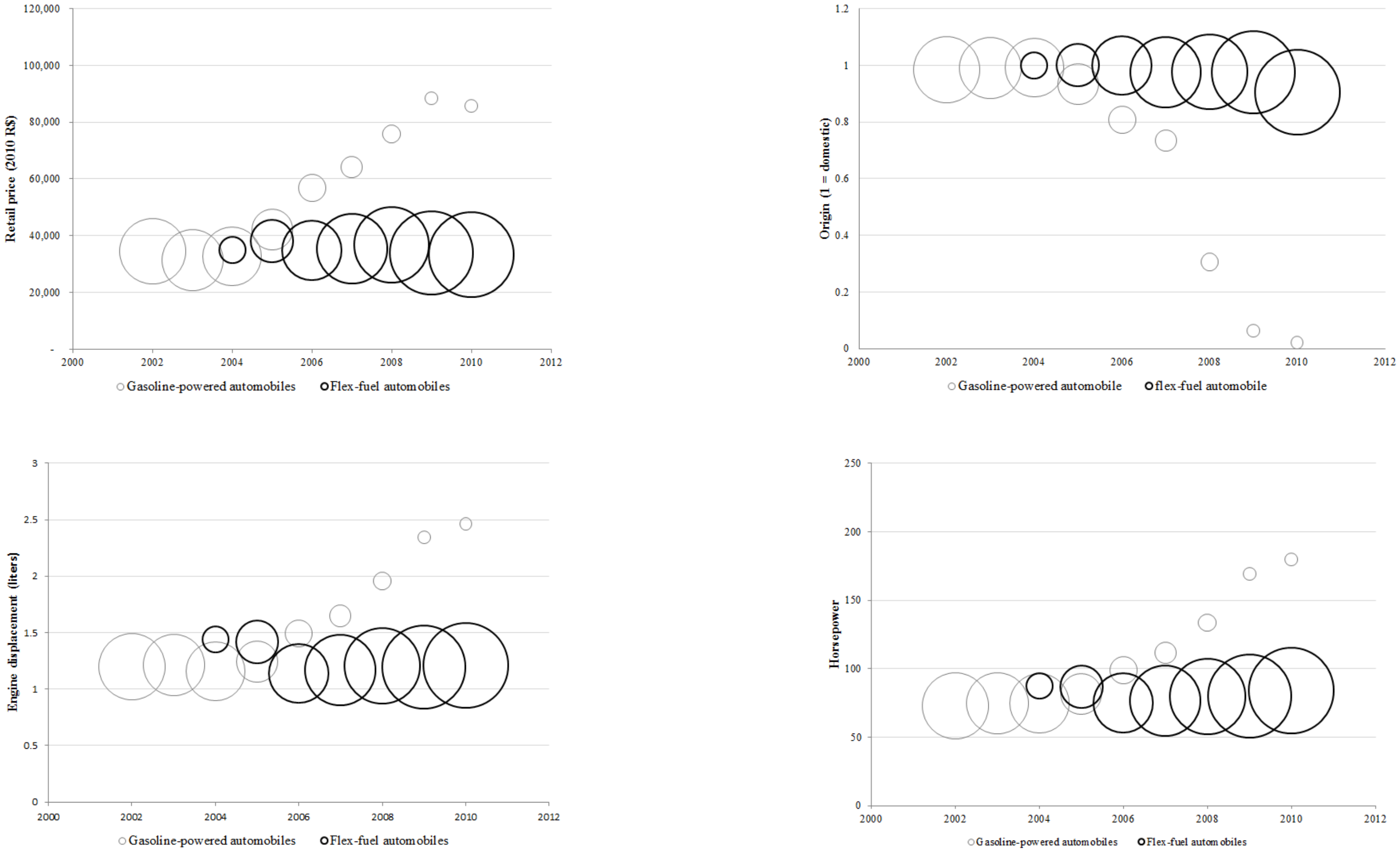


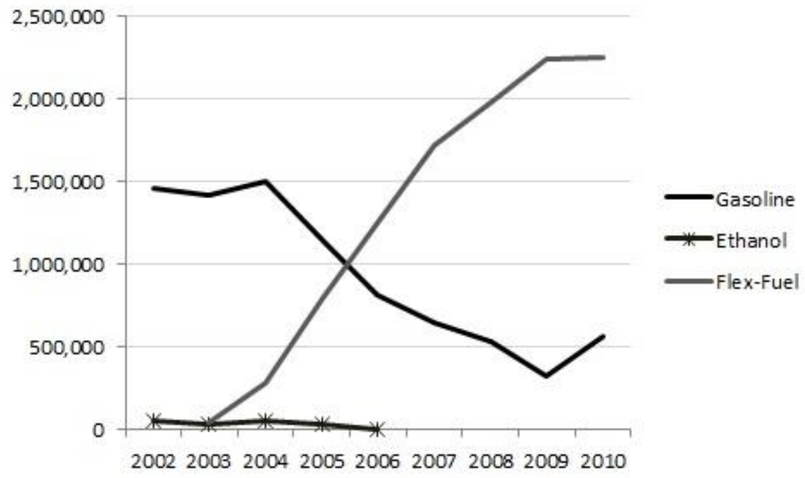
Table 2.4
Descriptive statistics by fuel type (cont.)

	Air Conditioning	Electric or hydraulic power steering	Power window	Power door locks	Automatic transmission	Air bag	ABS
Panel A: : Gasoline-Powered Automobiles							
2002	0.09	0.26	0.17	0.16	0.00	0.10	0.02
2003	0.13	0.39	0.20	0.20	0.01	0.05	0.02
2004	0.16	0.29	0.18	0.17	0.00	0.12	0.02
2005	0.33	0.40	0.35	0.32	0.01	0.21	0.06
2006	0.77	0.79	0.72	0.72	0.05	0.49	0.16
2007	0.78	0.79	0.75	0.75	0.20	0.64	0.43
2008	0.99	0.99	0.99	0.99	0.24	0.90	0.89
2009	1.00	1.00	1.00	1.00	0.59	0.99	1.00
2010	1.00	1.00	1.00	1.00	0.69	1.00	0.98
Panel A: : Flex-fuel Automobiles							
2002	-	-	-	-	-	-	-
2003	-	-	-	-	-	-	-
2004	0.00	0.29	0.00	0.00	0.00	0.00	0.00
2005	0.10	0.22	0.10	0.08	0.00	0.03	0.00
2006	0.09	0.18	0.08	0.08	0.00	0.00	0.04
2007	0.16	0.25	0.14	0.14	0.01	0.05	0.04
2008	0.18	0.29	0.19	0.19	0.00	0.10	0.05
2009	0.22	0.32	0.23	0.28	0.00	0.11	0.05
2010	0.24	0.33	0.28	0.32	0.00	0.13	0.04

From the supply side, Figure 2.7 shows that the production of flex-fuel automobiles followed an upward trend since its introduction in 2003. Similarly to the trajectory of the demand for automobiles, the production of gasoline-fueled engine automobiles fell sharply over the nine-year study. The decision to produce flex-fuel instead of gasoline cars was endorsed by most automobile producers in Brazil and, in 2007, accordingly to our database, buying an economy car with gasoline engine was already a hard task.

Besides several gasoline fueled automobiles being converted to flex-fuel cars, most new automobile launches refers to flex-fuel automobiles. Thus, although, at the beginning, flex-fuel automobiles were offer as an alternative to gasoline or ethanol engine automobiles, few years later its introduction, flex-fuel represents the only available option for some categories.

Figure 2.7
Automobile production in Brazil (in units)



About the conversion, it appears, from our data analysis, that the gasoline-fueled automobile converted into flex-fuel has the same standard equipment as its gasoline version although the flex-fuel automobile has more horsepower.[25] Regarding the engine displacement, the trend is not that obvious. While for some automobiles the engine displacement increases, for example, from 1.0 to 1.4, for other it has remained unaltered. Nevertheless, it is difficult to relate this changes to the flex-fuel technology since the automotive industry is always innovating towards automobiles with better performance and better benefits for consumers.

To gain some basic intuitions about the relationship between the flex-fuel technology and other automobile characteristics, we run hedonic regressions of price on observable characteristics.[26]

Table 2.5 presents evidence of a spurious correlation between flex-fuel and the other attributes, indicating that we should control for other characteristics to eliminate the bias from this correlation. Column 1 shows that flex-fuel automobiles are cheaper than the gasoline-powered automobiles. When we control for market fixed effects and for other characteristics the difference between both automobiles decreases significantly, from 84% to 4.96%. Column 6 shows that when we introduce automobile models fixed effects, the flex-fuel technology becomes marginally important to consumers. Although we should not draw major

[25] The comparison is done when flex-fuel cars are fueled with 100% gasoline.
[26] The hedonic approach states that the coefficients of the regression should be interpreted as marginal implicit price, i.e., the intrinsic value of each attribute.

conclusions from Table 2.5, the results found corroborate with the stylized fact presented previously in our database analysis: automobile prices tend to be equal, or very similar, when comparing, within the same year, automobile models that only differ in having the flex-fuel technology or not.

Table 2.5
Hedonic price model results

Variables	(1) ln(price)	(2) ln(price)	(3) ln(price)	(4) ln(price)	(5) ln(price)	(6) ln(price)
Flex-fuel	-0.840***	-1.207***	-0.00798	-0.0496***	0.120***	0.0250*
	(0.0432)	(0.0542)	(0.0191)	(0.0156)	(0.0255)	(0.0128)
Ethanol				-0.0707*	-0.0536	-0.0303
				(0.0408)	(0.0380)	(0.0207)
Origin (1 = domestic)				-0.103***	-0.121***	-0.109***
				(0.0249)	(0.0220)	(0.0339)
ln(engine displacement)				0.130	-0.0211	-0.00201
				(0.0855)	(0.0793)	(0.0539)
ln(horsepower)				1.109***	1.305***	0.531***
				(0.0772)	(0.0736)	(0.0675)
Air conditioning				0.0185	0.0277	0.0626***
				(0.0196)	(0.0219)	(0.0162)
Electric or hydraulic power steering				0.00724	-0.00295	0.0425*
				(0.0244)	(0.0257)	(0.0223)
Power window				0.0289	-0.00149	-0.0406
				(0.0413)	(0.0468)	(0.0281)
Power door locks				0.000682	0.0604	0.0716***
				(0.0386)	(0.0445)	(0.0244)
Automatic transmission				0.382***	0.373***	0.106***
				(0.0387)	(0.0329)	(0.0364)
Airbag				0.0476**	0.0449**	0.0374*
				(0.0229)	(0.0228)	(0.0203)
ABS brakes				0.0801***	0.0881***	0.0746***
				(0.0263)	(0.0244)	(0.0256)
Constant	11.51***	11.15***		5.674***	4.911***	
	(0.0383)	(0.0804)		(0.321)	(0.309)	
Market fixed effects?	N	Y	Y	N	Y	Y
Automobile models fixed effects?	N	N	Y	N	N	Y
Observations	870	870	870	870	870	870
R-squared	0.158	0.282	1.000	0.919	0.935	1.000

All in all, the data analysis suggests that the introduction of the flex-fuel technology was rapid and it was not exogenous to other characteristics. The flex-fuel technology was first introduced in economy and compact automobiles – the plainest and most common automobiles in Brazil. This finding suggests, therefore, a correlation between flex-fuel and other attributes that must be taken into account when estimating the full model.

2.4 Model

In this section, we present the methodology to estimate the demand parameters. Theoretically, we follow the discrete choice literature for differentiated products and obtain the aggregate demand by aggregating individual decisions. Different from the traditional discrete choice literature, demand is characterized by a set of continuous variables – representing the market-shares – instead of discrete variables. Empirically, we use the techniques developed in Berry (1994) and BLP (1995) to estimate demand and supply curves based solely on product-level data.

2.4.1 Theory: demand

The demand for an automobile model, j, in a given year, is obtained by aggregating the individual probabilities of buying j.

Within the automotive context, each consumer faces a choice among $J + 1$ alternatives: J automobile models and an outside alternative that represents the option of not buying any automobile.[27] For each one of these alternatives, consumer i derives a certain level of utility, u_{ij}.

Following Berry (1994), we assume that the utility of consumer i for an automobile model j is a function of both product characteristics, x_j, and consumers characteristics, ν_i: $u_{ij} = U(x_j, \xi_j, p_j, \nu_i; \theta)$, where ξ_j and p_j are the unobserved (by the econometrician) characteristics and the price of an automobile model j respectively; θ represents the demand parameters. The term ν_i captures taste preferences of consumer i regarding product characteristics. As we do not have consumer-level data, we assume ν has a known distribution. In this study, we follow BLP (1995) and assume that ν_i has a standard normal distribution.

Given the primitives of the model, consumer i chooses j if and only if:

[27] The existence of the outside alternative is a key factor to estimate the aggregate demand; it allows, for example, that the market demand declines if all within-market price increase.

$$U(x_j, \xi_j, p_j, \nu_i; \theta) \geq U(x_q, \xi_q, p_q, \nu_i; \theta), \qquad q = 0,1, \dots, J$$

Where alternative zero, or outside good, represents the option of not buying an automobile.

Assuming ties occur with zero probability, the individual probability of choosing j is:

$$P_{ij} = \Pr\big(U(x_j, \xi_j, p_j, \nu_i; \theta) > U(x_q, \xi_q, p_q, \nu_i; \theta)\ \forall j \neq q\big)$$

As in the traditional discrete choice literature, P_{ij} equals the individual demand for product j. The aggregate demand for product j is given by $\int P_{ij} d\nu$, where $d\nu$ provides the density of ν in the population. Different from the traditional approach, P_{ij} is not discrete and $\int P_{ij} d\nu$ is interpreted as the fraction of consumers that buy automobile model j, i.e., the market-share, $s_j(x_j, p_j, \xi_j, d\nu; \theta)$.[28]

For tractability reasons, the utility function is separable in two terms: one determined by the product characteristics (δ_j) and one determined by consumer characteristics (μ_{ij}), $u_{ij} = \delta_j + \mu_{ij}$, where $\delta_j = x_j\beta - \alpha p_j + \xi_j$ and $\mu_{ij} = \epsilon_{ij}$. As it is common in traditional logit models, we assume that ϵ_{ij} is independent and identically distributed (IID) across consumers. As a result, assuming that the variation in consumer tastes enters only through the additive term ϵ_{ij} imposes strong restrictions on the estimated own- and cross-price elasticities.

In traditional logit models, price elasticities are determined only by the market-shares, i.e., conditional on market-shares, substitution patterns do not depend on the observable product characteristics (BLP (1995)). This limitation of the logit models is well known in the discrete choice model literature and it is formally called Independence of Irrelevant Alternatives.

To overcome this problem, we assume that the utility function is described by the traditional random coefficient model and we allow for interaction between individual and product characteristics. In this case, consumers with different

[28] To be more specific, the demand for automobile model j is Ms_j, where M is the number of consumers in the automotive market and s_j is the market-share of good j.

preferences will have different utility levels and induce different substitution patterns. Within this model context, the own- and cross-price elasticities depend not only on market-share, but also on consumers and product characteristics. The substitution patterns obtain through this model are more realistic and more in accordance with economic theory.

Within this context, the utility obtained from buying an automobile model j in a given year, $t,$[29] is:

$$u_{ijt} = x_{jt}\beta + \xi_{jt} + \alpha^* \ln(y_i - p_j) + \sum_k \sigma_k x_{jtk} v_{ik} + \epsilon_{ijt} \quad \text{Eq.1}$$

Where:

$$\delta_{jt} = x_{tj}\beta + \xi_{jt} \qquad \text{Eq. 1.a}$$

$$\mu_{ijt} = \alpha^* \ln(y_i - p_j) + \sum_k \sigma_k x_{jtk} v_{ik} + \epsilon_{ijt} \quad \text{Eq. 1.b}$$

Where δ_j is interpreted as the mean utility, μ_{ij} is the deviation regards this mean and $\theta = (\alpha^*, \beta, \sigma)$ is the demand parameters vector we are interested in. Note that Equation 1 is slightly different from the logit specification. In the latter, price is introduced in the mean utility term while in Equation 1, following the BLP specification, we interact price with income.[30] Now, consumers with different income levels respond different to price changes.[31] Besides, to better capture the income effects, we allow the price coefficient to vary with different income groups.

$$\alpha^* = \begin{cases} \alpha_1, & y_i \leq \bar{y}_1 \\ \alpha_2, & \bar{y}_1 < y_i \leq \bar{y}_2 \\ \alpha_3, & y_i > \bar{y}_3 \end{cases}$$

About the coefficients interpretation in Equation 1, the contribution of the kth product characteristic, x_k, to the utility of consumer i is $(\beta_k + \sigma_k v_{ik})$ which depends on consumer preferences. Regarding the individual tastes, we assume that preferences do not change over years. This hypothesis is reasonable within a durable good market context.

[29] In BLP (1995), different years are interpreted as different markets.
[30] Besides the characteristics of the good purchased, utility is now also a function of expenditures on other goods and services.
[31] Adding demographics characteristics, such as income, improves the precision of the estimator.

To complete the model description, the utility level of not buying an automobile is:

$$u_{i0t} = \alpha^* ln(y_i) + \xi_{0t} + \sigma_0 v_{i0} + \epsilon_{i0t}$$

As we do not have information about the outside alternative and the market-shares depend on differences in utility,[32] we normalize the mean utility of the outside alternative to zero ($\delta_0 = \xi_0 = 0$) and add a constant term in the utility function of the inside goods.

Finally, for tractability reasons, we assume that ϵ_{ij} is IID type 1 extreme value, with density $f(\epsilon_{ij}) = e^{-\varepsilon_{ij}} \exp(-e^{\epsilon_{ij}})$. This assumption guarantees a closed form for the individual probabilities.

$$P_{ij} = \frac{e^{\delta_j + \mu_{ij}}}{1 + \sum_q e^{\delta_q + \mu_{iq}}} \qquad \text{Eq.2}$$

Knowing the probabilities functional forms, however, do not solve the problem of computing the integral, $\int P_{ij} P(dv)$. To solve this computational problem, we follow BLP (1995) and aggregate via simulation, i.e., we take *ns* random draws from the distribution on ν and compute:

$$s_j(x_j, p_j, \xi_j, dv; \theta) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{e^{\delta_j + \mu_{ij}}}{1 + \sum_q e^{\delta_q + \mu_{iq}}} \qquad \text{Eq.3}$$

[32] Considering the logit model, for example, we have that the individual probability of buying the automobile model j is $P_{ij}(u_{ij} > u_{iq},\ all\, j \neq q) = P_{ij}(u_{iq} - u_{ij} < 0,\ all\, j \neq q) = P_{ij}(\epsilon_{ij} - \epsilon_{iq} < \delta_j - \delta_q,\ all\, j \neq q)$.

2.4.2
Estimation procedure

To estimate the demand parameters in Equation 1 we follow the methodology developed in BLP (1995).

(i) Step 1 – Estimate the market-shares predicted by the model

The predicted market-shares, as well as the means of the consumers' utility, are obtained via iteration.

From the theory section, we know that the demand for an automobile model is given by the market-share of this model in the automotive market. Therefore, to obtain our demand system, we match the observed market-shares, S_j, to the market-shares that are computed using Equation 3, $s_j\left(x_j, p_j, \xi_j, dv; \theta\right)$.

$$S_j = s_j\left(x_j, p_j, \xi_j, dv; \theta\right) = s_j\left(\delta_j, dv; \theta\right) \qquad \text{Eq.4}$$

Equation 4 implicitly determines the mean utility levels, δ. Solving Equation 4, however, is not straightforward. The nonlinearity of Equation 4 prevents estimating the demand parameters analytically. Besides, as pointed out in Berry (1994), the presence of the unobserved product characteristics raises a difficult econometric problem: endogeneity in a nonlinear context. It is likely that price is positively correlated to the unobserved product characteristics.[33] As a result, if price endogeneity is not control for, then we would expect price coefficient to be attenuated. Our results would show that consumers respond less to changes in price than in reality.

To control for the price endogeneity in Equation 4, we use the Instrumental Variables (IV) approach. However, because of the nonlinearity of the

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[33] To account for the potential correlation between the unobserved and all the other observed characteristics, we would have to model the choice of all the observed product characteristics. In this study, given that the relationship between the price and the unobserved characteristics is more direct, we take into account only the price endogeneity. Besides, following BLP (1995), we assume that price is the only choice-variable in the firm problem. For more details, see Ackerberg et al. (2007).

demand system, we must first transform Equation 4 so that the unobserved product characteristics enter demand systems in a linear fashion.

Berry (1994) proposes transforming Equation 4 by inverting the predicted market-shares, i.e., $\delta_j = s_j^{-1}(S_j)$. This inversion transforms the demand system in a system of equations that is linear in the unobservable product characteristics, allowing us to use the traditional IV approach.[34]

Berry (1994) also shows that after some algebra and given the type 1 extreme value distribution of ϵ_{ij}, the mean utility is determined by:

$$\delta_j = \ln(S_j) - \ln\left(s_j(x_j, p_j, \xi_j, dv; \theta)\right)$$

BLP (1995) show that solving Equation 4 is equivalent to solve:

$$\delta_j = \delta_j + \ln(S_j) - \ln\left(s_j(x_j, p_j, \xi_j, dv; \theta)\right) \qquad \text{Eq. 5}$$

Therefore, from Equation 5, we find δ recursively. For some initial guess for $\delta,$[35] we obtain a new δ, say δ', as the output of Equation 5. We then substitute δ' in the right-hand side and compute the market-shares and obtain a new value for the mean utility. This procedure is repeated until convergence is achieved.

Regarding the tolerance level for this initial step, we use 10^{-14}. Dubé, Fox and Su (2012) argue that loose tolerance for the contraction mapping leads to incorrect parameters estimates and even the failure of the optimization routine to converge. Thus, using 10^{-14} for the inner loop is a conservative choice to eliminate the inner-loop numerical error.[36]

Before going to the second step, one may notice that the nonlinear search is only over the demand parameters associated with the heterogeneity between consumers, i.e., σ. Therefore, we are able to separate the parameters of the demand into two vectors, $\theta_1 = \beta$ and $\theta_2 = (\alpha^*, \sigma)$, where θ_1 and θ_2 correspond to the linear and nonlinear parameters respectively.

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[34] See Berry (1994) for more details about the transformation.

[35] Our first guess for the mean utility is the δ obtained via IV Logit. So, before estimating the random coefficients model, we estimate the demand parameters assuming no heterogeneity between consumers.

[36] For the outer loop, we use 10^{-6}.

All in all, in this first step we estimate the mean utility as a function of the nonlinear demand parameters, $\delta(\hat{\theta}_2)$. In the next step, using the mean utility implied by the observed and predicted market-shares, we solve for the demand unobservables.

(ii) Step 2 – Solve for the demand unobserved product characteristics

Once we have the mean utility vector, $\delta(\hat{\theta}_2)$, we are able to solve for the demand unobservables using Equation 1.a.

$$\xi_j = \delta_j(\hat{\theta}_2) - x_j\beta \qquad \text{Eq. 6}$$

Notice that the linear parameters θ_1 are a function of the nonlinear parameters and are estimated by Two Stage Least Square.

$$\hat{\theta}_1 = (X'ZA^{-1}Z'X)^{-1}X'ZA^{-1}Z'\delta(\hat{\theta}_2)$$

Where X is the matrix of the characteristics of the automobiles (excluding the price), Z is the matrix of instruments and $A = (Z'Z)$ is the weighting matrix.

(iii) Step 3 – Calculate the optimal instruments and define the moment conditions

Following BLP (1995), we use product characteristics – excluding the product characteristics of the model been studied – in a given year as instrument for the price in Equation 6. More specifically, BLP (1995) proposes using as instrument a function of the characteristics of other automobile models produced by the same firm and by the competing firms.

The reason for choosing these instruments comes from the oligopoly theory. It is well known that in oligopoly markets, firms set their prices above their marginal cost. So, the decision of the firm depends on the characteristics of products produced by the given firm and likely by the rival firm. The relationship between these characteristics affects demand only via price.

The set of instruments for the price proposed in BLP (1995) is the sum of the characteristics of the products produced by the same firm – $\sum_{q\neq j,q\in F_f} x_{qk}$ – and the sum of the characteristics produced by the competing firms – $\sum_{q\neq j,q\notin F_f} x_{qk}$, where F_f is the set of products produced by firm f and k is the kth product characteristic produced by firm q. In this study, however, instead of using the sum, we opt for using the mean. First stages regressions analysis indicates that, for this study, the mean is a stronger instrument than the sum.[37]

Once we have the optimal instruments, we are able to determine our sample moment conditions:

$$G_j = \frac{1}{J}\sum_{j=1}^{J} H_j(z)\xi_j$$

Where $H(z)$ represents the matrix of instruments which includes the instruments for the price and the exogenous characteristics in Equation 6.

The optimization procedure consists in estimating the demand parameters, θ, that minimizes:

$$\|G_j\| = \left\|\tfrac{1}{J}\textstyle\sum_{j=1}^{J} H_j(z)\xi_j\right\|, \text{ where } \|G_j\| = G'_j G_j$$

(iv) Step 4 – Compute the demand parameters standard-deviations

The final step consists in estimating the variance-covariance matrix of the estimated demand parameters. We use the asymptotic variance of the nonlinear Generalized Method of Moments estimator.

$$\hat{V}(\hat{\theta}) = N\left[\hat{D}'ZA^{-1}Z'\hat{D}\right]^{-1}\left[\hat{D}'ZA^{-1}\hat{S}A^{-1}Z'\hat{D}\right]\left[\hat{D}'ZA^{-1}Z'\hat{D}\right]^{-1}$$

Where $\hat{D} = \frac{\partial \xi}{\partial \theta'}$ and $\hat{S} = \frac{1}{N}\sum_j \hat{\xi}_j Z_j Z'_j$.

[37] We test the instruments by estimating the IV logit model.

To estimate the parameters of the supply side, we also follow the framework presented in BLP (1995)

(i) Step 1 – calculate the markups

Following the BLP methodology, markups are computed as a function of the parameters of the demand system and price.

$$b(p,x,\xi;\theta) = \Delta(p,x,\xi;\theta)^{-1}s_j\left(x_j,p_j,\xi_j,d\nu;\theta\right)$$

Where $b(p,x,\xi;\theta)$ is the markup and $\Delta(p,x,\xi;\theta)$ is a $J \times J$ matrix whose (j,r) element is given by:

$$\Delta_{jr} = \begin{cases} \dfrac{-\partial s_r}{\partial p_j}, & \text{if } j \text{ and } r \text{ are produced by the same firm} \\ 0, & \text{otherwise} \end{cases}$$

Where:

$$\frac{-\partial s_j}{\partial p_j} = \int P_{ij}\left(1-P_{ij}\right)\frac{\partial \mu_{ij}}{\partial p_j}P(d\nu) \text{ and } \frac{-\partial s_j}{\partial p_r} = \int -P_{ij}P_{ir}\frac{\partial \mu_{iq}}{\partial p_q}P(d\nu)$$

(ii) Step 2 – Obtain the pricing equation

We estimate the parameters of the supply side via Ordinary Least Square (OLS). The supply curve is given by the following pricing equation:

$$ln(p - b(p,x,\xi;\theta)) = w\gamma + \omega$$

2.5

Results

Other than retail prices, we use nine observable automobile characteristics: engine displacement, horsepower, and dummy variables indicating whether the automobile is domestically produced, has the flex-fuel technology, air conditioning, electric or hydraulic power steering, automatic transmission, airbag, and ABS brakes. For all of these variables, we assigned random coefficients – taste parameters – based on normal draws. [38]

Tables 2.6 and 2.7 show the results for our specifications. In total, three demand models are estimated: OLS Logit, Two Stage Least Square (TSLS) Logit with IV correction, and random coefficients with IV correction. For the first two models, we assume that consumers have homogenous preferences. Although this assumption leads to unrealistic substitution patterns, estimating these models is useful for baseline comparisons with the full model, i.e., with the random coefficient model.

Table 2.6 shows that not controlling for price endogeneity leads, as expected, to attenuated estimates. Column 2 shows that when we control for the simultaneity bias, the coefficient on price more than doubles. Its magnitude, however, is still low. Regarding the flex-fuel coefficient, it is robust to the new estimation strategy and statistically significant, suggesting that the average consumer likes flex-fuel automobiles. The magnitude of the flex-fuel coefficient, however, is high relatively to the price coefficient. In Column 2, for example, the flex-fuel parameter is more than 100 times the price parameter, suggesting that consumers would be willing to pay a premium of more than R$ 100,000 for an automobile with flex-fuel technology. This finding is unrealistic.

Table 2.6 also shows that, besides changing the price coefficient, the use of instruments[39] generates changes in some of the parameter estimates. Most characteristics now enter the utility positively, but for a few attributes, such as power steering and airbag, the negative signal remains. Also, because of the strong relationship between the variables, most characteristics are not statistically significant. Eliminating one of these variables, however, would potentially aggravate the omitted variable bias.

Based on the descriptive analysis, we also introduce a dummy variable for the year of 2005 in both models. Different from other years, in 2005 we were not able to obtain a good match between the data sets from Anfavea and *Quatro Rodas*. As a result, we have somewhat discrepant values for this year on, for

[38] Normal distribution with mean vector zero and an identity covariance matrix.
[39] In total, we have 16 instruments. As in BLP (1995), we choose arbitrarily which potential instruments to leave in and out because of the near multicollinearity between them.

example, sales and retail prices. So, to control for potential bias in our sample,[40] we introduce the 2005 dummy variable.

All in all, Table 2.6 shows that taking into account price endogeneity matters. The importance of the unobservable characteristics can also be seen from the simple logit specification: 38% of the variance in the mean utility level is due to unobserved characteristics. Logit models, however, are known for having unrealistic substitution patterns. The homogenous hypothesis regarding consumers' preference implies that price elasticity is a function solely of market-shares. So, to overcome this and estimate more reliable estimates, we estimate the random coefficient model (or full model).

[40] From the descriptive analysis, it seems that our sample in 2005 has more sophisticated automobiles, with higher prices, engine displacement and horsepower.

Table 2.6
OLS and IV demand estimations

Variables	OLS Logit Demand	IV Logit Demand
Flex	1.738***	1.752***
	(0.175)	(0.175)
Price (in R$ 1,000)	-0.005***	-0.012***
	(0.0008)	(0.002)
Origin	1.248**	1.200***
	(0.262)	(0.268)
Engine displacement	-0.268	0.031
	(0.205)	(0.265)
Horsepower	-0.122	0.566*
	(0.246)	(0.364)
Air conditioning	-0.216	-0.291
	(0.229)	(0.228)
Power steering	-0.552*	-0.741**
	(0.233)	(0.242)
Automatic transmission	-0.416*	-0.102
	(0.240)	(0.256)
Airbag	-0.345*	-0.357*
	(0.221)	(0.221)
ABS brakes	0.007	0.004
	(0.252)	(0.255)
Dummy_2005	-0.101	0.100
	(0.201)	(0.215)
Constant	-9.714***	-10.323***
	(0.350)	(0.399)
No. of Observation	870	870
R^2	0.620	n.a.

Notes: OLS and IV estimation of $\ln(market\ share\ of\ inside\ products) - \ln(market\ share\ of\ outside\ product)$ on product characteristics. Robust standard errors in parentheses. ***p<0.001, **p<0.01, *p<0.1. In both regressions we assume consumers are homogenous regarding their preferences. In the second column, we use Instrumental Variables to control for price endogeneity. A discussion regarding the instruments used in this study can be found in section 2.4.

Following BLP (1995), we introduce information on income across household. From the economic theory, consumers with high income are less sensitive to price variations and therefore should behave different from consumers with low income when deciding to buy (or not) an automobile. To help to capture the income effects, besides assuming a convex form for the interaction between price and income, we have also considered three income groups. Based on the National Household Sample Survey (PNAD, acronym in Portuguese), we determine the three income group thresholds: the low- and middle-income group, with annual income up to R$ 30,000; the high-income group, with annual income between R$ 30,000 and R$ 140,000; and, finally, the top 1% with annual income higher than R$ 140,000.[41]

Table 2.7 shows the demand parameters obtained using the full model.[42] Now, the effect of each product characteristics on utility varies across consumers so that we estimate a mean and a standard deviation for each attribute. Specifically about the flex-fuel technology, the positive sign of the mean taste coefficient for flex-fuel technology corroborates the results obtained when assuming no heterogeneous preferences and suggests that the average consumer likes flex-fuel automobiles. However, the mean taste parameter is not statistically significant at 10% significance level, indicating that, although the point estimate is in accordance with the previous estimate, we cannot rule out the possibility that the average consumer does not care about flex-fuel technology. Interestingly, the standard deviation for the flex-fuel technology is statistically significant, suggesting divergence between consumers' preference.

About the disposable income coefficients, we find, as expected, that consumers with high income are less sensitive to price variation: we find that while an increase of R$ 1,000 (about 3%) in the average price of automobiles decreases the utility of consumers in the middle income group by 0.48%, the decrease is about 0.05% for consumers in the top 1% income group.[43] These values are smaller than expected initially. When we compare the disposable income coefficients with the coefficients obtained in Petrin (2002) and Furlong (2010), both for the United States, the difference is substantial. For the low income group, for example, Petrin (2002) finds a price coefficient equal to 4.92 and Furlong (2014), 1.013. For the high income group, the difference is even

[41] All prices are in January 2010 Brazilian *Reais*.

[42] In Appendix A, we show the result for a simpler model. We assume that, besides income, consumers differ regarding their preferences toward flex-fuel and the outside good (constant term).

[43] To calculate the effect of a price change on consumers' utility, we use the average income of each income group and the weight average price of automobile. All measures are for the year of 2010.

larger. While we find a coefficient equal to 1.44, Petrin (2002) finds 37.92 and Furlong (2014), 11.56.

Table 2.7
Estimated demand parameters using the random coefficient model (BLP specification, 870 observations)

	Variable	Parameter estimate	Standard error
Means (β's)	Flex	0.734	4.260
	Origin	0.535	1.286
	Engine displacement	-4.043***	1.094
	Horsepower	-0.628	0.696
	Air conditioning	0.567	0.862
	Power steering	-0.682	1.246
	Automatic transmission	0.798	1.375
	Airbag	-0.891	1.547
	ABS brakes	0.016	1.240
	Dummy_2005	1.217**	0.695
	Constant	17.548	15.098
Std deviations (σ's)	Flex	4.753**	2.248
	Origin	1.484	2.320
	Engine displacement	2.011***	0.516
	Horsepower	0.000	0.650
	Air conditioning	0.000	2.012
	Power steering	3.706***	0.757
	Automatic transmission	0.912	2.935
	Airbag	1.610	2.028
	ABS brakes	2.364	2.645
	Constant	1.862	1.148
Term on price	α_1	1.790	1.377
	α_2	1.151***	0.430
	α_3	1.437***	0.297

Note: No. of consumers is 1,000.

In Brazil, different from the United States, the average income of consumers is low compared to the average price of an automobile. In 2010, for example, the annual average income was R$ 26,636 while the market-share weighted average price equaled R$ 34,357.[44] Within this context, the functional form for the interaction between price and income proposed in BLP (1995) may not be adequate.[45] To overcome this problem, we estimate the demand parameters assuming a more flexible functional form: we interact price with three dummy variables, one for each income group. This specification still allows price coefficients to accommodate heterogeneity between consumers with different income levels.

$$u_{ijt} = x_{jt}\beta + \xi_{jt} + \tilde{\alpha}_1 D_1 \mathrm{p_j} + \tilde{\alpha}_2 D_2 \mathrm{p_j} + \tilde{\alpha}_3 D_3 \mathrm{p_j} + \sum_k \sigma_k x_{jtk} v_{ik} + \epsilon_{ijt}$$

Where:

$D_1 = 1,\quad$ if $y_i \leq 30{,}000$ and 0 otherwise.

$D_2 = 1,\quad$ if $30{,}000 < y_i \leq 140{,}000$ and 0 otherwise.

$D_3 = 1,\quad$ if $y_i \geq 140{,}000$ and 0 otherwise.

Table 2.8 presents evidence that consumers are not very sensitive to price changes as expected initially. For an instance, an increase of R$ 1,000 in the price of automobiles decreases utility in, approximately, 0.03 for the high income group. Our results are in accordance with Lucinda (2010). He finds that for an increase of R$ 1,000 in price, the marginal utility decreases 0.05 for the average consumer. Ideally, we would like to compare these values with the other parameter estimates and obtain the monetary value of each characteristic, but, under this specification, no characteristic is statistically different from zero.

[44] Whenever consumers' income was less than the price, the expenditure on other goods and services was set equal to 0.0001 to avoid the problem of taking the log of a negative number.

[45] According to Barros, Curry and Ulyssea (2007), the household income available from PNAD is underestimated when compared with other surveys such as the Household Expenditure Survey (POF, in Portuguese). According to them, the difference between the incomes from POF and PNAD was 26% in 2003. Based on this result, we try to adjust the income from PNAD. First, we calculate the difference between both incomes for the year of 2009 (POF is available for 2003 and 2009). Second, different from PNAD, POF discloses information on income of consumers that buy an automobile (not necessarily a new one). And, third, assuming a linear growth rate from 2003 to 2009, we adjust the income from PNAD taking into account the divergence between both surveys and the income from consumers who buy an automobile. We find that, in 2010, the average annual household income was R$ 44, 256, 66% higher than the initial average annual income used. Based on this new income, we re-estimate the BLP. We find very similar results – especially for the low-income group, 1.189.

Table 2.8
Estimated demand parameters using the random coefficient model and income dummies (BLP specification, 870 observations)

	Variable	Parameter estimate	Standard error
Means (β's)	Flex	0.264	6.430
	Origin	0.801	4.324
	Engine displacement	0.355	1.501
	Horsepower	-7.096	4.696
	Air conditioning	-0.156	14.554
	Power steering	-0.215	4.462
	Automatic transmission	-0.857	8.188
	Airbag	-0.168	2.792
	ABS brakes	0.204	2.877
	Dummy_2005	-0.171	1.311
	Constant	-7.151**	4.296
Std deviations (σ's)	Flex	2.499	7.111
	Origin	1.396	7.116
	Engine displacement	0.217	2.236
	Horsepower	2.682	2.898
	Air conditioning	0.701	32.527
	Power steering	0.805	14.324
	Automatic transmission	1.322	5.388
	Airbag	0.357	9.350
	ABS brakes	0.036	40.811
	Constant	0.033	14.072
Term on price	$\tilde{\alpha}_1$	-0.012	0.013
	$\tilde{\alpha}_2$	-0.016	0.026
	$\tilde{\alpha}_3$	-0.035	0.679

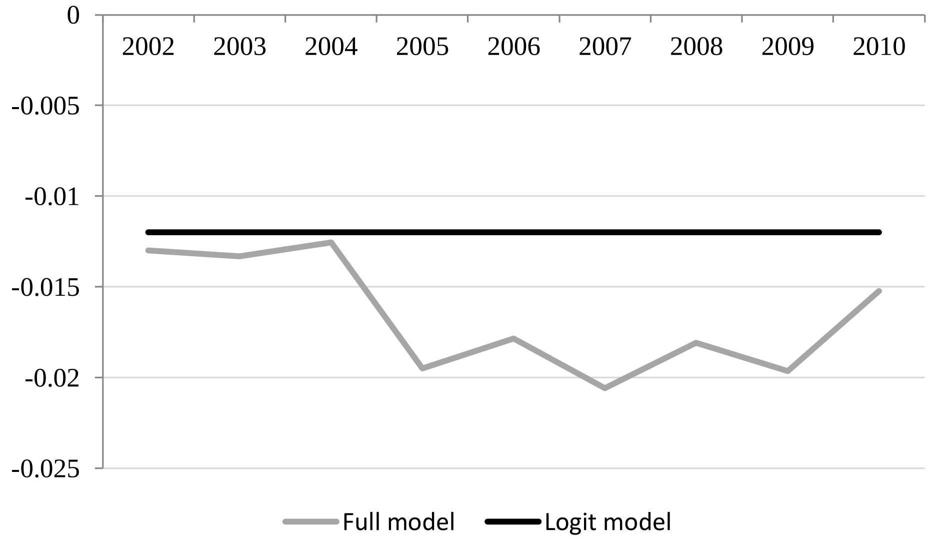
Note: No. of consumers is 1,000.

It is worth mentioning that the price coefficients in Table 2.8 are not comparable to the price coefficient from the logit model. To compare both results, we calculate the changes in market-shares (with regard to the outside good)[46] to an

[46] $\ln(\text{inside good}) - \ln(\text{outside good})$.

increase in the price of automobiles equal to 1%.[47] Figure 2.8 shows that taking into account consumers' heterogeneity leads to larger, in absolute values, own-price elasticities than the own-price elasticity obtained from the logit model. The magnitude, however, is still low, suggesting that the demand for new automobiles is price inelastic. De Negri (1998) corroborates with the low price elasticity, but he finds that the price elasticity of new automobile demand is about -0.6 in Brazil during the 90s.

Figure 2.8
Own-price elasticity of new automobile demand from the logit and the full models



Besides the low price coefficients in Table 2.8, it calls our attention the imprecision of our estimates. The low variability of some variables, such as the flex-fuel dummy,[48] and the presence of high collinearity among the explanatory variables prevent us from estimating precisely the demand parameters from the full model. We could drop some characteristics, but we would potentially introduce an omitted variable bias. In this sense, we prefer to introduce all available observable characteristics into our model.

---

[47] To calculate the price elasticity, we increase the price of each automobile – one by one – by 1% and recalculate the market-share. Then we compute the difference between both market-shares to obtain the own-price elasticity. To compare with the logit estimation, we average the own-price elasticities by market.

[48] The transition between flex-fuel and gasoline-powered automobiles was very fast and, consequently, only a few automobile models in our database are used to identify the flex-fuel parameter.

Specifically about the flex-fuel coefficient, Table 2.8 corroborates with our previous result. We find a positive sign for the mean taste coefficient, indicating that the average consumer likes flex-fuel automobiles. But, as before, the mean taste parameter is not statistically significant, suggesting that the average consumer does not care about flex-fuel technology when buying a new automobile.

All in all, the results found from different specifications suggest that the flex-fuel technology may not matter for automobile demand in Brazil. Our findings present evidence that the rapid introduction of flex-fuel automobiles in Brazilian automotive market resulted from automakers' decision to produce automobiles with this new characteristic.

Using the demand parameters and the methodology presented in BLP (1995), we estimate the supply side. Table 2.9 shows that all characteristics that enter with significant coefficients have the expected sign. Column 1 shows that automobiles with flex-fuel technology increases the marginal cost in 13%. This value is low relative to other attributes such as horsepower and automatic transmission. An automobile with automatic transmission, for example, costs 39% more than an automobile without this attribute. To capture unmeasured common shocks, we introduce a linear trend in the marginal cost regression. Column 1 shows that the term on trend is negative and significant, suggesting, for example, the occurrence of technical improvements over time. It is plausible, however, to believe that the linear trend may be correlated with the evolution of all automobile characteristics over the year, especially with the flex-fuel technology.[49] To test this hypothesis, we omit the linear trend from our regression. Column 2 presents evidence of this correlation. Without the linear trend, the impact of the flex-fuel technology on marginal cost is negative – it reduces the marginal cost in about 4%. This finding is in accordance with the results from the hedonic regression and suggests that the flex-fuel technology is not expensive relative to other characteristics which may have motivated automakers to convert gasoline-powered automobiles into flex-fuel automobiles.

[49] Based on our data analysis, we found that there was a trend toward more extensive standard equipment from 2002 to 2010.

Table 2.9
OLS supply estimation of marginal cost on product characteristics

Variables	Log of marginal cost	Log of marginal cost
Flex-fuel	0.130***	-0.043***
	(0.026)	(0.015)
Origin	-0.116***	-0.103***
	(0.023)	(0.025)
ln(Engine displacement)	0.014	0.124
	(0.079)	(0.084)
ln(Horsepower)	1.270***	1.116***
	(0.074)	(0.076)
Air conditioning	0.072***	0.032*
	(0.021)	(0.019)
Electric and hydraulic power steering	0.008	0.020
	(0.025)	(0.024)
Automatic transmission	0.390***	0.383***
	(0.034)	(0.038)
Airbag	0.039*	0.054**
	(0.023)	(0.022)
ABS brakes	0.105***	0.082***
	(0.026)	(0.026)
Constant	1.770***	1.568***
	(0.047)	(0.045)
Linear trend	-0.046***	
	(0.005)	

2.6 Conclusion

This study measured the importance of the flex-fuel technology for consumers when buying a new automobile using Brazilian auto data between the years 2002 and 2010. Also, through a detail descriptive analysis, we attempted to shed some light on the process of introduction of the flex-fuel technology in Brazil.

To measure the importance of the flex-fuel technology we followed the methodology proposed in Berry (1994) and in BLP (1995). We use a random coefficient utility model to estimate the parameters of the demand using solely market-level data. We also control for price endogeneity using the instruments proposed in BLP (1995).

Our results suggest that the flex-fuel technology is not an important attribute when all other automobile characteristics are controlled for. This result presents evidence that the rapid growth in sales might be explained by the supply side instead of the demand side.

Before concluding, it is worth mentioning that measuring the demand and supply parameters incorporating consumers' heterogeneity remains an active area of research. Based on our findings, understanding the low price elasticity of automobile demand in Brazil seems the natural next step.

Appendix A2

To capture all dimensions possible which new cars differ, the full model described in the main text considers all automobiles attributes available. The use of a large number of variables, however, may, within this context, leads to two important problems: multicollinearity and loss of variability.

As discussed previously, there is a high correlation between variables, such as engine displacement and horsepower, which may prevents us from estimate them precisely. Omitting one of them, however, will likely introduce an omitted variable bias in the estimation of the mean parameters. To overcome the high-dimensionality problem, studies as Gillen, Shum and Moon (2014) use standard machine learning approaches (e.g. LASSO) to select only a few important attributes and, therefore, identify all parameters (from the linear part of the model).

Regarding the loss of variability, we would like to compare automobiles which differ in only one dimension. When restricting our analysis to similar automobiles, however, we end up with only a few automobile samples to compare.

Besides, to make our model closest to reality, we allowed consumers to have different preferences regarding all attributes. This flexibility, however, increases the number of parameters to be estimated and, once again, decreased, the variability of our data. In this Appendix, we simplify our model and assume that consumers have homogeneous preferences regarding most attributes except for the price, the flex-fuel technology and the outside good.

The results from our simplified model are presented in Table A1. We find that, as before (Table 2.7), the average consumer does not value the flex-fuel technology, but consumers' preferences toward this attribute are heterogeneous. About the price coefficients, the results found are different than before. While price is important for the poorest in our sample, automobile price is not statistically significant for consumers with high income. The small coefficient, however, associated with the lower-income consumers is, when compared with other countries (Petrin (2002) and Furlong (2014)), low.

Therefore, despite changes in the value of the parameters the main conclusions found previously are sustained.

Table A2.1
Estimated demand parameters using the random coefficient model and income dummies (simplified BLP specification, 870 observations)

	Variable	Parameter estimate	Standard error
Means (β's)	Flex	1.754	1.645
	Origin	1.031***	0.293
	Engine displacement	-0.334	0.291
	Horsepower	0.961*	0.507
	Air conditioning	-0.185	0.248
	Power steering	1.104	0.693
	Automatic transmission	-0.296	0.512
	Airbag	0.168	0.285
	ABS brakes	-0.242	0.374
	Dummy_2005	-0.159	0.375
	Constant	10.582***	3.390
Std deviations (σ's)	Flex	1.058***	0.306
	Constant	0.344	0.265
Term on price	α_1	1.877***	0.180
	α_2	0.905	1.579
	α_3	0.886	0.739

Note: No. of consumers is 1,000.

3
The economic cost of government intervention in the gasoline market: a case study from Brazil

3.1
Introduction

In this study, we estimate the income transfer, and the economic and environmental losses associated with keeping the price of gasoline stable. Despite fuel market liberalization in the late 90s, gasoline prices in Brazil do not follow the fluctuations of the price of gasoline in the international market. The difference between both prices is the result of a pricing policy set by the government. Through Petrobras, a state-owned company, the Brazilian government is able to determine the price of the gasoline sold to distributors and, consequently, it can influence the price of gasoline to consumers. [50,51]

The stated purpose of the pricing policy is to keep the price of gasoline stable for consumers by preventing the pass-through of shocks in the exchange rate and in the international crude oil prices.[52] In addition to the stated purpose, some market analysts believe that the government uses its influence over Petrobras to dampen the inflationary impacts of the fluctuations of the price of gasoline in the international markets.[53] Regardless of the reason, controlling prices to obtain stability may impact negatively the economy. It is not clear yet whether the enforcement of price controls is beneficial to consumers, and if so, what is the size of the welfare gains.[54]

To calculate the income transfer, and the economic and environmental losses, we assume that the optimal price of gasoline is its price in the international market. This assumption is based on the fact that Petrobras buys gasoline in the spot market to attend consumer, but sells it at the price determined by the

[50] Petrobras is responsible for more than 95% of the gasoline – without ethanol anhydrous – sold in Brazil.
[51] Brazil's government controls Petrobras with a majority of voting shares.
[52] For example, Solowiejczyk, A. and Costa, R. P. F. (2013) and Roque, P. (2013).
[53] In Appendix A, we calculate the pass-through of the price of gasoline to inflation rate.
[54] Chapoto and Jayne (2010).

government. Under additional demand and supply assumptions, we build an alternative scenario and do different counterfactual exercises.

We find that from January 2002 to February 2015, government intervention in the gasoline market worked mainly as a subsidy intervention. As a result, the total cost of this policy during the approximately thirteen-year study was R$ 88 billion. During the same period, the income transfer to consumers as a result of this policy equaled R$ 75 billion and the deadweight loss R$ 24 billion.[55]

Keeping the price of gasoline lower than the gasoline price in the spot market for most of the period resulted in 29% more CO_2 emissions. While in the baseline scenario emissions equaled 798 million tons, in the alternative scenario, in which we assume domestic prices equal international prices, the emission of CO_2 was 618 million tons. Taking into account the price of CO_2, the economic cost – measured as the deadweight loss – increased almost 18%.[56]

Although our analysis focuses on the gasoline market, we estimate the impact of controlling the price of gasoline on the consumption of ethanol – the closest substitute to gasoline. The control of the price of gasoline decreases the competitiveness between both fuels and leads potentially to a welfare loss. Our results show that under the baseline scenario, the consumption of ethanol is 18% lower than the consumption in the alternative scenario.

The remainder of this paper is organized as follows. Section 3.2 describes the data set used in this study. Section 3.3 and 3.4 details the estimation of the income transfer and the deadweight loss. Section 3.5 shows the relationship between the stable price and the emissions of CO_2. Section 3.6 details the impact of enforcing stable prices in the gasoline market on the consumption of ethanol. Section 3.7 concludes the paper.

[55] All prices are in January 2013.
[56] US$ 12 per ton of CO_2 in 2014. Source: World Bank, State and trends of carbon pricing 2014.

3.2 Data

3.2.1 Variables' description

In this study, we use different sources. For the price and the consumption of gasoline and ethanol in Brazil, we use data from the National Agency of Petroleum, Natural Gas and Biofuels (ANP, acronym in Portuguese). For the prices of crude oil and gasoline in the international market, we get the data from the Energy Administration Information. We use the WTI Spot Price (FOB)[57] and the U.S. Golf Coast Conventional Gasoline Regular Spot price (FOB) respectively.

The price of crude oil is measured in dollars per barrel and the price of gasoline in the spot (international) market is in dollars per gallon. We use the exchange rate available from the Central Bank of Brazil to convert from dollars to Brazilian *Reais*. To deflate prices, we use the Extended National Consumer Price Index available at the Brazilian Institute of Geography and Statistics (IBGE, in Portuguese). All prices are in January 2013. Also, we transform all volume measures to liters.

From IBGE, we also get data on industrial production. We use the Industrial Production Index deseasonalized.

To compare the spot price with the domestic price of gasoline, we use the price paid by the distributors to the refineries. The price of gasoline that refineries received is available at ANP. This price data, however, is not yet comparable to the spot price. To make them comparable, we subtract from domestic price the national taxes PIS/PASEP, Cofins and CIDE. Data on tax rates is obtained directly from Brazilian legislation.

[57] Free on board.

From the International Energy Agency (IEA), we obtain the amount of CO_2 emissions from conventional gasoline – 2.8 Kg per liter – and from ethanol from sugar cane – 0.3 Kg per liter.[58]

For all variables, we have monthly data from January 2002 to February 2015. In total, we have 158 observations.

3.2.2
Gasoline prices

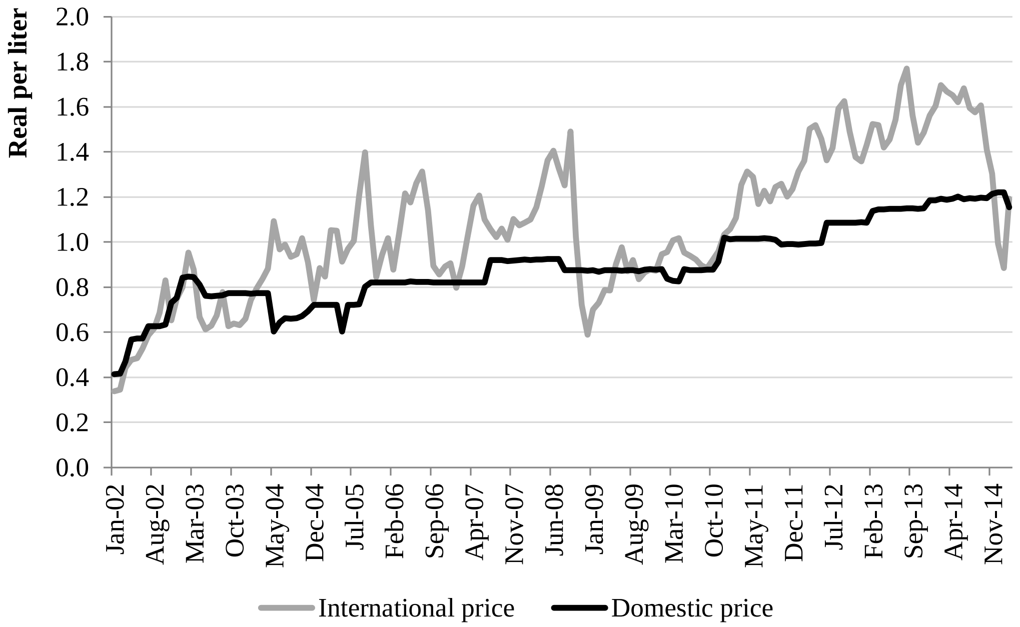
Figure 3.1 shows the evolution of the prices of gasoline in Brazil and in the spot market for gasoline. The domestic price is the price of gasoline sold by refiners minus the federal taxes PIS/PASEP, Cofins and CIDE. Both gasoline prices are in Brazilian *Reais* per liter.

Despite the end of the liberalization process in December 2001, the price of gasoline in Brazil does not follow the price of gasoline in the international market. Part of the divergence is explained by the exchange rate. But, according to Colomer and Tavares (2012), the divergence between prices is mainly the result of a pricing policy aimed to dampen the inflationary impacts of the fluctuations of the price of gasoline in the international market. Most Brazilian analysts agree with this hypothesis.[59] The gasoline price represents 3.87% of the Extended National Consumer Price and its relative weight in the inflation index of the regulated prices equals 16.77%, the highest one.[60]

Figure 3.2 shows that since the end of 2010, the inflation rate has pressured the upper bound of the inflation target. At the same time, Figure 3.1 shows that the divergence between both prices increased. These facts corroborate with the widely accepted standpoint that there is a correlation between government intervention and inflation rate. Our objective, however, is not to provide a causal inference between inflation and the price of gasoline. Rather we wish to outline the economic and environmental consequences of this intervention.

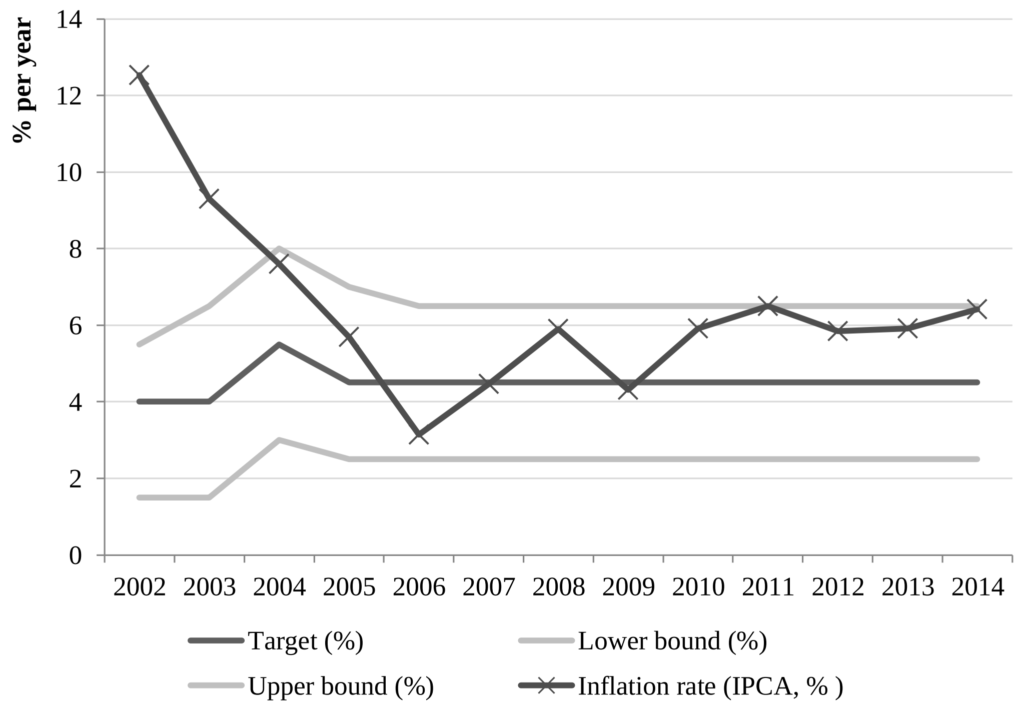
[58] The values of 2.8 Kg per liter and 0.3 Kg per liter take into account the emission of CO_2 along the entire production chain – well to wheels.
[59] See, for example, Solowiejczyk, A. and Costa, R. P. F. (2013) and Roque, P. (2013).
[60] March 2014.

Figure 3.1
Gasoline price in the international market and the wholesale gasoline price in Brazil



Note: Nominal prices. To calculate domestic prices we use the price data available from the National Agency of Petroleum, Natural Gas and Biofuels. From the price paid to the refineries, we subtract the taxes PIS/PASEP, Cofins and CIDE.

Figure 3.2
Inflation target



Source: Central Bank of Brazil

Figure 3.3 shows that since the end of 2010, the consumption of gasoline followed an upward trend. Because domestic price of gasoline is lower than the price of gasoline in the international market, we expect consumption to be higher than the consumption of gasoline under the alternative scenario in which domestic prices equal spot prices.

Government intervention in the gasoline market contributed to decrease the competitive between gasoline and ethanol. Figure 3.4 shows that the ratio between the prices of ethanol and gasoline since the end of 2010 was favorable to the consumption of gasoline. This movement in prices certainly explains part of the observed increase in the demand for gasoline.

Figure 3.3
Gasoline consumption in Brazil (in liters)

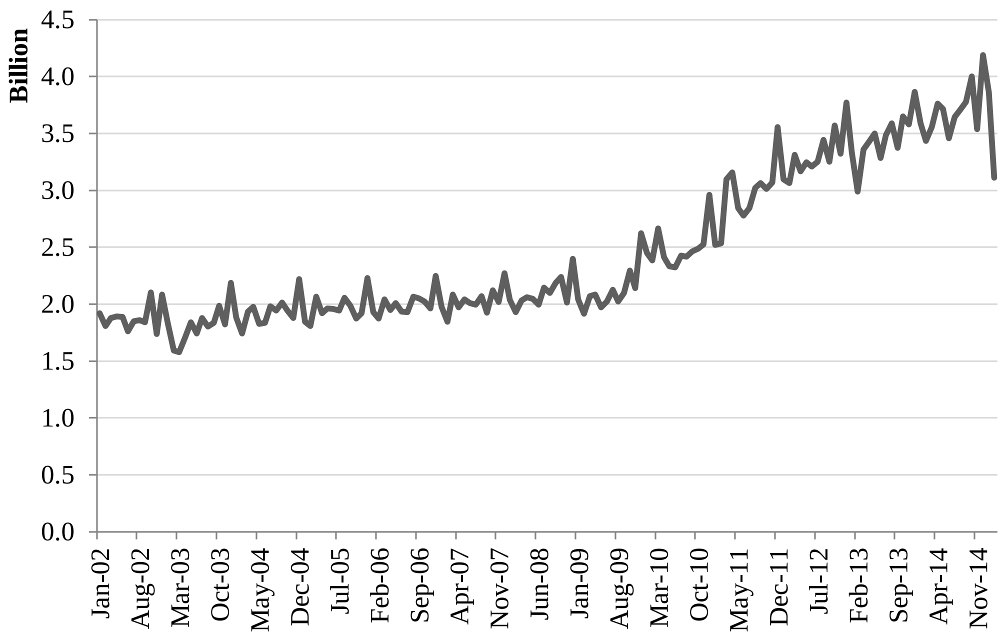
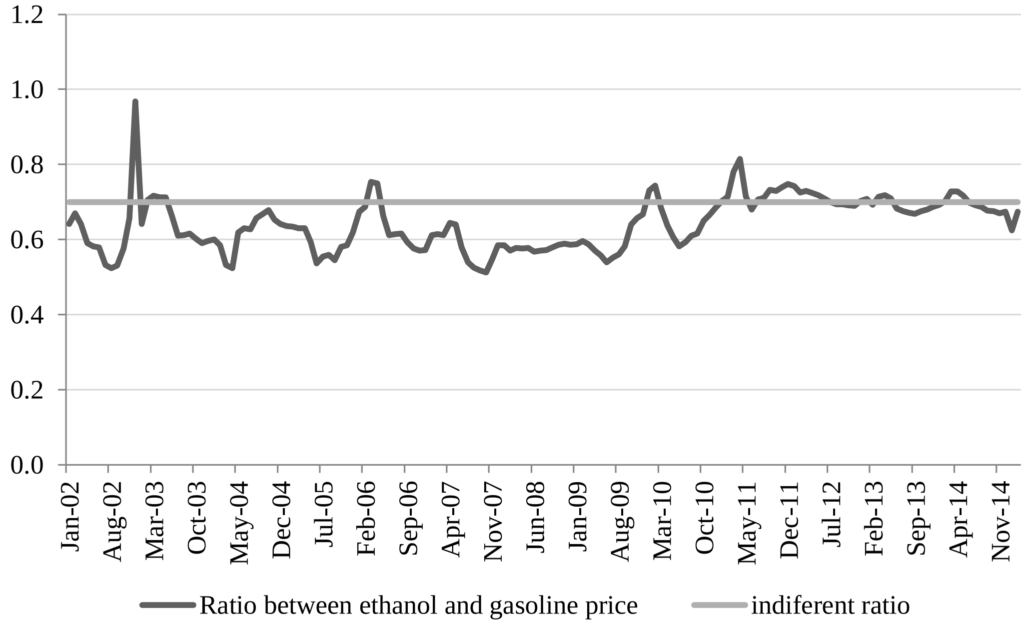


Figure 3.4
Ratio between the prices of ethanol and gasoline



Note: The indifferent ratio equals 0.7. The automobile's performance when fueled with ethanol is 30% lower than the performance with regular gasoline. The 0.7 value is obtained from the National Institute of Metrology, Quality and Technology.

Studies, such as Klier and Linn (2010) and Busse, Knittel and Zettelmeyer (2013), show that changes in the price of gasoline affect not only the intensive margin (consumption per automobile), but also the extensive margin (number of automobiles). These studies find that, for the United States, when the price of gasoline increases, automobile sales fall. Also, they show that consumers are not myopic to current and future gasoline price changes. Therefore, it is possible that the policy to ensure stable prices of gasoline has stimulated automobiles sales in Brazil which may explain part of the consumption behavior. Although important, this study focuses solely on the intensive margin.

3.3
Income transfer from distorted gasoline prices

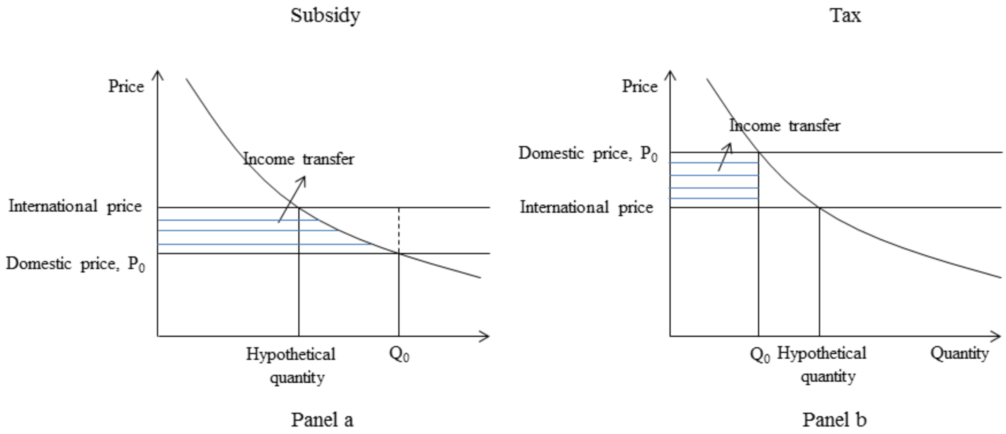
Besides the misallocation of resources, the intervention in the gasoline market also results in income transfer. Under the assumption that the supply is perfectly elastic, i.e., that the producer surplus is zero, the income redistribution occurs between Brazilian government and consumers.

Figure 3.5 Panel a shows that when domestic prices are lower than the prices in the international market, the cost of gasoline subsidies – $(P_{international} - P_{domestic}) \cdot Q_0$ – is higher than the income transfer to consumers. Our result shows that from January 2002 to February 2015, the income transfer was about R$ 75 billion and the total cost equaled approximately R$ 98 billion (prices are in January 2013).

Within a context of tax policy, Figure 3.5 Panel b shows that consumer surplus equals the government revenue plus the deadweight loss. The revenue – $(P_{domestic} - P_{international}) \cdot Q_0$ – represents the income transfer from consumers to government. Our findings suggest that the transfer income of keeping domestic prices higher than international prices was, in real terms, R$ 10 billion during the approximately thirteen-year study.

The government faces a well-known dilemma between the short-run welfare of the population and the long-run efficiency of resource allocation. Based solely on these results, it seems that keeping gasoline prices stable brings benefits to consumers in Brazil. However, a more accurate analysis is necessary. Besides the fiscal costs associated with this policy, studies, such as Granado et al (2010), show that higher income groups benefit the most from gasoline subsidies. It is not, however, the goal of this paper to study the social impact of the price policy.

Figure 3.5
Income transfer resulting from the gasoline price policy



3.4
Efficiency losses caused by gasoline price distortion

There is a consensus among researchers that government intervention is sometimes needed to overcome market failures, such as the presence of externalities. Fossil fuel markets – gasoline and diesel – are examples of goods that generate negative externalities. Studies such as Parry and Small (2005) calculate the second-best optimal gasoline tax. They find that gasoline tax in the United States should be US$ 1.01 per gallon and, in the United Kingdom, US$ 1.34 per gallon. While in developed countries government intervention has increased fuel prices to incorporate external costs, gasoline and diesel are subsidized in most developing countries. According to the International Energy Agency (2013), the global cost of fossil-fuel subsidies expanded to $ 544 billion in 2012 despite efforts at reform.

Davis (2014) examines global fuel subsidies and finds that subsidies for gasoline and diesel totaled $ 110 billion in 2012 (approximately, R$ 215 billion). Assuming that demand is described by a constant elasticity demand function with a time-varying scale parameter and supply is perfectly elastic, Davis (2014) calculates the deadweight loss. He finds that the total deadweight loss worldwide equaled $ 44 billion in 2012 (about R$ 86 billion). When incorporating external costs, such as an increase in CO_2 emissions, the economic loss increases substantially.[61]

To quantify the deadweight loss created by the gasoline pricing policy in Brazil, we follow Davis (2014) and assume that the demand for gasoline is described using a constant elasticity demand function with a time-varying scale parameter and that the supply is perfectly elastic – Petrobras must attend demand regardless the price.

Under these hypotheses, the deadweight loss results from a misallocation of consumption. If supply were positively inclined, then besides consumption misallocation there would also be a production distortion. In this case, the loss would be larger than the first one. In this sense, our analysis can be seen as a lower bound to the deadweight loss calculation.

[61] Prices are in 2012.

We also assume four additional hypotheses. First, we do not take into account the externalities generated by gasoline consumption. Second, no other market failure (such as imperfect competition in the distribution market) is considered. Third, the analysis is a partial equilibrium one in the sense that no other fuel market is modeled. And fourth, we assume that there is no storage in the gasoline market. These simplifying hypotheses allow us to understand the mechanisms and effects of the stability pricing policy on the gasoline market with more analytical transparency. After showing the main results, we discuss the likely biases introduced by each of these hypotheses.

The demand for gasoline is described as:

$$D_{gasoline_t} = A_t \cdot P_{gasoline_t}^{\epsilon_1} \cdot P_{ethanol}^{\epsilon_2},\ t = \text{January 2002 to February 2015} \qquad \text{Eq. 1}$$

Where $D_{gasoline}$ is the quantity of gasoline sold in time t, A is the scale parameter in t, $P_{gasoline}$ and $P_{ethanol}$ is the gasoline and ethanol prices in t, and ϵ is the long run price elasticity of demand. [62]

A critical point in our analysis concerns the long run own- and cross-price elasticity of gasoline demand. The price policy determines the price of gasoline sold by the refiners (Petrobras) to the distributors, but we are ultimately interested on the impact of government intervention on consumers. So, we assume that distributors behave competitively, so that the price faced by consumers is simply the price paid by distributors plus a constant distribution cost. Under this assumption, we ignore the distribution market and use the price-elasticity of gasoline demand of consumers.

The price of ethanol is the retail price. The difference between the $(p_{ethanol} - p_{gasoline}(wholesale))$ and the $(p_{ethanol} - p_{gasoline}(retail))$ is, approximately, constant over the time. Therefore, as we are interested in percentage changes, we use the retail price of ethanol even though we are using the wholesale price of gasoline.

The magnitude of the deadweight loss depends on the elasticity of the gasoline demand. In the first chapter of this thesis, we estimate the long-run own-

[62] Although we use the long run elasticity, we are not taking into account the extensive margin. This study focuses on the intensive margin.

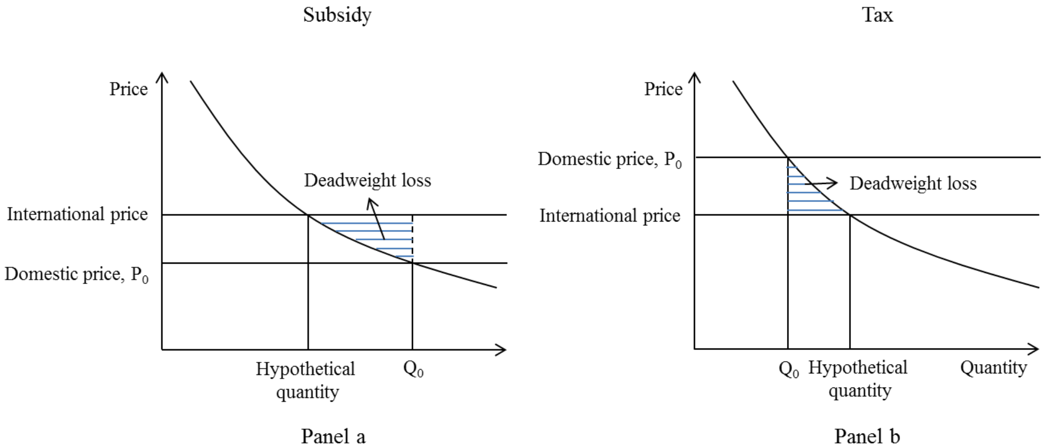
and cross-price elasticity of gasoline demand to be -1.6 and 0.8. We use these values to calibrate the scale parameter and, then, to calculate the deadweight loss.

To calculate the scale parameter, we use the amount of gasoline sold by distributors and the domestic prices of gasoline and ethanol. The distributors buy gasoline produced or imported by the refineries. But, regardless gasoline origin (local or imported), the price paid by the distributors is determined by Petrobras.

For example, in January 2002, the cost of gasoline to distributors in nominal terms was R$ 0.413 per liter.[63] For the same period, Brazilians consumed 1,921 millions of liters of gasoline. If we substitute these values in the demand function (Equation 1) and rearrange it, we are able to determine the scale parameter. In this case, A is approximately 426. This information, along with the gasoline price in the spot market, allows us to calculate the hypothetical consumption in Brazil if domestic prices were equal to international prices.[64]

From January 2002 to February 2015, the price stability policy worked either as a subsidy or a tax. Most of the time (68%), the gasoline price policy implemented by Petrobras can be viewed as a subsidy. Although both policies – subsidy and tax – generate deadweight loss, it is important to distinguish them to precisely estimate the economic loss of each policy.

Figure 3.6
The economic cost of gasoline price policy



[63] This price does not include tax.
[64] As gasoline price is determined internationally reflecting global demand and supply conditions, all (free) countries face similar import and export gasoline prices. Within this context, we should expect that, without government intervention, prices converge. Otherwise, countries, or companies, could arbitrage. Of course, national taxation of gasoline and distribution costs differs among countries and cause significant price differences, but still some convergence might be expected.

Figure 3.6 depicts graphically the efficiency loss generated by the pricing policy adopted by Petrobras. The stability pricing policy creates a wedge between the international and the domestic gasoline prices and, consequently, implies in an inefficiency allocation of resources. To estimate the loss generated by each policy, we calculate the shaded are in Figure 3.6 Panels a and b.

In Panel a, the deadweight loss occurred because domestic prices are lower than the price of gasoline in the international market. In this case, the consumption of gasoline is higher than the optimal consumption. To calculate the efficiency loss from this allocation, we calculate the shaded area in Panel a.

$$DWL_{subsidy} = \left(P_{g_{international}} - P_{g_{domestic}}\right) \cdot Q_0 - \int_{P_{g_{domestic}}}^{P_{g_{international}}} A \cdot p_g^{\epsilon_1} \cdot p_e^{\epsilon_2} dp_g$$

$$DWL_{subsidy} = \left(P_{g_{international}} - P_{g_{domestic}}\right) \cdot Q_0 - \frac{A \cdot P_e^{\epsilon_2}}{(1+\epsilon_1)} \cdot \left(P_{g_{international}}^{(1+\epsilon_1)} - P_{g_{domestic}}^{(1+\epsilon_1)}\right)$$

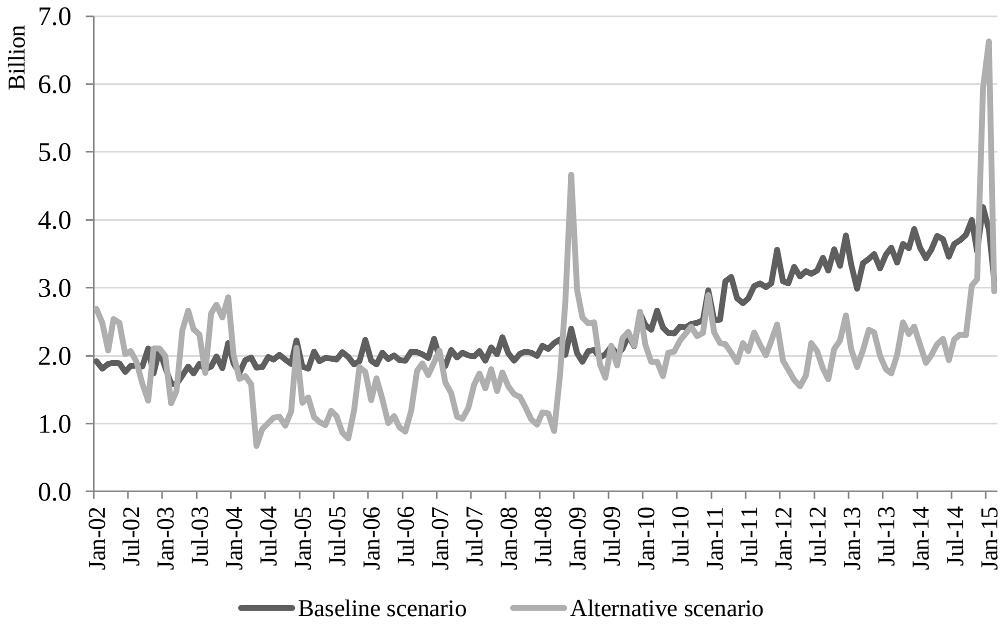
Panel b shows the economic loss from having domestic prices higher than international prices. In this situation, the optimal consumption – hypothetical quantity – is higher than the actual consumption. The deadweight loss is calculated as the shaded are in Panel b.

$$DWL_{tax} = \int_{P_{g_{international}}}^{P_{g_{domestic}}} A \cdot p_g^{\epsilon_1} \cdot p_e^{\epsilon_2} dp_g - \left(P_{g_{domestic}} - P_{g_{international}}\right) \cdot Q_0$$

$$DWL_{tax} = \frac{A \cdot P_e^{\epsilon_2}}{(1+\epsilon_1)} \cdot \left(P_{g_{domestic}}^{(1+\epsilon_1)} - P_{g_{international}}^{(1+\epsilon_1)}\right) - \left(P_{g_{domestic}} - P_{g_{international}}\right) \cdot Q_0$$

Under the assumptions about demand and supply stated above, we calculate the consumption of gasoline under the international and domestic price (Figure 3.7). As most of the time the price stability policy worked as a subsidy policy, it led to an overconsumption of gasoline throughout this period. The total deadweight loss created by the Brazilian stability policy was, from January 2002 to February 2015, R$ 24 billion (prices are in January 2013). As expected, this economic loss is not constant during the years. While in 2009, the loss equaled R$ 218 million, in 2012, the loss was approximately R$ 4 billion (Table 3.1).

Figure 3.7
Gasoline consumption (in liters)



Note: To obtain the hypothetical consumption of gasoline in the alternative scenario, we construct a counterfactual where the price of gasoline in Brazil equals the price of gasoline in the international market. Also, using a constant elasticity demand function with a time-varying scale parameter and an estimate of the long-run price elasticity of gasoline demand, we are able to obtain the hypothetical consumption of gasoline.

The relative magnitude of deadweight loss in 2012 in the gasoline market in Brazil compares to Indonesia (R$ 4.2 billion in 2012) and Iran (R$ 3.9 billion in 2012). According to Davis (2014), Venezuela and Saudi Arabia are the top two countries in terms of gasoline subsidy policy. In 2012, the deadweight loss in those countries were, approximately, R$ 15 and R$ 10 billion respectively.

It is worth mentioning that the magnitude of the consumption inefficiency generated by the price policy depends on the elasticity of demand. If we assume that all market variables are held constant, then a higher elasticity leads to a larger loss.

Table 3.1
Deadweight loss from the gasoline price stability policy in Brazil

	Deadweight loss (in million *Reais*)	Gasoline consumption (in million liters)	Average gasoline prices (R$ per liter)	
			Domestic	International
2002	419.604	22,610	1.114	1.068
2003	603.402	21,790	1.322	1.192
2004	2.071.184	23,173	1.099	1.417
2005	2.612.017	23,553	1.089	1.489
2006	1.855.690	24,007	1.156	1.477
2007	1.063.528	24,325	1.181	1.414
2008	2.757.883	25,174	1.161	1.475
2009	218.344	25,409	1.071	1.033
2010	262.252	29,843	1.026	1.111
2011	1.281.388	35,491	1.103	1.325
2012	4.120.047	39,697	1.086	1.503
2013	3.589.331	41,426	1.084	1.499
2014	3.405.109	44,364	1.100	1.412
Jan-Feb 2015	353.972	6,970	1.043	0.912

Note: All prices are in January 2013 Brazilian *Reais*.

Discussion: implications of our model hypotheses

We made four simplifying hypotheses to better understand the mechanisms and effects of the pricing policy on the gasoline market with more analytical transparency.

The first assumption concerns the externalities associated with the use of gasoline. It is well stablished in the literature that the use of gasoline generates negative externalities such as local and global pollution. Parry, Walls and Harrington (2007) calculate the extra cost of gasoline due to local and global air pollution, oil dependency, traffic congestion and traffic accidents, as well as other externalities. They find that gasoline-related externalities[65] add 18 cents per gallon while mileage-related externalities[66] are equivalent to $ 2.10 per gallon. Thus, incorporating the external costs associated with the use of gasoline leads to a higher social cost than the one estimated in this paper – where we focus solely on the deadweight loss resulting from the price stability policy. As the price policy

[65] Greenhouse warming and oil dependency.
[66] Congestion, accidents and local and global pollution.

during the almost thirteen-year study was primarily a subsidy policy, our estimates can be thought as a lower bound for the economic cost of the government intervention in the gasoline market.

The second hypothesis is of no other market failure, such as imperfect competition in the gasoline market. This assumption is controversial. Petrobras holds a dominant position in the fuel market in Brazil. It is responsible for 98% of Brazilian refining capacity and it is the leader in the distribution of oil products and biofuel. The liberalization process in the crude oil industry started in 1995,[67] but high logistic costs, bureaucracy, and political interventions discourage potential entrants from entering in the gasoline market.[68]

Within this context, Petrobras faces little competition. But, contrary to private monopolists that maximize profits, the goals of Petrobras are less well known. Decisions about production and fuel prices are based not only on market conditions, but also on (short-term) social and political interests. Within this scenario, an intervention in the gasoline market, such as the price stability policy,[69] leads potentially to an increase in the market concentration, and, consequently, to economic inefficiency.

Regarding the partial equilibrium analysis assumption, the problem by holding prices and quantities of other goods fixed is that we ignore the possibility that events in the gasoline market affect other markets' equilibrium prices and quantities. When calculating the deadweight loss, for example, we do not take into account the direct impacts of the price stability policy on the consumption of ethanol – the closest substitute to gasoline. The control of the price of gasoline decreases the competitiveness between both fuels and, therefore, potentially leads to a welfare loss larger than the one estimated under this hypothesis.

Finally, we assume that there is no storage. Under this assumption, producers cannot arbitrage with price. If arbitrage were allowed, then we would have to incorporate dynamic elements in our analysis. This assumption is in accordance with the Brazilian market structure. Petrobras does not have regulatory storage. In cases where domestic demand for gasoline is less than the production

[67] Ninth Constitutional Amendment: new wording to Article 177 of the Federal Constitution.

[68] The retail segment is an exception in the oil industry in Brazil. Although there are few gasoline cartels, the segment is competitive.

[69] Because of the monopoly of Petrobras and the stability of the price of gasoline, two major oil companies, Exxon and Chevron, left the distribution segment in Brazil (Freitas (2011)).

of gasoline, Petrobras exports the surplus. When the opposite happens, Petrobras imports gasoline. It must attend domestic demand.

3.5
Price stability and CO_2 emissions

3.5.1
Calculating CO_2 emissions

To estimate the impact of Brazilian policy to ensure stable gasoline prices on CO_2 emissions, we follow two steps. First, we calculate CO_2 emissions from gasoline used in Brazil. Different from most countries, the gasoline sold in Brazil contains 20% to 25% of anhydrous ethanol. And, second, we calculate CO_2 emissions based on total consumption of gasoline obtained from ANP and from the alternative scenario, in which the price of gasoline is set equal to the price of gasoline in the spot market.

According to the International Energy Agency (IEA), CO_2 emissions from conventional gasoline is 2.8 Kg per liter and from ethanol from sugar cane is as low as 0.3 Kg per liter.[70] If we assume that gasoline contains 25% of ethanol, then the amount of CO_2 emitted by the use of gasoline in Brazil equals 2.175 Kg per liter.[71]

3.5.2
CO_2 emissions estimates

Larsen and Shah (1992) show that removing world energy subsidies – more than \$ 230 billion – could reduce global carbon emissions by 9%. Also, they find that the welfare costs of these subsidies are more than \$ 20 billion even without including the negative environmental externalities.

More recently, according to the IPCC report, Climate Change 2014, CO_2 emissions from fossil fuel reached 32 billion tons in 2010 and grew further by

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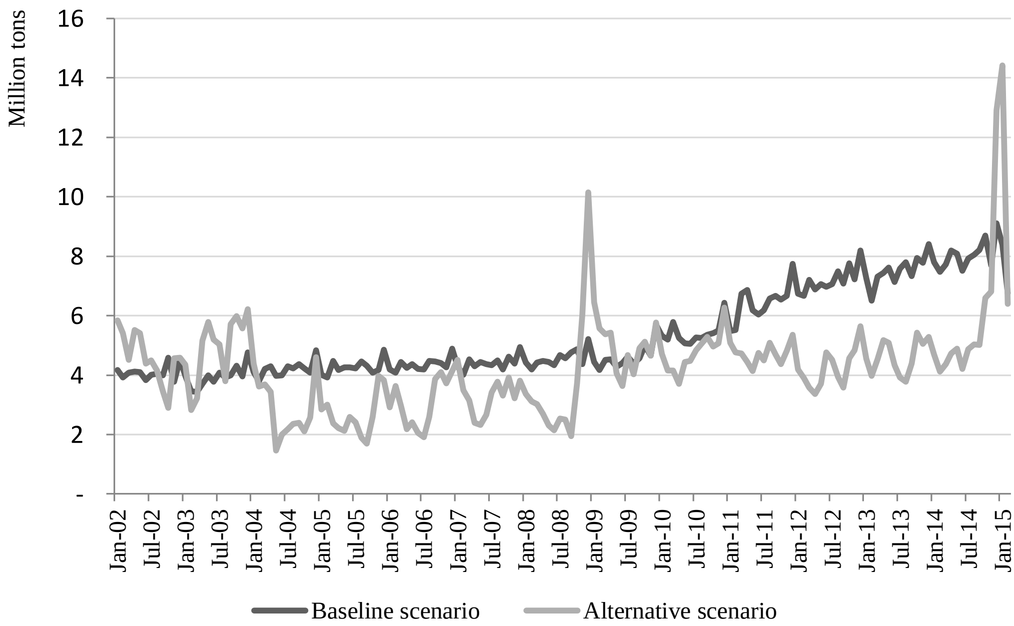
[70] For many researchers (EPE, 2005), CO_2 emissions from ethanol is 0. The amount of CO_2 emitted during combustion is compensated by the absorption of this gas through photosynthesis. However, during production, fossil resources, such as diesel, are used and this must be taken into account.

[71] $0.25 * 0.3 + 0.75 * 2.8 = 2.175$.

about 3% between 2010 and 2011, and by about 1% to 2% between 2011 and 2012.

Figure 3.8 shows the emission of CO_2 from January 2002 to February 2015. As expected, CO_2 emissions under the baseline scenario are higher than CO_2 emissions under the alternative scenario. This is because the policy to ensure price stability led, most of the time, to an overconsumption of gasoline. Throughout the period, total CO_2 emissions equaled 798.90 million tons. If the price of gasoline were equal to the price of gasoline in the international market, then total CO_2 emissions would be 618.58 million tons during the same period. As a result, the policy to maintain the price of gasoline stable led to an increase in CO_2 emissions of 180.32 million tons – or 29% – during the thirteen-year period.

Figure 3.8
CO_2 emissions resulting from the gasoline pricing policy in Brazil



The estimates found here are in accordance with other studies. In 2005, for example, we find that CO_2 emissions from gasoline were 51 million tons for 23 billion liters of gasoline consumed. According to EPE – the Brazilian federal energy planning company – for the same year, CO_2 emissions were 52 million tons.[72]

[72] To calculate CO_2 emissions, EPE uses the gasoline E25 – 25% of anhydrous ethanol and 75% of gasoline.

More recently, Gazzoni (2012) finds that, in 2011, total CO_2 emissions from conventional gasoline[73] in Brazil were, approximately, 70 million tons. For the same year, our estimates for CO_2 emissions are about 77 million tons.

According to the Ministry of Mines and Energy (MME), total CO_2 emissions in Brazil equaled 440 million tons in 2012. Based on our estimates, total CO_2 emissions from gasoline equaled 86 million tons in 2012, i.e., 19% of total CO_2 emissions in Brazil.

3.6
The effects of price stability on the consumption of ethanol

Studies on the effect of fossil fuel subsidies on the ethanol market are more limited. Besides, most studies are qualitative rather than quantitative. Market analysts agree that controlling the price of gasoline decreases the competitiveness between gasoline and ethanol and leads to allocative distortions in both markets.

Different from most countries, fuel market in Brazil is characterized by the existence of a close substitute to gasoline: ethanol. Consumers, when filling their automobiles, can choose between gasoline, ethanol or any mix between both fuels. In the first chapter of this thesis, we show that, from January 2002 to January 2013, the cross-price elasticity of the demand for gasoline is, approximately, 0.8, suggesting a high degree of substitutability between gasoline and ethanol.

In the first chapter, we focused our analysis on the gasoline market and, therefore, we did not estimate the demand for ethanol. To calculate the effects of changes in the price of gasoline on the ethanol market, we need the cross-price elasticity of ethanol demand. If there were no income effect, then we could use our previous estimate to obtain the cross-price elasticity. However, we believe this is a too strong assumption for the fuel market. Therefore, we use the estimate from Santos (2013).[74]

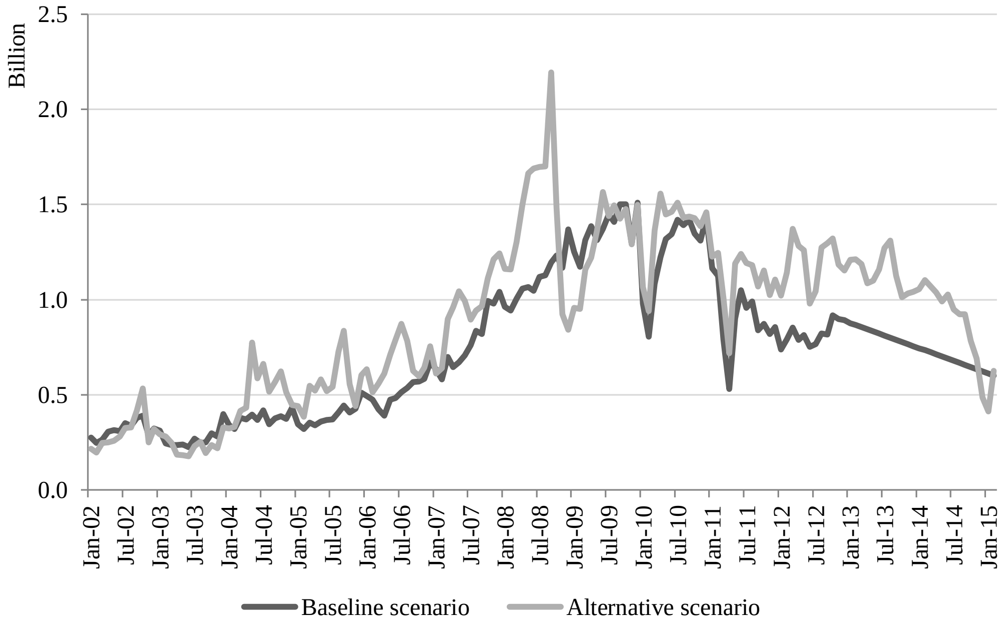
Using a dynamic panel data approach, Santos (2013) suggests that the short-run[75] cross-price elasticity of ethanol demand is 1.182. So, a change of 1%

[73] Gasoline without the addition of ethanol anhydrous.
[74] Santos (2013) is the paper closest to our first paper.
[75] To analyze the effect of the pricing policy in Brazil on the ethanol market, we use the short-run elasticity. Deciding whether to fill the automobile with gasoline or ethanol (or any combination between both fuels) is a short and not a long run decision.

in the price of gasoline leads to an increase of 1.182% in the demand for ethanol. Adopting this value and under the assumptions about gasoline demand and supply elasticities, we are able to calculate the consumption of ethanol under an alternative scenario, where the price of gasoline in Brazil equals the price of gasoline in the international market.

Figure 3.9 shows ethanol consumption under both scenarios – the baseline and the alternative one – from January 2002 to February 2015. Under the alternative scenario, ethanol consumption is higher than under the baseline scenario, which may imply that the price policy to maintain the price of gasoline stable has indeed an impact over the ethanol market. Our results suggest that during the thirteen-year period, ethanol consumption should have been – considering all other economic variables constant, except for the price of gasoline –, approximately 142 billion liters instead of 116 billion liters, an increase of 22%.

Figure 3.9
Ethanol consumption under the baseline and the alternative scenarios (in liters)



Notes: the baseline scenario correspond to the current situation, where domestic prices diverge from the prices in the international market. Under the alternative scenario, we assume that the domestic price of gasoline equals the price of gasoline in the international market. Also, to obtain the ethanol consumption under the alternative scenario, we use an estimate for the cross-price elasticity of ethanol demand found in the literature.

If we assume that the demand for fuel is inelastic, then the difference between the consumption of ethanol under both scenarios, approximately 25 billion liters, should be allocated to the gasoline market. In this case, the consumption of gasoline should have increased about 20 billion liters.[76] However, we calculated that the overconsumption of gasoline due to the price policy was 60 billion liters. Therefore, the difference between these two values is not explained by the impact of the price policy solely on the ethanol market.

Studies such as Klier and Linn (2010) and Busse, Knittel and Zettelmeyer (2013) show that changes in the price of gasoline affect not only the intensive margin, but also the extensive margin. Thus, it is possible that the policy to ensure stable prices of gasoline stimulates automobiles sales in Brazil. More study, however, is needed in this area to validate (or not) this assumption.

3.7
Conclusion

To measure the impact of the gasoline price policy in Brazil, we constructed an alternative scenario where the price of gasoline in Brazil equals the price of gasoline in the spot market. Under additional demand and supply assumptions, we measured the income transfer, the deadweight loss and the effects of this policy on the emission of CO_2 and the consumption of ethanol.

Our study suggests that the total cost of this policy during the approximately thirteen-year study was R$ 88 billion. From January 2002 to February 2015, income transfer to consumers equaled R$ 75 billion and the deadweight loss R$ 24 billion.[77] Under the baseline scenario, while CO_2 emissions were 29% higher than in the alternative scenario, the consumption of ethanol was 18% lower.

All in all, our findings show that the fiscal and environmental costs of this policy are substantial.[78] Brazilian government should allow the pass-through of international prices to domestic prices to promote efficiency and to mitigate the impact on the balance of payments, as well as negative externalities.

[76] According to the National Institute of Metrology, Quality and Technology in Brazil, 1 liter of ethanol is equivalent to 0.78 liter of gasoline.
[77] All prices are in January 2013.
[78] Petrobras – the state-owned oil company – absorbs most of the losses associated with the gasoline price policy.

APPENDIX A3

The pass-through of the price of gasoline to inflation rate

The literature on exchange rate pass-through is vast. We focus on the pass-through of commodity prices to domestic price inflation. De Gregorio, Landerretche, and Neilson (2008) present evidence of a decline in the pass-through of the price of crude oil to the inflation rate during recent decades. To calculate the pass-through, they use rolling vector autoregression estimations. In a sample of 34 countries, they find that the fall in the pass-through is more pronounced in industrial than in emerging economies. According to them, the reduction in the oil intensity of economies around the world, the reduction in the exchange rate pass-through, and a more favorable inflation environment are the most important factors for explaining the declining in the pass-through.

Zoli (2009) shows that shock in commodity prices have a significant impact on domestic inflation. The inflation response, however, is asymmetric for positive and negative shocks. Using a panel model for 18 European emerging economies, with quarterly data, Zoli (2009) finds that, on average, in the long run, a 1 percentage point surge in oil price inflation leads to an increase in headline inflation by 0.02 percentage points, whereas a decline in oil price inflation by the same amount results in a drop in headline inflation by 0.04.

Gelos and Ustyugova (2012) show that countries respond different to commodity price shocks. In a sample of 25 countries and using several approaches, they find that economies with higher food shares in the Consumer Price Index baskets, fuel intensities, and pre-existing inflation levels were more prone to experience sustained inflationary effects from commodity price shocks.

In Brazil, De Melo (2010) presents evidence that shocks in the international prices of commodities after June 2005 have a lower impact on inflation rate. While from January 2000 to May 2005, the pass-through of a 1% shock in commodity prices on inflation rate equaled, approximately, 30%, from June 2005 to May 2010, the pass-through was almost null 3 years after the shock.
Ono (2014) shows that an increase of 10% in the price of commodities increases the inflation rate in 0.132% ten months after the shock. He uses vector

autoregression models and database from January 2004 to April 2013 to calculate the pass-though.

Following the literature on the effects of changes in the exchange rate on the economy, we use vector autoregressions with exogenous variables (VARX) to calculate the gasoline price pass-through to the inflation rate in Brazil. Besides the price of the gasoline to consumers and the inflation rate, we consider the price of crude oil, the exchange rate and the industrial production index – a measure of economic activity. These macroeconomic variables are added in the model to control for potential correlation between these variables and the price of gasoline and the inflation rate. The reduced-form of the model is:

$$Y_t = \Lambda_0 + \Lambda_1 Y_{t-1} + \cdots + \Lambda_p Y_{t-p} + \Theta X_t + \varepsilon_t$$

Where Y is a vector with the endogenous variables, i.e., the nominal exchange rate, the industrial production index, the nominal price of gasoline to consumers and the inflation rate; X is the vector with the exogenous variables, i.e., the nominal price of crude oil, 11 monthly dummy variables and 2 annual dummies, 2002 and 2008 to capture the presidential election in Brazil and the international financial crises respectively; and p is the optimal number of lags.

When estimating the VAR model, we transform the variables,[79] using the first-difference of the natural log of the variables to obtain stationarity.[80]

More specifically, to identify our model and capture the pass-through of gasoline price to inflation, we assume that the price of crude oil is an exogenous variable. The price of crude oil is determined in the spot market as a function of, mainly, global demand and supply. Despite the recent discoveries and the development of large crude oil and gas reserves, Brazil is not yet a major player in the crude oil market.

The exchange rate, the industrial production index, the price of the gasoline, and the inflation rate are assumed to be endogenous variables. To obtain the causal relationship between them, we assume a recursive chain of causality among the shocks (or innovations) of these four variables. First, we assume that

[79] Except for the inflation rate that is already stationary.
[80] Except for the inflation rate, we use the variables in log to obtain the percent variation when taking the first-difference.

the exchange rate is affected contemporaneously by the shock to itself. According to Meese and Rogoff (1983) and Cheung, Chinn and Pascual (2005), the exchange rate is better explained by a random walk than by more complex models.[81] Without being too restrictive, we allow that the past values of the other macroeconomic variables used in this study offer improvement in forecasting exchange rate movements. Second, we assume that industrial production is not affected contemporaneously by shocks in the gasoline market and in the inflation rate.[82] Third, we allow that the price of gasoline be affected contemporaneously by the economic activity. It is plausible to think that when the economy increases, the income also increases and, as a result, people drive more, using, therefore, more gasoline. And, fourth, we assume that the inflation rate may respond to contemporaneous changes in the exchange rate, the economic activity and the gasoline price.

In matrix notation, those assumptions imply that the reduced-form vectors – ε– are related to the shocks (structural disturbances) – u – in the following way:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ \emptyset_{21} & 1 & 0 & 0 \\ \emptyset_{31} & \emptyset_{32} & 1 & 0 \\ \emptyset_{41} & \emptyset_{42} & \emptyset 0_{43} & 1 \end{bmatrix} . \begin{bmatrix} \varepsilon_t^{exchange\ rate} \\ \varepsilon_t^{industrial\ production} \\ \varepsilon_t^{gasoline\ price} \\ \varepsilon_t^{inflation\ rate} \end{bmatrix} = \begin{bmatrix} u_t^{exchange\ rate} \\ u_t^{industrial\ production} \\ u_t^{gasoline\ price} \\ u_t^{inflation\ rate} \end{bmatrix}$$

All in all, to identify our model and to calculate impulse response functions, we assume that the errors are orthogonalized using the Cholesky decomposition. To obtain the pass-through we calculate the accumulated impulse response functions. Following the literature on exchange rate pass-through, we use the ratio between the accumulated responses of inflation rate to one standard deviation shock j horizons after the shock to measure the gasoline pass-through to inflation.[83]

[81] Knowing the determinants of the exchange rate is still an active area of research.
[82]We assume that the common shocks between the price of gasoline and the industrial production that could bias our estimates are the shocks in the crude oil market and in the exchange rate; both shocks are taking into account in our model.
[83]After estimating the VAR model, we conduct several tests (shown in Appendix 1) to ensure that the model captures well the dynamics between the variables.

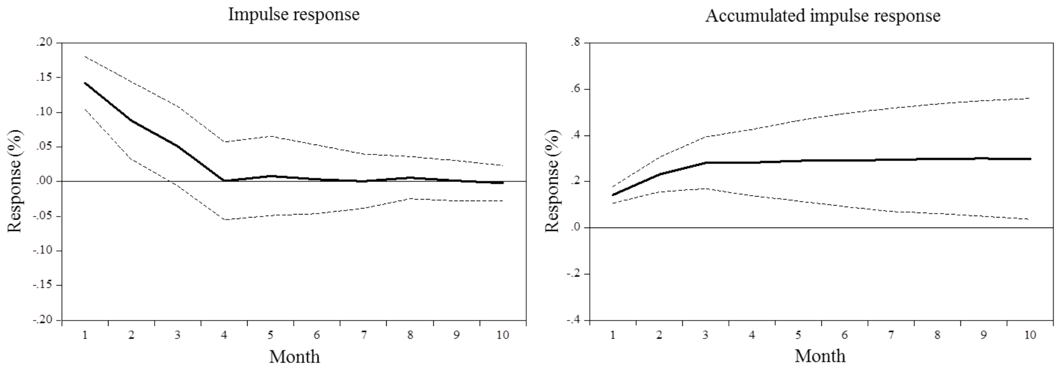
Figure A3.1 displays the response and the accumulated response of the inflation rate to a one-standard deviation shock in the price of gasoline.[84,85] The dashed lines in Figure A3.1 represent the two standard deviation confidence intervals, which are calculated using Monte Carlo simulations with 1,000 replications. The impulse response in Figure A3.1 suggests that an increase of one standard deviation (about 5.22%) in the price of gasoline leads to an instantaneous increase of 0.14% in the inflation rate. It is worth mentioning that as the inflation rate is not in log, the increase is additive. So, for example, if the monthly inflation rate in January 2013 is 0.86%, then, within a context where everything else is constant except for the shock in the price of gasoline, the monthly inflation rate in February 2013 would be 1%, an increase of approximately 16%.

The accumulated impulse response in Figure A3.1 suggests that six months after the shock, the accumulated response is 0.29% and after one year, 0.3%. As mention before, we can interpret this change as percentage points, so, within a scenario where we forecast an annual inflation equal to 6%, we should, after the gasoline price shock, adjust our forecast to 6.3%.

Based on the exchange rate pass-through literature, the pass-through of the shock in the price of gasoline to inflation rate is 5.74% one year after the one-standard deviation shock. This pass-through seems small and present evidences that the government intervention in the gasoline market prevents a higher pass-through.

[84] The accumulated impulse-response functions for the other variables are shown in Appendix A.
[85] As the price of gasoline was transformed to log first difference, the one-standard deviation shock is interpreted as a permanent shock.

Figure A3.1
Response of the inflation rate to a one-standard deviation shock in the price of gasoline with two standard error bounds



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