Heinz 90-904: Project Proposal

Abstract – This paper examines to which extent a better informed consumer can actually perform better decisions. The focus on this paper is on Brazilian market fuel and the substitutability of gasoline and ethanol. Since the introduction of flexible-fuel vehicles in 2003, i.e., vehicles that could run both with gasoline and ethanol, there's been an increasing demand for ethanol, even though its effectiveness as fuel is lower than that of gasoline. It is well known among population that the ratio between prices that makes them even is around 70%, but consumers rarely compute it at the time of purchase. Since 2007, some Brazilian States established some laws mandating all gas stations to show this ratio to consumers, to help them make better decisions. This paper address this policy, evaluating the effectiveness of this law.
Key-words – fuel markets, gasoline, flexible-fuel vehicles

1 Introduction

In the pursuit of better study designs, specially in cases where a randomized control trial is not possible, many different techniques were developed to restore a setting similar to a randomized trial, from which causal inferences could be measured and studied. It was in this pursuit for methods that could give us back the causal impact of some treatments that all matching methods were introduced, including propensity score methods. As described by [RR83], propensity score was firstly designed as a conditional probability to assign some individuals to a treatment, given some sufficient statistic comprised of a vector of observational covariates.

Many studies were done based on these methods and recently, in the field of supervised machine learning, the structure of propensity score were revisited, including some improvements derived in the weighting methods for achieve the propensity score. Basically, most papers used to rely on estimating propensity scores based on logistic regressions (see [LS09]). It was the introduction of new techniques for classification that allowed further improvements in the estimation of propensity scores.

This paper will focus on a specific policy applied in some States in Brazil, trying to evaluate its effectiveness in providing more relevant information to general population in these States. To achieve this purpose, it will be applied a propensity score method, based on calibrated classifier method, to improve the efficiency of the propensity score and refine the results.

The paper is organized as follows: section 2 will describe the main problem, addressing its features and challenges, while section 3 will provide description of the dataset used in this paper, and also the methodology applied. Section 4 discuss the results and present final statements.

2 Background

Since 1908's, due to the petroleum shocks in the 70's, Brazilian authorities started pursuing alternative sources of fuel in order to become less susceptible to fossil fuels market. One viable source was ethanol, which was quite popular in the 80's, becoming almost forgotten through the 90's, specially because most car engines, by then, were unable to handle at the same time both fuels. Having to choose in advance, in the vehicle's purchase, the kind of fuel on which it would work, it is of no surprise vehicles moved on ethanol could never become the majority in the national fleet.

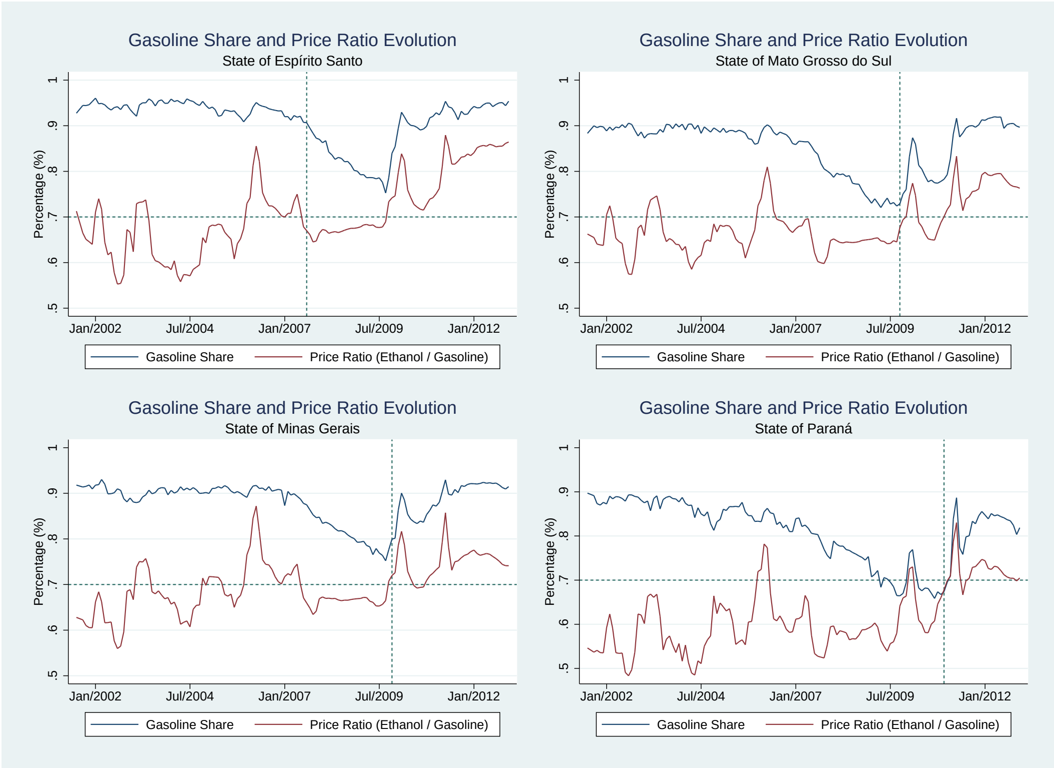
This scenario started changing in 2003, when the first flexible-fuel vehicle (FFV) began to be sold in Brazil. Capable to run by ethanol, gasoline or any mixture of both, soon this type of vehicle became the majority among new vehicles purchases. To complement this scenario, the international financial crisis in 2008 was the trigger to make Brazilian authorities to publish a series of incentives to automobile industries, as a counter-cyclical policy, which made the FFV fleet increase even faster.

But with all these new cars moved by both fuels, another problem arise: how to choose between gasoline and ethanol, i.e., how to know which fuel would be more efficient at given prices? The answer to this question is based on the actual effectiveness of both fuels, and the price at which both fuels become equally efficient is when ethanol prices equal 70% of gasoline prices. Although simple to compute and intuitive, in practice it was soon clear that for the general population, it would be impossible to compute the ratio of the prices every time they went to a gas station. Old habits as pumping the same fuel they were used to, without even comparing prices, would soon be preferable to have to compute prices and decide (see [SH13]).

Starting in 2007, a number of States introduced a similar law, mandating all gas stations to provide visible banners with the ratio of the prices, and also to provide clear explanation on which fuel had better cost-effectiveness at the time of the purchase. Espirito Santo was the first state to address this law, followed by other states along the past 10 years. The table below presents each state and the year they promulgated this law.

State		State Law	Start
Espírito Santo	ES	8.526/2007	08-Jul-07
Mato Grosso do Sul	MS	3.755/2009	07-Oct-09
Minas Gerais	MG	3.368/2009	21-Nov-09
Paraná	PR	16.756/2010	29-Dec-10
Mato Grosso	MT	459/2011	25-Aug-11
Bahia	BA	19.518/2011	17-Oct-11
Sergipe	SE	7.272/2011	17-Nov-11
Pernabuco	PE	14.838/2012	22-Nov-12
Piauí	PI	6.503/2014	18-Mar-14
Goiás	GO	286/2014	03-Jun-14
Paraíba	PB	10.356/2014	12-Nov-14

Next figure shows some States and how gasoline share react since the introduction of the law. Notice that after 2009, there's a clear correlation between prices ratio and gasoline share, suggesting that people started to react to prices changes, choosing the best fuel at each pumping time.



The data used in this paper comprises different sources. First, fuel prices came from a weekly survey managed by Brazilian National Petroleum Agency (ANP) - the office responsible for fossil fuels market regulations -, which also provided monthly volume data for all cities in Brazil. Flex fleet and total fleet came from our National Traffic Agency (Denatran), while other demographics were obtained from Datasus, a Brazilian database with most demographic information. To control for possible endogeneities in prices, international prices on sugar and oil were also gathered.

3 Methodology

Following previous studies on evaluation of public policy, this paper will apply propensity score to evaluate if the introduction of the mentioned law in fact was relevant to contribute for the decision-making process when pumping fuel.

Our data provide us with panel of cities long before and after most laws' introduction. Our model will be based on a bottom-level equation of an *Almost Ideal Demand System (AIDS)*, in which we are interested in estimating the share of gasoline based on fuel prices, dummies for the treatment states (to capture some state-fixed effect) and law impact (the variable of interest), and some demographics that might work as confounders and control.

Most of the data adjustment was previously done in Stata, merging all data, averaging weekly prices into monthly prices, and creating all dummies, share and other variables we needed. Those data were imported to Python, which was the platform on which we estimated our models.

As suggested in the introduction, we are going to use a calibrated classifier method to estimate the propensity scores used in the pooled OLS. The idea is using a calibrated classifier (CV) method and use the propensity score estimated with inverse probability of treatment weighting. Then, we will proceed to a Generalized Method of Moments using this IPTW as weighting matrix to retrieve the coefficients of interest. Since we haven't run other machine learning models for comparison, our standard model considered will be the classical gmm with no propensity score method (simple pooled OLS model). We also estimated a propensity score method using instrumental variables for prices and obtained interesting results, as will be further discussed in the next section.

4 Results

The tables for the three models are in the appendix section. In all three models, we notice a significant coefficient for the law variable ("Lei"). In the pooled OLS we can notice a much stronger coefficient (+ 0.0460), while in the second model using the inverse probability of treatment weighting and propensity scores we obtain a much lower impact (+0.0338).

If, for the same model using IPTW, we include instrumental variables for prices, we notice that the coefficient for the law is small (+0.0344) and very close to the coefficient found in the second model. This happens because the Inverse Probability of Treatment Weighting already weighs each confounder in a way to improve efficiency and reduce bias, including fixing the inconsistency caused by endogenous variables.

From our results, we can conclude that there seem to be some significant , though small impact of this law. This means that consumers in fact became more aware of the best option available when they need to go to any gas station to pump fuel.

5 Appendix

Below is the model for the pooled OLS.

	coef	std err	z	P>|z|	[0.025	0.975]
logExpend_nt	-0.0014	0.001	-2.695	0.007	-0.002	-0.000
frota_flex	-1.254e-07	8.77e-09	-14.302	0.000	-1.43e-07	-1.08e-07
Pr_int_gas	-0.3624	0.006	-61.578	0.000	-0.374	-0.351
Pr_int_etl	0.3937	0.002	159.641	0.000	0.389	0.399
Lei	0.0460	0.001	31.309	0.000	0.043	0.049
pop	1.314e-08	7.44e-10	17.678	0.000	1.17e-08	1.46e-08
homens	1.0811	0.022	48.480	0.000	1.037	1.125
trend_id	-2.823e-06	3.31e-08	-85.383	0.000	-2.89e-06	-2.76e-06
educ1a3	0.4327	0.015	29.427	0.000	0.404	0.462
educ4a7	0.8086	0.013	61.998	0.000	0.783	0.834
educmais8	0.5218	0.014	36.866	0.000	0.494	0.550
ES	-0.0357	0.002	-17.599	0.000	-0.040	-0.032
MS	-0.0619	0.003	-23.010	0.000	-0.067	-0.057
MG	-0.0443	0.001	-38.984	0.000	-0.047	-0.042
PR	-0.0374	0.001	-25.845	0.000	-0.040	-0.035
MT	-0.0792	0.003	-28.954	0.000	-0.085	-0.074
BA	-0.0347	0.001	-24.088	0.000	-0.037	-0.032
SE	0.0761	0.004	21.274	0.000	0.069	0.083
PE	0.0150	0.002	9.975	0.000	0.012	0.018

The following table shows the model using inverse probability of treatment weighting in a propensity score design.

	coef	std err	z	P>|z|	[0.025	0.975]
logExpend_nt	-0.0050	0.000	-13.939	0.000	-0.006	-0.004
frota_flex	-2.522e-08	3.91e-09	-6.442	0.000	-3.29e-08	-1.75e-08
Pr_int_gas	-0.3659	0.004	-82.954	0.000	-0.375	-0.357
Pr_int_etl	0.4011	0.002	208.759	0.000	0.397	0.405
Lei	0.0338	0.001	42.981	0.000	0.032	0.035
pop	1.094e-08	5.94e-10	18.421	0.000	9.78e-09	1.21e-08
homens	1.2749	0.016	80.297	0.000	1.244	1.306
trend_id	-2.642e-06	2.51e-08	-105.293	0.000	-2.69e-06	-2.59e-06
educ1a3	0.3696	0.011	34.585	0.000	0.349	0.391
educ4a7	0.6889	0.010	71.358	0.000	0.670	0.708
educmais8	0.4479	0.010	45.954	0.000	0.429	0.467
ES	-0.0624	0.001	-58.455	0.000	-0.064	-0.060
MS	-0.0611	0.001	-45.853	0.000	-0.064	-0.058
MG	-0.0309	0.001	-39.069	0.000	-0.032	-0.029
PR	-0.0412	0.001	-45.200	0.000	-0.043	-0.039
MT	-0.1121	0.002	-61.934	0.000	-0.116	-0.109
BA	-0.0308	0.001	-30.284	0.000	-0.033	-0.029
SE	0.1065	0.002	53.266	0.000	0.103	0.110
PE	0.0195	0.001	16.583	0.000	0.017	0.022

Next table shows the model using inverse probability of treatment weighting in a propensity score design.

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
logExpend_nt	0.0007	0.0009	0.7409	0.4587	-0.0011	0.0025
frota_flex	-9.475e-08	1.217e-08	-7.7869	0.0000	-1.186e-07	-7.09e-08
Lei	0.0344	0.0018	19.320	0.0000	0.0309	0.0379
pop	1.117e-08	8.974e-10	12.449	0.0000	9.413e-09	1.293e-08
homens	1.1104	0.0487	22.804	0.0000	1.0150	1.2058
trend_id	-2.647e-06	7.845e-08	-33.746	0.0000	-2.801e-06	-2.493e-06
educ1a3	0.4347	0.0304	14.289	0.0000	0.3751	0.4944
educ4a7	0.7330	0.0318	23.073	0.0000	0.6708	0.7953
educmais8	0.4859	0.0312	15.580	0.0000	0.4248	0.5470
ES	-0.0550	0.0018	-30.933	0.0000	-0.0585	-0.0515
MS	-0.0607	0.0032	-19.197	0.0000	-0.0669	-0.0545
MG	-0.0273	0.0011	-24.192	0.0000	-0.0295	-0.0251
PR	-0.0425	0.0018	-23.405	0.0000	-0.0461	-0.0390
MT	-0.1237	0.0050	-24.559	0.0000	-0.1335	-0.1138
BA	-0.0351	0.0021	-16.358	0.0000	-0.0393	-0.0309
SE	0.0923	0.0034	26.986	0.0000	0.0856	0.0990
PE	0.0158	0.0015	10.570	0.0000	0.0129	0.0188
Pr_int_gas	-0.4072	0.0279	-14.610	0.0000	-0.4618	-0.3525
Pr_int_etl	0.4585	0.0079	58.035	0.0000	0.4430	0.4740

Endogenous: Pr_int_gas, Pr_int_etl
Instruments: oil, white_sugar
GMM Covariance
Debiased: False
Robust (Heteroskedastic)

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