AN ESTIMATION OF THE SURVIVAL OF RETAIL GASOLINE PRICES *

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ABSTRACT

This paper studies how competition works in the fuel industry, by estimating the survival prices for the Chilean retail gasoline markets. We use a rich data set of prices available online that tracks changes in fuel costs. Every Thursday at zero hour, publicly announced new costs are in effect, thus gas-stations react by changing their prices. We estimate a piece-wise exponential model, separating for the different gasoline qualities (93, 95 or 97) and for diesel. The evidence shows that retail prices slowly change during the following days to the announcement, and that this behavior is asymmetric regarding the sign and the magnitude in costs changes. The asymmetric pricing response is explained by characteristics at the gas-station level, such as brand, country's geographic region, and some amenities offered by gas-stations. Given the structure of these markets, the most reasonable explanation for this asymmetric behavior is the strategic use of pricing as a reaction to soft competition.

Keywords: Asymmetric pricing, Gasoline, Fuel, Survival, Duration, Hazard rate, Chile

JEL Classification: C41, L13, M21

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1. INTRODUCTION

By far the change in the international oil price is the main source of variation of retail fuel prices (gasoline, kerosene, GLP, and diesel). Chile, a small country that imports almost 100% of its fuels consumption, has a state owned firm -ENAP- that is the only company that refines crude in the country. ENAP sells fuels to wholesale distribution companies based on production (ex-refinery) costs, following a policy that change prices every week according to the change in the international oil price. Downstream, firms are privately owned and there is no price regulation at all. Therefore, one of the main concerns of both the antitrust authority ant the sector regulator is how retail companies use their market power to extract rents from consumers, by choosing the timing of pricing. [1]

Recently, in order to have more information on the behavior of retail gasoline markets in Chile, the National Energy Commission (CNE, the regulator of the energy sector) mandated each gas-station to inform online its prices through the website www.bencinaenlinea.cl. Implemented during 2012, this website provides the prices of each fuel sold by over 1,500 gas-stations, the universe of these retailers in the country.

This paper analyzes the duration of retail prices after a change in costs. It is important to mention that ENAP publicly announces the change in its prices on Wednesday afternoon. The new costs become effective on Wednesday midnight. Hence, it is of our interest to study how fast gas-stations change their prices, and in particular whether this response varies depending upon both the sign and the magnitude of the change in costs. It is also important to investigate what economic characteristics influence the survival function of prices, such as the fuel itself, the brand of the wholesale distributor, geographical location, or some amenities that gas-stations offer.

A different but related question is to assess the size of the change in prices relative to the size of the change in costs; in other words, how big is the pass through in retail gasoline markets. There is evidence for developed economies showing an asymmetric response to change in cost in this industry (Bacon, 1991; Kirchgässner & Kübler, 1992; Borenstein, Cameron & Gilbert, 1997; Asplund, Eriksson & Friberg, 2000; Godby, Lintner, Stengos, & Wandschneider, 2000; Bachmeier, & Griffin, 2003; Bettendorf,

[1] Unfortunately, we do not have information regarding vertical ownership between a wholesale distributor and retail firms. We just observe when a gas-station is using a brand of a major distributor, but not whether the former is or not an ancillary of the latter. Hence, we assume in the rest of the paper that wholesale distributors do not use their market power against rivals in the retail segment of the industry.

Van der Geest, & Varkevisser, 2003; Deltas, 2008; Verlinda, 2008). Recent studies show that this behavior may be explained in a search model context where non-informed consumers search more when costs increase than when costs decrease (Tapatta, 2008; Cabral & Fishman, 2010; Lewis, 2011).

This empirical issue was also studied for Santiago, Chile (Balmaceda & Soruco, 2008) based upon a sample of gas-stations pricing. As most of the empirical literature, these authors use a time series model. They find asymmetric pricing and explain this phenomenon arguing that the ENAP's policy of announcing new wholesale prices may facilitate collusion.

We find the same asymmetric behavior strategy for the universe of gas-stations in Chile. Since we have a richer data set with an online and instantaneous change in retail prices, that is a minute-to-minute pricing, we use the survival literature to asses this problem. We do so because we are interested in the (strategic) timing of price changes chosen by gas-stations. So, the data provides us with the hazard rate and the velocity of the price changes, both conditional on the characteristics of each gas-station. We find that the asymmetric response behavior is perfectly consistent with strategic dynamic pricing considering three complementary explanations: strategic behavior of firms that have some market power, multi-product firms, and the limited rationality of consumers that do not use the full available information on retail prices.

This paper is structured as follows. Next section shows the asymmetric pricing in retail gasoline markets by using a non-parametric approach, the Kaplan-Meir method that estimates the survival function of prices. Section three explains the methodology modeling and the data that we use in this paper. We present the main results in section four, estimating models with and without heterogeneous effects at the gas-station level. In section five we check the robustness of our main findings by estimating alternative semi-parametric models of the hazard rate function. Finally, section six concludes.

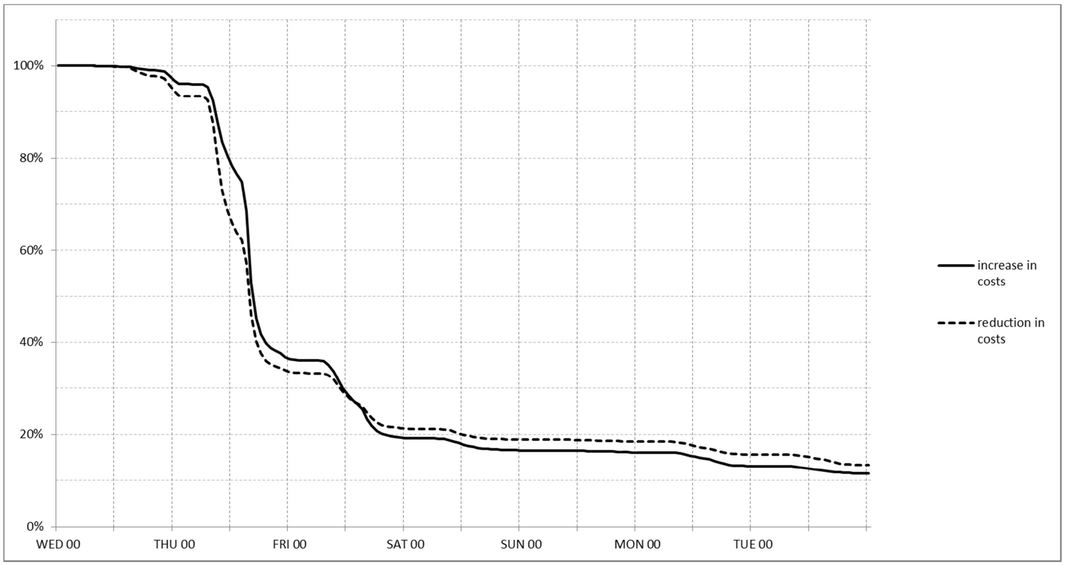
2. A Non Parametric Approach to the Survival Function

A first glance of the gas-stations pricing strategy, following a change in their costs, is provided by an estimation of the survival function. To this end, we use the Kaplan-Meier estimator. Figure 1 depicts this function for more than 125,000 pairs of weekly prices and gas-stations, 55% of the times the price goes up and 45% of the times it goes down.[2] We

[2] Details on econometric results may be provided upon request.

observe that retail prices are clearly sticky. Gas-stations start changing prices after six hours of the new costs are in effect. After two days still there are 20% of gas-stations that keep their old prices; and after a week, there are 12% to 15% of them that do not react to new market conditions.

Figure 1. Survival Function for All Prices, up & down costs

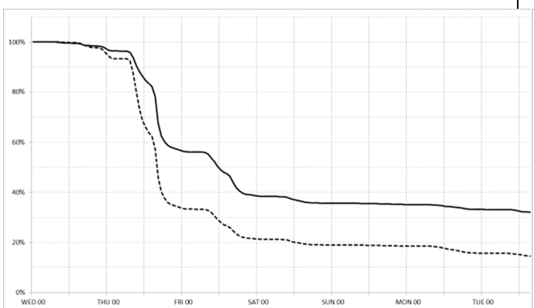


Note: The long-rank test for identical survival functions rejects this null hypothesis: Chi-2(1) = 73.9.
Source: Own estimation based on National Energy Commission – Chile data.

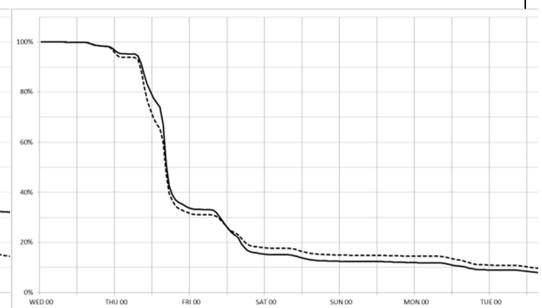
The second result that is illustrated by Figure 1 is that the response of retail prices is asymmetric regarding the movement on costs. However, contrary to Balmaceda & Soruco (2008) and Borenstein, Cameron & Gilbert (1997), it is not clear from this figure the direction of the asymmetry. One feasible explanation is that gas-stations cares more about the new costs as the magnitude of the change becomes higher, as depicted in Figures 2a) to 2d).

Figure 2. Asymmetry in Pricing for alternative Magnitudes of Cost Changes

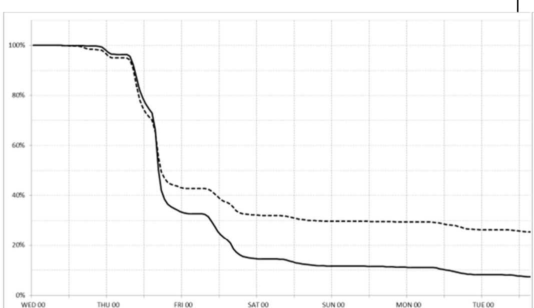
a) Change: 0% - 0.5%



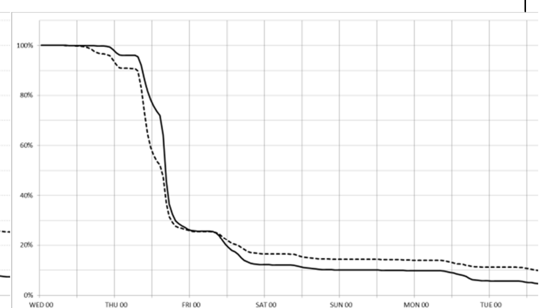
b) Change: 0.5% - 1%



c) Change: 1% - 1.5%



d) Change: More than 1.5%



Note: The long-rank test for identical survival functions rejects this null hypothesis for all cases.
Source: Own estimation based on National Energy Commission – Chile data.

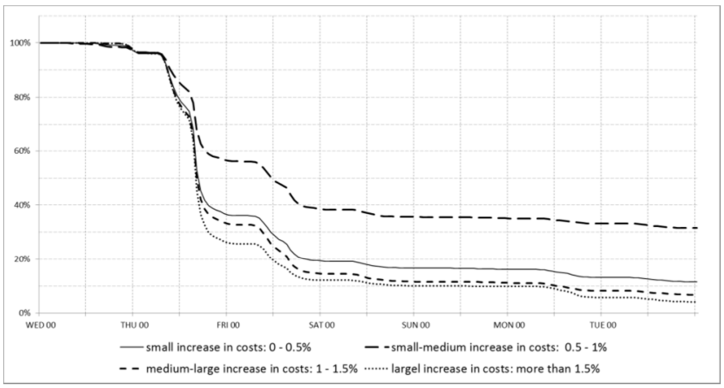
The non-monotonicity of this asymmetry is better understood observing Figures 3a) and 3b). Figure 3a) tells us that the larger the increase in costs, the faster the reaction of each gas-station to adjust its prices, except for small changes. Similarly, Figure 3b) shows us that the larger the decrease in costs, the faster the reaction of gas-stations to new cost conditions, except for small changes in costs.

We also estimated the survival function per fuel, brand, geographical region, and alternative gas-stations amenities. Statistically different survival functions per fuel tell us that the industry shows a non-perfectly competitive behavior, since once decided to fix new prices, the change should be done at the same moment for all fuels. This is not the case when comparing any gasoline's survival function with diesel's survival function. The brand that each gas-station uses to sell fuels to consumers also matters. Different survival functions suggest that gas-stations using the brand of the two major wholesale distribution companies, Copec and Shell, react by moving their retail prices faster (Copec) and finally more (Shell) than the rest of their rivals.

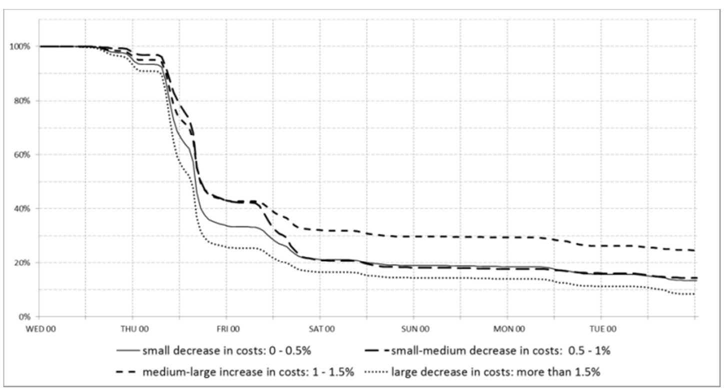
We also found that prices are stickier in Santiago, the capital city than in the rest of the country, and that the amenities that gas-stations offer to consumers are relevant in explaining their pricing behavior. The rest of the paper aims to put all these gas-stations heterogeneity together.

Figure 3. Asymmetry in Pricing for Increase and Decrease in Costs

a) Increasing Costs



b) Decreasing Costs



Note: The long-rank test for identical survival functions rejects this null hypothesis for both cases.
Source: Own estimation based on National Energy Commission – Chile data.

3. Methodology and Data

In order to study the price change behavior of firms, we model the probability of changing prices in an event-history framework. The hazard function $h_i(t; Z_i(t))$ for firm i at time t will be assumed to take the proportional hazard form

$$h_i(t; Z_i(t)) = \lambda_0(t)\exp(Z_i(t)\beta) \qquad (1)$$

where $\lambda_0(t)$ is the baseline hazard function, $Z_i(t)$ is a vector of possible time-dependent explanatory variables for firm *i* at time t and β is a vector of parameters to be estimated. We model the baseline hazard using a piecewise-constant exponential (PCE) model. The PCE model is an example of a semi-parametric continuous time hazard specification, in which it is directly estimated whether the baseline hazard increases or decreases with survival time. In order to do so, we partition survival time in K periods (we chose intervals of 6 hours from t =12 to t = 48, and after that we set up 12-hour intervals), and define

$$\lambda_0(t) = \begin{cases} \theta_1 \text{ if } t \in (0, \tau_1) \\ \theta_2 \text{ if } t \in (\tau_1, \tau_2) \\ \cdots \\ \theta_\kappa \text{ if } t \in (\tau_{\kappa-1}, \tau_\kappa) \end{cases}$$

That is, we are letting the data to tell what the shape of the hazard is, , but we are restricting it to be constant within pre-specified (and relatively short) time intervals. This type of model is in between a Cox proportional model (in which the baseline hazard is estimated non-parametrically) and a parametric model, in which a specific functional form is assumed for the hazard. In any case, the covariates included in Z will have a multiplicative effect on the hazard function. The dependent variable in model (1) is an indicator variable that assumes the value one if the firm changes the price in a given week,[3] the value zero if the firm does not change the price.

That is, after the authority makes the announcement each firm must decide whether to change or not to change prices. In our data base, then, each record is the weekly behavior for a given firm. We do have, then, multiple observations for each firm, what could cause failure times to be correlated for a given firm, which violates the assumptions of the traditional hazard models. We will have to take into account this issue in our estimation.

We rewrite (1) in order to reflect the existence of multiple price changes per gas station. Following Therneau's (1998) notation we can rewrite this expression as

$$h_{ij}(t; Z_{ij}(t)) = \lambda_0(t)\exp(Z_{ij}(t)\beta + C_i v_i) \qquad (2)$$

[3] Petersen (1995) address specifically the observability issue of the dependent variable in hazard models. The dependent variable in Hazard models can be viewed as either a dummy variable that takes the value one when an event takes place in the interval t - t+Δt (event-history formulation) or the time that elapses before an event (or censoring) takes place. Under both interpretations the dependent variable is fully observable.

where $C_i = 1$ only for a record j that belongs to firm i, and ν is a random variable from a known distribution. Two approaches are extensively used in the literature to model this kind of situation. In the first approach (random effect model) the association between failure times is explicitly modeled as a random effect while in the second approach (marginal model) the covariance matrix of the estimators is adjusted to account for such correlation.

In random effect or *frailty* models, the unobservable heterogeneity is assumed to have a multiplicative effect on the individual hazard. In terms of (2) the model is written as

$$h_{ij}(t; Z_{ij}(t), v_i) = \alpha_i h_{ij}(t; Z_{ij}(t)) \tag{3}$$

where α_i is assumed to be a random positive quantity as the hazard cannot be negative. Whenever the value of the frailty is greater than one, the individual will have a larger than average hazard. The most frequently used model assumes that the frailties follow a gamma distribution with mean one and variance θ. In terms of estimation, a variant of the E-M algorithm is used. First, the likelihood for the observed history on a firm conditional on observable and unobservable variables is derived. Then, one should compute the average value of the likelihood, where the averaging is done over all possible values of α_i. Then this average likelihood is maximized using standard procedures.[4]

The marginal models or *variance-corrected* models propose to estimate parameter β in (2) assuming independence of the failure times. That is, in terms of the likelihood function set up, if the failure times are independent conditional on the explanatory variables, the likelihood of the entire job history of a given person consists of the sum of the log-likelihood functions of each job. In terms of (2) we can estimate

$$h_{ij}(t; Z_{ij}(t)) = \lambda_0(t)\exp(Z_{ij}(t)\beta) \tag{4}$$

The estimator $\hat{\beta}$ obtained from (4) or (5) will be consistent for β and asymptotically normal under the assumption that either (4) or (5) are correct specifications of the failure process. The traditional estimator of the covariance matrix, however, is no longer correct since it does not take into account the correlation across

[4] See Therneau (2000) for a simple (although complete) description of this methodology. Therneau & Grambsch (2000), and Petersen (1995) offer a more formal treatment; while Hosmer (1999) offers a more applied approach.

failure times.[5] Lin & Wei (1989) propose an extension of White's robust variance estimator to account for the correlation of failure times for the same individual. Clayton (1994), Therneau (1998), & Hosmer (1999) provide a complete coverage of this methodology and robust variance-covariance matrix calculations.[6]

Then the two models to be estimated are be given by

$$h_{ij}(t;Z_{ij}(t),v_i)=\alpha_i h_{ij}(t;Z_{ij}(t))=\alpha_i\lambda_0(t)\exp(Z_{ij}(t)\beta) \qquad (5)$$

where α_i is assumed to follow a gamma distribution with mean one and variance θ, and

$$h_{ij}(t;Z_{ij}(t))=\lambda_0(t)\exp(Z_{ij}(t)\beta) \qquad (6)$$

In both cases the baseline function is assumed to be piecewise constant within certain specified time intervals.

Regarding the data that we use in this paper, fuels retail prices for all gas-stations in Chile was provided by the energy agency regulator of Chile, the National Energy Commission. Thanks to a mandatory order enacted by this regulator, each gas-station has to enter their retail prices to an online system. This policy started on June 2012, thus we use the universe of consumer prices from June 2012 to November 2012. The regulator also provided us with information about each gas-station, such as its brand, location, and related services (convenience store, pharmacy, autoservice, public restroom, and car maintenance service).

We also use the announced ex-refinery prices that ENAP, the state-owned firm in the upstream, establishes every week and enter into effect on Thursdays at hour zero. ENAP announces their new prices every Tuesday afternoon to the wholesale distributors and make public such announcement on Wednesday afternoon. Thus, new costs for retailers are perfectly known for everybody at least 12 hours before they become in effect on Thursday midnight. Therefore, just for the empirical work, we will assume that the announcement is in between of these two actual announcements, that is on Wednesday at zero hour.

It is important to mention two facts. First, we clean the original data on retail prices by eliminating typos (e.g., prices whose change differs ten times or more than ENAP's announced change) or trembling-hand mistakes (e.g., prices that gas-stations

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[5] The usual estimator of the covariance matrix will be given by the inverse of the Information Matrix $I^{-1}=\vartheta^2\log L(\beta)/\vartheta\beta\vartheta\beta'$.

[6] Cleves (1999) specifically addresses the estimation of *variance-corrected* models in STATA.

change after seconds of being entered into the system). Secondly, the difference between the retail price and the cost announced by ENAP corresponds to the gross margin, and it includes taxes, transportation costs, and the net margin of the wholesale distributor. Since the latter is unknown to these researchers, we assume that it remains constant during June and November 2012.

4. RESULTS

As it was stated in the methodology section, we will estimate the hazard models with and without heterogeneous effects at the firm level. In other words, the heterogeneity corresponds to the characteristics of each gas-station. We assume that the heterogeneous effect follows a gamma distribution.[7] We estimate a piece-wise exponential model, with cutting points at 6-hours intervals up to four days after the announcement and cutting points at 12-hours intervals afterwards. We estimate separated models for the different gasoline qualities (93, 95 or 97) and for diesel.

In matrix Z we include dummy variables for the size of the price announcement,[8] interaction among these dummies, and whether the gas station offers other services (we define a dummy variable that equals to one if the gas station has a pharmacy, a convenience store or offers maintenance services) and other dummy variables to control for region and brand.

In Table 1 we present the results for the model with heterogeneous effect. In other words, we take into account that the moment in which a gas-station changes its price could be correlated week after week. So, this table provides the estimation for equation (5).

[7] Our results are robust to different assumptions. Moreover, our results are also similar between the model with and without frailty.

[8] We consider eight categories, depending of the size of the ENAP's announced cost changes (see Table 1 for a definition).

Table 1. Estimation Results. Model with Heterogeneous Effects

	Gasoline 93		Gasoline 95		Gasoline 97		Diesel	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
w/o related business								
Reduction > 2.5%	.	.	.	.	.	.	.	.
-2,5%-to -1,5%	0.398***	(0.011)	0.320***	(0.010)	0.326***	(0.011)	0.258***	(0.011)
-1.5% to -0.5%	0.504***	(0.039)	0.661***	(0.022)	0.692***	(0.023)	0.695***	(0.023)
-0.5 to 0%	0.686***	(0.031)	.	.	0.513***	(0.023)	0.326***	(0.016)
0%-0.5%	0.154***	(0.006)	0.319***	(0.010)	0.324***	(0.011)	.	.
0.5-1.5%	0.714***	(0.019)	0.582***	(0.015)	0.289***	(0.017)	0.801***	(0.026)
1.5%-2.5%	0.803***	(0.034)	0.820***	(0.035)	0.694***	(0.021)	0.861***	(0.029)
Increasing > 2.5%	0.765***	(0.021)	0.802***	(0.022)	0.744***	(0.027)	0.972	(0.046)
w/ related business								
Reduction > 2.5%	1.144***	(0.043)	1.126***	(0.039)	1.126***	(0.041)	1.169***	(0.058)
-2,5%-to -1,5%	0.439***	(0.017)	0.375***	(0.015)	0.385***	(0.016)	0.306***	(0.016)
-1.5% to -0.5%	0.552***	(0.042)	0.773***	(0.032)	0.701***	(0.029)	0.823***	(0.037)
-0.5 to 0%	0.759***	(0.040)	.	.	0.513***	(0.025)	0.381***	(0.022)
0%-0.5%	0.181***	(0.009)	0.346***	(0.014)	0.358***	(0.015)	.	.
0.5-1.5%	0.761***	(0.029)	0.598***	(0.022)	0.334***	(0.020)	0.884***	(0.039)
1.5%-2.5%	0.859***	(0.044)	0.853***	(0.042)	0.722***	(0.028)	0.916*	(0.042)
Increasing > 2.5%	0.786***	(0.030)	0.818***	(0.031)	0.787***	(0.034)	0.990	(0.056)
Public restroom, Yes	0.971	(0.032)	0.987	(0.031)	0.988	(0.033)	0.978	(0.034)
Autoservice, Yes	0.922*	(0.046)	0.958	(0.044)	0.957	(0.043)	0.936	(0.049)
Zone								
Atacama Dessert	.	.	.	.	.	.	.	.
Central Coast	1.009	(0.064)	0.991	(0.058)	0.967	(0.056)	0.889*	(0.059)
Santiago	0.844***	(0.050)	0.844***	(0.046)	0.760***	(0.041)	0.597***	(0.037)
Central Rural	1.155**	(0.074)	1.088	(0.065)	1.092	(0.067)	1.015	(0.069)
Southern	1.078	(0.066)	1.046	(0.060)	1.074	(0.061)	0.978	(0.063)
Patagonia	1.123*	(0.076)	1.094	(0.069)	1.050	(0.067)	1.029	(0.073)
Brand								
Copec	.	.	.	.	.	.	.	.
Shell	0.686***	(0.025)	0.756***	(0.026)	0.773***	(0.026)	0.833***	(0.033)
Petrobras	0.671***	(0.027)	0.729***	(0.028)	0.720***	(0.028)	0.714***	(0.031)
Terpel	0.636***	(0.028)	0.674***	(0.027)	0.710***	(0.033)	0.683***	(0.031)
Independents	0.611***	(0.031)	0.660***	(0.031)	0.645***	(0.044)	0.649***	(0.034)

Notes: * $p<0.10$; ** $p<0.05$; *** $p<0.01$
Source: Own calculations based on National Energy Commission - Chile data.

When analyzing the price change behavior of firms in response to different sizes of the announced cost changes, we must distinguish between gas-stations that offer other services (pharmacy, convenience stores, and car maintenance services) from gas-stations that do not have these amenities. In both cases and for any fuel, the higher probability of changing the price occurs when big cost cuts are announced (up or down). Although, there is not a monotonic relationship between the amounts of the announced cost changes and the hazard of retail prices changes, the higher probability of prices changes occurs at both extremes. This result is consistent when the stylized fact mentioned in section 2 after estimating alternative non-parametric survival functions.

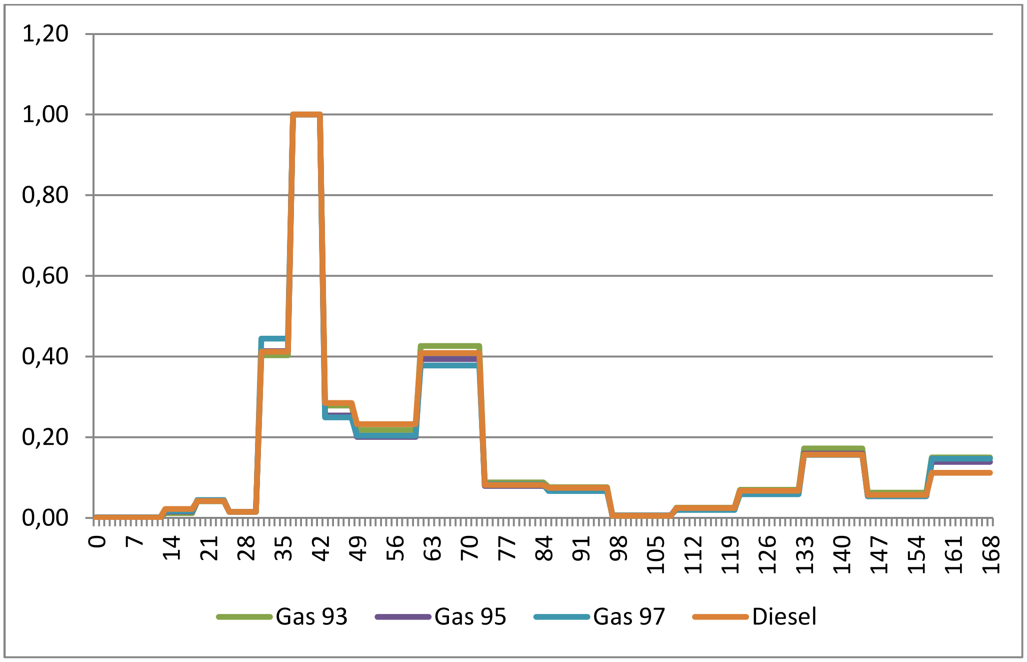
Overall, gas-stations that have related business –pharmacy, convenience store, or car repairing service– respond much faster to cost cuts, but they do not behave so differently from other firms when bigger price changes are announced. That is, in all cases big cost changes increase the likelihood of changing prices, but the reaction of firms to cost cuts is much bigger if they have the gasoline business connected to other business activities. An explanation to this behavior is the strategic pricing of multi-products firms, since as they sell complement goods they are more averse to increase gasoline prices compares to cut gasoline prices. In this sense, the gasoline is a customer attractor of the whole business.

We also find that for all the types of fuels, prices changes are less often in Santiago than in other regions of the country. This result may reflect that competition is softer in the capital city, either because it is more difficult for consumers to move in a big congested city than in smaller cities or the entry into the gasoline market has more barriers in a big city.

Another interesting result is that gas-stations branding COPEC (55% of the market share) are by far the more likely to change prices, suggesting a source of leader-follower behavior in the industry. There are no such big differences in the behavior of gas-stations under other brands or without brand (independents).

For all types of fuels, the hazard reaches a maximum at 36-42 hours of the ENAP's announcement, as we may expect since costs change at 24 hour (Thursday midnight). In Figure 4 we plot the baseline hazard (normalized to be one at 36-42 hours).

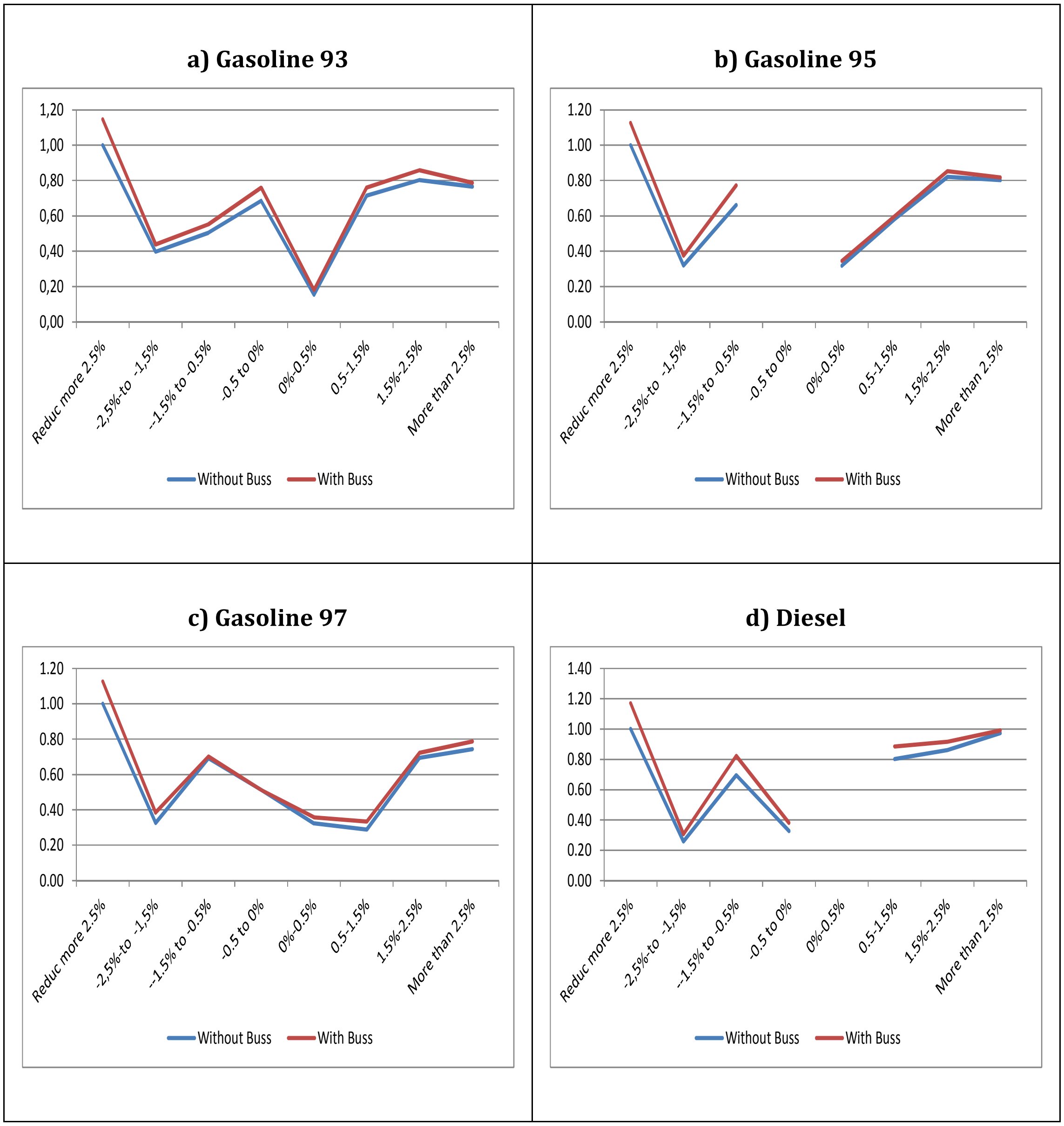
Figure 4. Hazard Ratio as a Function of hours since Announcement (36-42 hrs = 1)



Source: Own calculations based on National Energy Commission - Chile data.

We also show this result in Figure 5a) to 5d). The fact is that for most types of fuel it is clear that the higher the cost changes announced by ENAP, even up or down, the higher the reaction on prices of gas-stations.

Figure 5. Hazard Ratios vs. Magnitude of Price Change Announcement



Source: Own estimation based on National Energy Commission – Chile data.

Using the same methodology developed in section three, we estimated equation (6), which means that we assume no heterogeneity on firms. That is, each gas-station chooses to change its prices randomly week after week, and we correct by clustering to the level of each gas-station. The results of this regression are in Table 2.

Comparing Tables 1 and 2 we observe that the main results hold. That is, after a “large” announced cost reduction, gas-stations react by reducing their prices almost immediately with the largest probability. The second reaction in importance is for the largest cost increase. So, the U-shaped is even clearer in this regression. We also found here that the hazard rate for non-related business is above one when a gas-station does not have a pharmacy, convenient store or car maintenance service, the same pattern that we observed in Table 1 (and plotted in Figure 5).

The same consistency results are observed regarding both the higher hazard rate found for Santiago and Copec’s leadership in price changes.

Table 2. Estimation Results. Var-Cov Corrected Model (w/o heterogeneous effects)

	Gasoline 93		Gasoline 95		Gasoline 97		Diesel	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
w/o business								
Reduction > 2.5%	.	.	.	.	.	.	.	.
-2,5%-to -1,5%	0.453***	(0.011)	0.366***	(0.010)	0.374***	(0.012)	0.332***	(0.011)
-1.5% to -0.5%	0.536***	(0.035)	0.672***	(0.019)	0.703***	(0.019)	0.734***	(0.022)
-0.5 to 0%	0.686***	(0.028)	.	.	0.546***	(0.024)	0.410***	(0.014)
0%-0.5%	0.198***	(0.007)	0.365***	(0.010)	0.373***	(0.012)	.	.
0.5-1.5%	0.723***	(0.020)	0.628***	(0.015)	0.349***	(0.013)	0.808***	(0.023)
1.5%-2.5%	0.805***	(0.029)	0.828***	(0.031)	0.717***	(0.022)	0.865***	(0.026)
Increase > 2.5%	0.773***	(0.022)	0.815***	(0.022)	0.769***	(0.026)	0.956	(0.034)
w/ related business								
Reduction > 2.5%	1.146***	(0.045)	1.130***	(0.042)	1.134***	(0.045)	1.173***	(0.052)
-2,5%-to -1,5%	0.504***	(0.017)	0.429***	(0.015)	0.439***	(0.017)	0.392***	(0.015)
-1.5% to -0.5%	0.587***	(0.036)	0.777***	(0.033)	0.728***	(0.030)	0.851***	(0.034)
-0.5 to 0%	0.760***	(0.040)	.	.	0.558***	(0.025)	0.474***	(0.018)
0%-0.5%	0.230***	(0.009)	0.400***	(0.014)	0.414***	(0.015)	.	.
0.5-1.5%	0.783***	(0.029)	0.652***	(0.021)	0.402***	(0.017)	0.885***	(0.036)
1.5%-2.5%	0.876***	(0.042)	0.868***	(0.039)	0.754***	(0.029)	0.921**	(0.037)
Increase > 2.5%	0.801***	(0.031)	0.833***	(0.031)	0.809***	(0.033)	0.983	(0.047)
Public restroom, Yes	0.974	(0.030)	0.985	(0.030)	0.989	(0.031)	0.980	(0.032)
Autoservice, Yes	0.947	(0.035)	0.972	(0.036)	0.975	(0.035)	0.968	(0.038)
Zone								
Atacama Dessert	.	.	.	.	.	.	.	.
Central Coast	1.017	(0.061)	1.001	(0.058)	0.969	(0.055)	0.962	(0.065)
Santiago	0.902*	(0.048)	0.889**	(0.046)	0.813***	(0.041)	0.726***	(0.044)
Central Rural	1.115*	(0.068)	1.063	(0.062)	1.052	(0.063)	1.042	(0.071)
Southern	1.090	(0.061)	1.061	(0.058)	1.085	(0.058)	1.042	(0.067)
Patagonia	1.022	(0.075)	1.015	(0.072)	0.961	(0.071)	0.978	(0.078)
Brand								
COPEC	.	.	.	.	.	.	.	.
Shell	0.805***	(0.023)	0.856***	(0.024)	0.876***	(0.024)	0.934**	(0.031)
Petrobras	0.759***	(0.029)	0.795***	(0.029)	0.784***	(0.030)	0.808***	(0.032)
Terpel	0.701***	(0.029)	0.726***	(0.028)	0.761***	(0.033)	0.744***	(0.031)
Independents	0.681***	(0.032)	0.702***	(0.034)	0.699***	(0.049)	0.712***	(0.035)

Notes: * p<0.10; ** p<0.05 ; *** p<0.01
Source: Own calculations based on National Energy Commission - Chile data.

5. ROBUSTNESS

Are our results still more robust to alternative estimations methodology? We compare the exponential form of the baseline hazard to other functional forms: Gompertz and Weibull's, and to Cox's non-parametric approach.

Unfortunately, these other models do not converged when estimated by gasoline. Hence, as a comparative exercise, we estimate regressions aggregating all fuels, as if they were belonging to the same market. We assume that there is neither heterogeneity on firms and nor interaction between the size of the cost change and the amenities. Table 3 provides the results of these four regressions.

Table 3. Estimation Results. Comparative Regressions (for all fuels)

	Exponential		Cox		Gompertz		Weibull	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Fuel								
Gasoline 93	.	.	.	.	.	.	.	.
Gasoline 95	0.973***	(0.008)	0.955***	(0.008)	0.971***	(0.008)	0.951***	(0.008)
Gasoline 97	0.962***	(0.009)	0.945***	(0.009)	0.960***	(0.009)	0.936***	(0.009)
Diesel	1.004	(0.009)	1.027***	(0.009)	1.004	(0.009)	1.000	(0.009)
Size in the cost change								
Reduction > 2.5%	2.103***	(0.027)	2.370***	(0.030)	2.138***	(0.027)	2.471***	(0.032)
-2,5% to -1,5%	1.239***	(0.018)	1.301***	(0.019)	1.242***	(0.018)	1.271***	(0.018)
-1.5% to -0.5%	1.992***	(0.030)	2.010***	(0.030)	2.026***	(0.031)	2.335***	(0.035)
-0.5 to 0%	1.685***	(0.027)	1.628***	(0.026)	1.707***	(0.027)	1.905***	(0.031)
0%-0.5%	.	.	.	.	.	.	.	.
0.5-1.5%	2.073***	(0.028)	1.986***	(0.027)	2.113***	(0.029)	2.490***	(0.034)
1.5%-2.5%	2.116***	(0.030)	2.029***	(0.029)	2.160***	(0.031)	2.576***	(0.037)
Increase > 2.5%	2.116***	(0.032)	2.302***	(0.032)	2.389***	(0.033)	2.938***	(0.041)
Amenities								
Pharmacy, yes	1.042*	(0.022)	1.021	(0.022)	1.044**	(0.022)	1.060***	(0.022)
Conv. store, yes	1.054***	(0.008)	1.083***	(0.008)	1.056***	(0.008)	1.071***	(0.008)
Repairing serv., yes	1.049***	(0.008)	1.056***	(0.008)	1.051***	(0.008)	1.064***	(0.008)
Public restroom, Yes	0.969***	(0.008)	0.975***	(0.008)	0.968***	(0.008)	0.955***	(0.008)
Autoservice, Yes	0.969***	(0.011)	0.958***	(0.011)	0.968***	(0.011)	0.958***	(0.011)

Continue …

... continued

	Exponential		Cox		Gompertz		Weibull	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Zone								
Atacama Dessert	.	.	.	.	.	.	.	.
Central Coast	1.028*	(0.016)	1.029*	(0.016)	1.029*	(0.016)	1.036**	(0.016)
Santiago	0.912***	(0.013)	0.887***	(0.013)	0.910***	(0.013)	0878***	(0.013)
Central Rural	1.084***	(0.017)	1.110***	(0.013)	1.087***	(0.017)	1.111***	(0.013)
Southern	1.096***	(0.016)	1.104***	(0.016)	1.099	(0.016)	1.130***	(0.017)
Patagonia	0.986	(0.016)	1.036**	(0.017)	0.984	(0.016)	0.968**	(0.016)
Brand								
COPEC	.	.	.	.	.	.	.	.
Shell	1.032***	(0.009)	0.882***	(0.008)	1.035***	(0.009)	1.047***	(0.009)
Petrobras	0.878***	(0.008)	0.791***	(0.008)	0.875***	(0.008)	0.844***	(0.008)
Terpel	0.861***	(0.009)	0.747***	(0.008)	0.859***	(0.009)	0.832***	(0.009)
Independents	0.824***	(0.010)	0.703***	(0.009)	0.821***	(0.010)	0.789***	(0.010)

Source: Own calculations based on National Energy Commission - Chile data.
Notes: * p<0.10; ** p<0.05 ; *** p<0.01. Standard errors may be provided upon request.

We observe that most coefficients are very similar for all regressions. We also observe the same pattern regarding i) gas-stations tend to react faster to new prices as cost changes becomes higher in magnitude, forming a U-shaped as shown in Figure 5; ii) amenities that improve the gas-station global service matter, in particular convenience store and car repairing service; iii) prices in Santiago are stickier than in the rest of the country; and, iv) it seems that the industry behaves as having a leader (Copec) and many followers others than Shell.

6. Conclusions

Several papers have shown that retail gasoline prices in liberalized markets do not react quickly to new market conditions. The bad news is that this behavior is clearer when prices goes down that when they are goes up, producing what the literature calls asymmetric pricing. Using a rich data set of online prices for the universe of gas-stations in Chile, we do not only find the same pattern, but also we find that gas-stations asymmetric behavior is strongly explained by both variables that are specific to each of them and other variables related to the size of the shock in costs.

Variables that are specific to each gas-station are its brand, the geographic region in which it is located, the existence of some amenities that allow it to offer complementary goods to gasoline and diesel (pharmacy, convenience store, or car repairing services), and other services that are offered for free to customers (public restroom or autoservice).

The size and the sign of cost changes also explain the reaction of gasoline retailers. We found that the higher the cost changes the faster the firm's reaction to new cost conditions, except for small shocks. However, such a pricing reaction differs whether prices go up or down. These results, which are robust to different empirical specifications, tell us that the asymmetric pricing in gasoline markets may perfectly being explained by gas-stations strategic behavior.

Further research needs to be considered. First, we will incorporate a variable that measure the degree of rivalry in the relevant market of each gas-station. Since our location variable is too widely specified (several regions of the country), we will use the geo-referenced location of each gas-station to build its relevant market, thus considering the number of rivals, their brands and other characteristics to control for each firm's market rivalry. A second further research is to incorporate some consumers' characteristics, such are their income condition. Since Chile is an unequal country, counties are segregated according their income. The data may provide an explanation of how gas-stations set prices taking into account these and other county specific characteristics. Lastly, and perhaps the more important, we should jointly consider the pass-through of cost changes and the moment in which each gas-station decided to move its prices as a part of the same strategic pricing behavior in retail gasoline markets.

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