The Dynamics of Gasoline Prices: Evidence from Daily French Micro Data*

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Abstract

Using millions of individual gasoline prices collected at a daily frequency, we examine the speed at which market refined oil prices are transmitted to consumer liquid fuel prices. We find that on average gasoline prices are modified every five days and the distribution of price changes displays a M-shape as predicted by a menu-cost model. Using a reduced form state-dependent pricing model with time-varying random thresholds, we find that the degree of pass through of wholesale prices to retail gasoline prices is on average 0.77 for diesel and 0.67 for petrol. The duration for a shock to be fully transmitted into prices is less than 15 days. There is no significant asymmetry in the transmission of wholesale price to retail prices.

Keywords: price stickiness, menu costs, (S,s) models, gasoline price.

JEL Codes: E31, D43, L11

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1 Introduction

At which speed agents incorporate specific or common shocks into their prices is a crucial issue in macroeconomic models. Why prices are sticky and do not adjust immediately to their fundamentals? Using individual gasoline prices collecting at a daily frequency in more than 10,000 gas stations in France, we examine in this paper to which extent retail gasoline prices are rigid and how long it takes for a gas station to incoporate an oil price shock.

The first contribution of the paper is to investigate the degree of price rigidity of gasoline prices in France. For that purpose, we use a rich and unique data set of daily price quotes collected by the French Ministry for the Economy, Industry and Employment for diesel and unleaded petrol. Prices are collected in almost all retailers selling gas in France (ie more than $11,000$ gas stations). The time dimension of the data set is also quite large, data are collected every day between January 2007 and June 2009 (about 850 days). All in all, the data set consists of more than 8.5 million individual price quotes. We first examine the basic patterns of price rigidity in French gas stations and the main findings are the following: (i) prices are modified on average once a week; (ii) there is some heterogeneity between firms, supermarkets change their prices more often than other gas stations; (iii) prices are more likely to be modified on Tuesday and Friday than between Saturday and Monday; (iv) price decreases are as frequent as price increases; (v) the average price change in absolute values is around 2.5%; (vi) small price changes are scarce: less than 10% of absolute price changes are smaller than 0.5%. By comparison, using French monthly consumer price data, Baudry et al. (2007) obtain the price duration for energy products is between one and two months. However, infra monthly price changes can not be observed in their data set. For the United States, Hamilton and Davis (2004), Douglas and Herrera (2010), and Davis (2007) use daily price quotes to examine the degre of gasoline price rigidity. Davis and Hamilton (2004) and Douglas and Herrera (2010) both use prices collected in 9 wholesalers and find that prices are modified every three days and the average price change is on average a little less than 1%. Davis (2007) uses data from 4 gasoline retailers and obtain that the frequency of price changes is about 10% on average. One nice pattern of our data set is its large coverage of gas stations, which can help us to provide more precise information on the degree of price rigidity.

Our paper also contributes to the empirical literature on price rigidity models. One key issue is to understand why prices remain constant during a certain period of time though the price of oil fluctuates every day: how can we rationalize that prices are on average modified only once a week? Different theoretical models are used in macroeconomics to reproduce the infrequent changes of prices. Several recent papers examine patterns of price changes to assess the relevance of the different price setting models (see for instance Nakamura and Steinsson (2008) or Klenow and Kryvtsov (2008) for the United States or Dhyne et al. (2006) or Vermeulen et al. (2011)). However, at the micro level, one difficulty is to observe firm-level determinants of firms' pricing behaviour. Many empirical studies used the sectoral inflation rate to identify aggregate shocks on micro prices (see for example Fougere et al. (2007)). More recently, Ratfai (2006) used wholesale price of meat to capture the marginal cost of meat retail prices and Fougere et al. (2010) approximated the labour cost of restaurants by using the national minimum wage. Dhyne et al. (2011) estimate an unobserved synthetic factor to identify price fundamentals. In our study, we use daily prices of diesel an unledaded petrol set at the Rotterdam market to approximate the marginal cost of diesel and unleaded petrol retail prices. Moreover, diesel and unleaded petrol are homogenous goods, which helps us to control in the estimation for the presence of heterogeneity of products in the pricing behaviour. In this paper, we estimate a model of price rigidity that links prices to costs. This model is a semi-structural form of a time-varying adjustment cost model. The probability of price changes depends on the gap between the nominal price and the price that would be observed without friction. If this gap exceeds a certain threshold, prices are adjusted; the threshold trigerring price changes is assumed to depend positively of the adjustment cost. We also suppose that the adjustment cost can be random over time and depend on the day of the week because price reviews are more likely to be made for example after the week end. This allows us to predict an heterogeneity of price changes for the same gas station. This model is an extension of the model proposed by Davis and Hamilton (2004) since we take explicitly into account the size of price changes and allow for time-varying adjustment costs. Moreover, like in Hamilton and Davis (2004) we estimate a menu cost model at the firm level and are able to provide a distribution of parameters of the whole population of 10,000 firms contained in our sample. Moreover, we compare the predictions of price rigidity models by estimating a fixed menu cost model and a Calvo model for all gas stations. We find that the time-varying menu cost model helps to predict the M-shape of the price change dsitribution. Several results are obtained from those estimations: (i) the degree of pass through of wholesale prices to retail prices is on average 0.77 for diesel and 0.67 for unleaded petrol; (ii) this pass through is larger in supermarkets than in other gas stations; (iii) adjustment thresholds are quite large but show also a large variability.

The third contribution is to examine how long it takes for gas stations to incorporate a shock on wholesale prices to their retail prices and whether this response is symmetric (or not). A large empirical literature deals with this issue but using aggregate data collected either at a monthly or weekly frequency. Using parameter estimates of the menu cost model, we first test the presence of asymmetries in the probability of price changes after a shock. More specifically, we test whether the threshold triggering price increases is lower than the threshold triggering price decreases. We find almost no asymmetry in the response of gasoline retail prices to Rotterdam price shocks: a very small proportion of gas stations are asymmetric in their pricing behaviour and the size of this asymmetry is rather small. In the macroeconomic literature, results are quite contrasted depending on the methodology or data used but it seems that asymmetry is not pervasive (Frey et Manera, 2007). For France, Audenis et al. (2002), using macro monthly time series find no asymmetry at the retail level but a significant asymmetry at the refinery level. In our study, we also use simulations of the micro-level models to assess the delay for prices to incorporate a change in the Rotterdam price of gasoline. We find that the adjustment is rather quick, it takes around 10 days for a shock to be fully transmitted into prices. We are able to compare price rigidity models and find that the longest delay is obtained for the Calvo model where it takes more than two weeks for a shock to be fully transmitted. Audenis et al (2002) find a duration aoround 3 months whereas in a recent macro contribution Meyler (2009) obtains a 4-week duration for a shock to be incorporated into gasoline prices.

The layout of the paper is as follows. Section 2 describes the data set we use in this study and the main fetaures of the gasoline retail market in France. In section 3, we provide the main stylised facts on gasoline price rigidity. Section 4 presents the price rigidity model we estimate and the main results. We also test the presence of asymmetry and the fit of the model to the data. In section 5, we estimate the delay for retail prices to respond to aggregate shocks and examine how prices are adjusted after the shock depending on the price rigidity model. Section 6 concludes.

2 Daily Micro Data on Gasoline Prices

In this section, we describe the micro data set of gasoline prices we use. This data set consists of individual prices reported by all gas stations selling more than 500 m^3 of gasoline per year in France. Since January 1st 2007, the French gas stations are legally obliged to report the level of their prices for unleaded petrol and diesel to the Ministry for the Economy, Industry and Employment. The data collected by the Ministry of Economy are then made available on a governmental website http://www.prix-carburants.gouv.fr. From a competitive standpoint, this website is intended to correct a problem of imperfect information. Some other private websites provide the same service but the updating of prices is only participatory whereas in our case, the public administration may force the retailer to report its price changes. The main variables available in our data set are the following. First, the price of a liter of diesel and unleaded petrol, this price includes all taxes, expressed in euros with three decimals. Another variable is the date of the report expressed in DD/MM/YY, which unables us to follow the same price in a given retailer. An idenfication number is associated to each retailer. We have only little information on the retailer: brand and some information on the location. We use historical data from this governmental website for the period from January 1st 2007 to May 31th 2009. It contains a backup of prices in the database every day at 23:59. So, price changes can be examined on a daily basis. The frequency of our data collection does not allow to examine the infra daily changes. This may cause an upward bias in the duration of sequences of observed prices. However, first descriptive statistics show that these cases are quite infrequent. All in all, our price data contains more than $11,000$ gas stations selling diesel and unleaded petrol and represent approximately 8.5 million price records by fuel are used. An example of two indivuidual sequences of prices are plotted presented on Figure 1.

This article focuses on diesel and unleaded petrol, the two main type of liquid fuels consumed in France. In view of its consumption and its refining capacity, France produces unleaded petrol in excess and not enough diesel. The diesel consumption has indeed increased significantly. In 2007, the level of diesel consumption was three times higher than the unleaded petrol consumption. On the characteristics of the French market of gasoline, four types of retailers can be considered: (i) stations belonging to major oil companies like Total, Elf, Shell...; (ii) stations associated to supermarkets, those stations are located very close to or in supermarkets; (iii) small independent retailers which do not depend from big oil companies and only sell consumer liquid fuels; (iv) gas stations located on motorways which often belong to oil companies. One important observation is that the level of prices is on average lower in supermarkets than in other gas stations. The number of gas stations has steadily declined since the 1980s. There were more than 40 000 stations in 1980 whereas there are only about 13,000 stations in 2007. At the same time, the proportion of gasoline sold in stations belonging to supermarkets rose sharply: supermarkets represent 60% of the total market share in 2007 whereas only 40% of stations belong to supermarkets. We will distinguish in this study supermarkets from other stations. Our data set includes about 4,500 stations associated with supermarkets and about 5,500 stations for other gas stations (including major oil companies, small independent retailers and stations on motorways).

Three main components of the retail gasoline price can be considered: (i) the wholesale price of fuel (after refining) which represents according to sectoral national accounts published by Insee about 75 to 85% of total operating expenses of the gas stations. In this study, we approximate this cost by using the price of refined fuels quoted in Rotterdam[1], refined fuel imported comes mainly from Rotterdam and Rotterdam refined gasoline could be considered as a wholesale price which already includes refining costs contrary to Brent prices for example; (ii) distribution costs include labor and transportation costs, they are not observed *per se* in our study, those costs might not change at a daily frequency and may depend on each gas stations,

[1]As noted by Meyler (2010), Rotterdam is one of the three major trading areas for refined products (168 million tonnes). However, some Mediterranean ports handle also smaller amounts of liquid petroleum products (Marseille (66 million tonnes) and Trieste(36 million tonnes)).

they will be considered as idiosyncratic; (iii) taxes will be excluded from our analysis. In 2009, the two main taxes (VAT and TIPP) represented 65% of the petrol prices and 60% of diesel prices. The TIPP (domestic tax on petroleum products) depends on the volumes and not on the selling price of the product. So it is a fixed amount in euro per liter. TIPP tax can be revised on the first of January each year, however it remains fixed from 2007 to 2009, to 60.69 euros per hectolitre for unleaded petrol and 42.84 euros per hectolitre for diesel. The VAT rate is 19.6% and is calculated on the price including the TIPP. We here use prices excluding all taxes and we calculated them using the following formula: $p_{excl\_taxes} = \frac{p_{inclu\_taxes}}{1+VAT} - TIPP$.

Gasoline prices are usually displayed with three decimal places in gas stations and prices are collected and reported with three digits. The posting of 2 or 3 digits is a choice of gas stations and not a technical constraint. So prices with three decimal places will be considered in the following sections. However, the distribution of the last digit (the third) in prices including all taxes is not uniform: 31% of gasoline prices ends with "9", 29% with "0", 9% with "5", 7% with "4" whereas for other last digit figures this proportion is smaller than 5%. On the contrary the distribution of the penultimate digit appears uniform (see Table A in appendix for details).

We also correct for some measurement errors. Occurences of price increases followed by decreases equivalent next day and breaks in the series have been identified and corrected. These adjustments affect about 1% of gas stations in our microdata set and few dates. The initial micro data set includes very long prices durations, we consider that price durations longer than one month are outliers, which represent less than 2% of price trajectories. These outliers can be explained by the learning process of the price collection and the absence of obligation to provide information for gas stations selling less than 500 cubic meters of fuel per year. We also drop observations with a majority of price trajectories longer than one month, and gas stations whose prices are observed less than 3 months. After treatment of outliers and measurement issues, our sample contains $10,169$ gas stations for diesel and $10,013$ for unleaded petrol and 7 million of price quotes for each type of liquid fuel.

We have no information on the demand addressed to each individual gas station (like the number of liters sold) or on the quality of the product. However, we can consider that the product is rather homogenous in terms of quality. Our data set is not exhaustive in terms of gas stations because there is a threshold requirement for participation. It still includes a significant number of stations. We test the consistency of our information coming from individual data set by confronting our data to other sources. The French Ministry for the Economy, Industry and Employment publishes every week the aggregate average price of unleaded petrol and diesel (with and without taxes) sold in France. Those prices correspond to the weighted (by market share throughout the distribution network) average prices and charged to the final consumer every Friday. Figure A in Appendix compares the simple average of prices from our data set (after measurement issues corrected) and prices coming form the macro data set of the Ministry of Economy. These prices are very close and follow the same variations. The difference for prices excluding taxes is on average 0.009 euros for diesel and 0.016 for unleaded petrol. One possible explanation is that prices in supermarkets are lower and may be underrespresented by a simple average. Differences still remain very low. Finally, market prices of Rotterdam and retail gasoline prices co-move rather closely.

3 Stylized Facts on Gasoline Price Rigidity

In this section, we describe the main patterns of price setting behaviour of French gas stations using basic indicators of price rigidity.

3.1 Frequency of price changes and price durations

Usually, the frequency of price changes or the duration between two price changes are considered as good indicators of price rigidity. The longer a price lasts, the more rigid this price is considered to be. Gasoline prices may be the less rigid prices; in most empirical studies using individual price quotes (Nakamura and Steinsson (2008), Bils and Klenow (2004) or Dhyne et al. (2006) and Vermeulen et al (2011)), energy prices are estimated to last one month. Table 1 summarizes results on the frequency of price changes and on the duration of prices using our daily price quotes. We find that on average diesel prices are modified every 5 days if we consider all individual price quotes together and every 6.5 days if we consider the distribution of average firm-level durations. Unleaded petrol prices are modified a little less frequently since the average firm-level duration of prices is about 7 days. The average frequency of price changes is between 16.5% and 17.6% for unleaded petrol and diesel prices. Those figures are difficult to compare with monthly frequency data since all gasoline prices collected at a monthly frequency would imply a 100% frequency of price changes. Weekly data are even difficult to use since a majority of firms change their price each week. Davis and Hamilton (2004) and Douglas and Herrera (2010) both use daily prices collected in US wholesalers and find that prices are modified every three days, which implies a frequency of price changes close to 30%. Using data from 4 gasoline retailers, Davis (2007) obtains that the frequency of price changes is on average close to 10%, this is quite lower than what we obtain on French data. However, we find that retail price changes occur each week on average whereas oil market prices are modified every day (even more frequently), so gasoline prices may appear as rigid and appear as a relevant product to test price stickiness models.

Figure 2 plots the distribution of average firm-level price durations for diesel and unleaded petrol prices. We find some heterogeneity among firms on price durations. 25% of gas stations change their prices on average every 8 days or more whereas another quarter of firms change their prices every 4 days or less. We calculate the average price duration for supermarkets selling gasoline and other gas sellers. We find that on average supermarkets modify more frequently their prices than other gas stations which often belong to oil companies. Table 2 provides some results on this difference: the average duration of gasoline prices in oil companies stations is larger than 7 days whereas it is close to 6 days for supermarkets.

Figure 3 plots the hazard rate of price durations for diesel and petrol prices (i.e. the instantaneous conditional probability of a price change given that price change has occured since the last price change). Several patterns of price durations appear on this figure. First, there are some peaks at durations 7, 14 and 21 days and to a lesser extent at durations 3 and 4 days. This finding imples some strong regularities in the day of price changes for gas stations. Firms prefer changing their price once a week at the same day. Table 3 summarizes results on the proportions of price changes observed over days of the week. About 40% of price changes occur on Tuesday and Friday whereas price changes are less frequent on Monday, Saturday and Sunday[2]. Similar

[2]Many gas stations are open on Sunday but it is more doubtful that an employee is present to change prices

evidence is also reported by Asplund et al. (2000) on Swedish gasoline prices. We also find that this ”seasonality” in price setting behaviour is sligthly different for supermarkets and other gas stations. Supermarkets are a little more likely than other stations to change their prices on Friday (a little more than 22% of price changes versus less 20%). Such regular patterns over the week may be the consequence of differences in the costs associated to price changes over the week. Zbaracki et al. (2004) but also Muller et al (2010) both mention that adjusting prices involve a rather long process because managers of firms have to collect information on costs, prices from competitors... Since the Rotterdam market is closed on Saturdays and Sundays, we can suppose that managers in gas stations wait for observing the market oil prices on Monday before deciding to change their prices on Tuesday and may also be more likely to change their prices on Friday because facing a higher demand during the week end, it might be less costly to change their prices before than during the week end.

Two other findings concerning the hazard rates could be interesting to note. The hazard rate does not show a strong upward or downward trend and it is rather flat for the first week whereas in many empirical studies, a decreasing slope is found for the hazard rate (see Nakamura and Steinsson 2008 for example). Finally, the hazard rate for supermarkets is higher than the hazard rate for other gas stations which confirms that supermarkets prices are more flexible than in other stations where price durations are longer. However, the two hazard rates show a parallel and similar movement.

3.2 The distribution of price changes

On the size of price changes, we first obtain that on the sample period, price increases are almost as frequent as price decreases. The frequency of diesel price increases is on average 8.7% versus 8.9% for price decreases whereas for petrol prices the frequency of price increases is 8.7% versus 7.8% for price decreases (see Table 1). This might suggest no asymmetry in price changes or at least a small one for petrol prices. However, from those statistics we do not detect a strong and significant downward price rigidity.

Figure 4 plots the distributions of all price changes for diesel and petrol prices. One important

or even to decide to change prices.

and quite original pattern of those distributions is their M-shape. Very small price changes are very rare[3]. Table 4 summarizes the main statistics on the size of price changes. The fisrt quartile of the distribution is about 1.2% in absolute values for diesel prices and 1.4% for petrol prices whereas the median price change is closer to 2% in absolute values. Contrary to many empirical studies examining the degree of price rigidity, we do not find here a distribution with a large proportion of small price changes like in Baudry et al. (2007) or Klenow and Kryvtsov (2008)[4]. For instance, Klenow and Kryvtsov (2008) report that around 40 % of price changes are smaller than half the median of price changes whereas in our case, it should be less than 25%. This M-shape would appear as consistent with a distribution of price changes predicted by a standard menu-cost model. This small proportion of small price changes could be due to large changes in costs, we show on Figure 4 the distribution of market price changes and this distribution is closed to a normal distribution with zero mean. Another explanation might be related to the number of digits used to display prices. In a large majority of outlets, prices are displayed with three digits after the comma and prices are collected with three digits after the comma in our data set. So, in principle price changes could be smaller than 1% and a menu-cost model can explain why we observe so few small price changes. We also observe some heterogeneity in the size of price changes among firms. Price changes are larger for supermarkets than for other gas stations. The average price change in supermarkets is about 2.5% for diesel and 3.1% for petrol whereas it is respectively $2.2-2.3\%$ and $2.6-2.7\%$ for other gas stations (Table 4).

We also examine the correlation between the average price duration and the size of price changes. All standard price rigidity models (Calvo or menu-cost model) without idiosyncratic shock would predict a rather strong correlation between the time since the last price change and the size of price changes in absolute values. Figure 5 displays the average price changes in absolute values depending on price durations. We find that the the size of price changes is rising slightly with price duration. This patttern is also quite new since other empirical studies find no correlation. However, the correlation is rather small and suggests that idiosyncratic shocks

[3] Asplund et al. (2000) using Swedish daily gasoline prices find such a distribution for price changes: there is no price changes less than 2%.

[4] This result has been recently challenged by Cavallo and Rigobon (2011) who use explicitly a test of unimodality in price change distributions.

are significant here as noted by Klenow and Kryvtsov (2008).

3.3 Adjustment hazard functions

Finally, we construct the adjustment hazard function which provides a relationship between the probability of price change and the log difference between the nominal price the last time the price was updated and the frictionless price (ie the price that would have been observed without rigidity). In a standard menu cost model, there is a cost to adjust prices called menu costs and firms trade off between the opportunity cost of deviating from the optimal price (i.e. the foregone profit) and the adjustment cost. As soon as the gap between the nominal price and the frinctionless price exceeds a certain threshold, the price is adjusted. So the adjustment function is equal to 0 inside a zone determined by the thresholds and 1 elsewhere. In a time-dependent model (Calvo (1983) or Taylor (1980)), the probability of price changes is exogenous and does not depend on the economic environment of the firm. In that case, the adjustment function would rather flat equal to this exogenous probability of price change for every values of the gap $p - p*$. Figure 5 plots empirical adjustment functions calculated in our sample and assuming in a first approximation that the frictionless price is the Rotterdam market price and the pass through is equal to 1. For both diesel and unleaded petrol prices, the probability of price increases or decreases depends on the difference between the observed price and the frictionless price as predicted by the standard menu cost model. However, if the probability of price changes is lower when $p - p*$ is about 0, this probability is not equal to 0. This would imply some degree of time dependence here on the decision of price change. Moreover, the probability of price changes increases rather slowly: for diesel prices, the frequency of price increases is equal to 7% when $p - p*$ is about 0 and raises to 12.5% when the frictionless price exceeds by 5% the nominal price. This result can come from the heterogeneity of menu costs among firms or from variations in the size of menu costs for a given firm. This figure would suggest however that there is a selection effect in price changes, prices are more likely to be modified when $p - p*$ is large in absolute values. But this selection effect seems to be mitigated by heterogeneity among firms or over time of adjustment costs.

A last observation is the rather significant degree of symmetry of the adjustment hazard function. For diesel prices, if the frictionless price exceeds by 5% the nominal price, the probability of price increase is equal to 12.5% whereas the probability of price decreases is about 13.5% when the frictionless price is 5% lower than the nominal price. For unleaded petrol, there is a small asymmetry, the frequency of price decreases is 9.5% when $p - p*$ equal 5% and the frequency of price increases is 7% when $p - p*$ equal -5%. However, those results depend on two assumptions: the degree of pass through is one for all firms and the frictionless price is well approximated by the Rotterdam market price.

4 Price rigidity model: estimation and results

4.1 Price rigidity model

Price changes in gas stations are infrequent whereas marginal costs are modified every day, price changes are on average rather large and very small price changes are rare. Gasoline prices appear as a textbook example to illustrate price stickiness models. However, one key issue in most empirical studies on price rigidity is to measure at the firm level the determinants of prices. In price rigidity models, firms set their prices in a monopolistic competition framework. The price level that would be observed in the absence of rigidity called the frictionless prices is given by a markup over marginal costs. One difficulty is to measure at the firm level the marginal costs. Some empirical studies suppose that prices depend on aggregate inflation (Cechetti 1986 or Fougere et al 2007 for example). Other studies use better approximations at the aggregate level like wage costs or wholesale prices (see Fougere et al 2010, Ratfai 2006 or Dutta et al 2002). In a recent contribution, Dhyne et al (2011) using a statistical decomposition, identify the marginal cost to an unobserved factor specific to the product. In our case, the marginal cost of gasoline prices will be the wholesale prices of gasoline set at the Rotterdam market.

In this paper, we estimate a rather flexible form of state-dependent model. For every firm, there is a fixed cost to adjust prices, this cost could be different among firms. Sheshinski and Weiss (1977) show that in presence of a menu cost and a deterministic exogenous shock, the optimal price setting behavior is an (S, s) rule. In this model, firms tolerate that their price deviate from the frictionless price as long as this deviation is not too large. Dixit (1991) and

Hansen (1999) extends this result to non-deterministic shocks. The optimal frictionless price would be defined as:

$$p_{it}^{*} = \alpha_i + \beta_i p_t^o + \varepsilon_{1,it} \tag{1}$$

where p_{it}^{*} is the logarithm of the optimal price in the gas station i at date t and p_t^o the logarithm of the price of refined oil sold in Rotterdam at the spot market at day t. $\varepsilon_{1,it}$ is a firm- and time-specific shock. We could interpret p_t^o as a common shock to the frictionless price and $\varepsilon_{1,it}$ as a specific or idiosyncratic shock to the frictionless price. Under some conditions shown to be of the (S, s) type, the optimal adjustment rule is then to adjust the price only if the difference between the optimal price p_{it}^{*} and the price $p_{it-\tau}$ modified at period $t-\tau$ (where τ is the duration since the last price change), exceeds some threshold S_i (for price decreases) or s_i (for price increases). When prices are reset they are set at the optimal frictionless price.The firm's pricing decision depends on the distance covered by p_{it}^{*} between dates $t-\tau$ and t (the date at which the decision is taken). However, the (S, s) model puts strong restrictions on the patterns of price adjustments. In particular, in a standard menu-cost model, the size of the price change will be the same for all price decreases equal to S_i and all price increases equal to s_i. This prediction is not consistent with the variance of price changes for a given firm over time. Moreover, a large adjustment cost would imply infrequent and large price changes. Relative small price changes would be difficult to predict with such a model.

We rely here on a time-varying (S, s) band model. As shown by Caballero and Engel (1999) in a model of investment decision, thresholds that fluctuate over time can be obtained under such the assumption of a random menu cost. In the context of prices, Dotsey *et al.* (1999) assume such random menu costs. In our model, the threshold can vary over time and across firms. Overall, our approach is related to the adjustment hazard model developed by Caballero and Engel (1999): the probability of a price change is a function of the gap between the current price and a frictionless optimal price. That gap is the relevant state variable, so that despite the fact that an optimization problem underlies the decision rule, no expectation term is explicitly present. The adjustment hazard model is rather flexible. For instance, our model encompasses the Calvo model: when the threshold varies a lot, the model predicts a constant probability for a price change and can generate small price changes (see also Dhyne et al. (2011), Fougere et al. (2010) and Gautier and Le Bihan (2011)).

The price decision rule could summarized as follows:

$$\begin{array}{rl} \text{if } p_{i,t-\tau} - p^*_{i,t} \geq S_{it} & p_{it} = p^*_{i,t} \\ \text{if } p_{i,t-\tau} - p^*_{i,t} \leq s_{it} & p_{it} = p^*_{i,t} \\ \text{if } S_{it} > p_{i,t-\tau} - p^*_{i,t} > s_{it} & p_{it} = p_{it-\tau} \end{array} \tag{2}$$

where upper and lower bands are defined as:

$$S_{it} = \gamma_{iS} X_{it} + \varepsilon_{2,it} \tag{3}$$

$$s_{it} = \gamma_{is} X_{it} - \varepsilon_{2,it} \tag{4}$$

where S_{it} and s_{it} are the upper and the lower stochastic bands, X_{it} are exogenous variables explaining adjustment costs and $\varepsilon_{2,it}$ is firm- and time-specific shock to the adjustment cost. Consistent with the theoretical models of random menu cost (e.g. Dotsey *et al.*, 1999), the menu cost shock is independent from the shock $\varepsilon_{1,i,t}$ on the optimal price.

This specification is close to the model considered in Davis and Hamilton (2004) or Douglas and Herrera (2010). However, we depart from those studies in one dimension. Many studies examining price rigidity (including Hamilton and Davis (2004) and Douglas and Herrera (2010)) focus on the probability of price change and estimate binary response or durations models but they do not consider information on the size of price adjustments. Following Dhyne et al. (2011) and Fougere et al. (2010) we here use information on the size of price changes to identify first the idiosyncratic shock on the frictionless price (which might play a key role in predicting some specific features of price rigidity patterns) and second to disentangle the volatility of the frictionless price and the volatility of the adjustment cost over time. This is not possible in a simple binary response model.

The time dimension is quite large since we observe each gas station during more than 800 days. So, following the strategy proposed by Davis and Hamilton (2004), we estimate a pricing decision rule for every single gas stations. Davis and Hamilton (2004) consider 8 wholesale firms in their sample we have here more than $10,000$ firms. So, we are able to estimate the distributions in the gas station population of γ_s, γ_S, σ_2, β, α and σ_1 and we assess the degree of heterogeneity in the pass through of oil prices to retail prices and in the adjustment costs over time and among firms.

Finally, we should note that contrary to other models especially those estimated on time-series aggregate data, we do not assume here asymmetry in the response of the frictionless price to the wholesale price. We do not suppose two different βs for price increases and decreases. This hypothesis would be difficult to make in our simple theoretical framework. However, we here allow for an asymmetry in the adjustment thresholds, a lower value of s compared to S in absolute values would imply a quicker adjustment to wholesale price increases than to wholesale price decreases. We extend here Dhyne et al. (2011) by allowing S and s to be not necessarly equal in absolute values. However, in the long term, all firms will incoporate the wholesale price variations in their prices and the degree of pass through is equal to β.

In our econometric specification there are two main stochastic processes and two groups of paramaters to estimate: the first process is the one associated to the frictionless price, we estimate for each gas station i, α, β and σ_1 ($\varepsilon_{1,it}$ are supposed normally distributed with mean 0 and variance σ_{1i}^2). The second group of parameters is associated to the time-varying adjustment thresholds where we estimate γ_{iS}, γ_{is} and σ_2 ($\varepsilon_{2,it}$ are supposed normally distributed with mean 0 and variance σ_{2i}^2). Formally, our model is a bivariate sample selection model where the first equation gives the price change decision and the other one the size of the price changes. If the same regressors appear in both equations, the identification comes from the functional form (Wooldridge 2002). We here use an exclusion restriction, following Fougere et al (2010) we assume that the adjustment costs vary with the day in the week. As shown below, the frequency of price changes varies a lot over the week, prices are more likely to be changed on Tuesday and Friday than on Saturday, Sunday or Monday. Those differences could be explained by two causes: first, some gas stations may be closed during the week end or at least there is no employee to physically change prices, second, this seasonality could reflect the process of information acquisition (as noted for instance in Asplund et al. (2000)). Gas companies observe oil prices on Monday and decide at a more or less centralized level to change their prices on Tuesday conditionally on changes in oil prices at the beggining of the week. Then price change decisions should be communicated to all gas stations and it could be costly and rather long (see

Muller et al 2010, Woodford 2003 or Zbaracki et al 2004). This seasonality would affect the adjustment costs but not the frictionless price which is mainly governed by wholesale prices. Woodford (2009) and Alvarez et al. (2011) propose models where firms have to face a cost of information and a menu cost and they show that their models are able to match most of empirical fetaures of price data.

We estimate this model using standard maximum likelihood function procedures. An Appendix provides details of calculations for the likelihood function.This model is estimated separately for diesel and unleaded petrol. We restrict our sample to all firms observed more than one year in order to have a sufficiently large time dimension. For diesel prices, the sample contains $7,917$ gas stations and for unleaded petrol prices, it contains $7,211$ gas stations. We also exclude observations made on Sundays since there are very few price changes on Sundays and identification of thresholds associated to Sunday observations might be difficult.

4.2 Results

Table 5 reports estimation results of the time-varying (S, s) models separately for diesel and unleaded petrol prices. We report statistics on the distribution of paramaters estimated firm by firm.

The first three lines of the table 5 report results associated with the frictionless price p^*. The pass through of the wholesale market price (Rotterdam prices) to retail prices is always positive and significant in all firms but it is different from 1. For diesel prices, the average pass through of French gas stations is 0.77 and its median is 0.80 whereas for unleaded petrol prices this pass through is somewhat lower close to 0.67 on average and to 0.68 for the median. This parameter is supposed to capture in our specification the weight of wholesale gasoline in the firm cost function of the firm. Using national accounts in the retail gasoline sector, we can assess the share of wholesale gasoline cost in total costs, this share is about 75 to 85%. This result is quite consistent with our results.

Figure 7 displays the whole distribution of β parameters estimated using gas station data. For both diesel and unleaded petrol prices, we find that the distributions of the β coefficients have two different modes. This heterogeneity corresponds to differences in the degree of pass through between supermarkets and other gas stations. As shown in Table 6, we find that for diesel prices, the average pass through is 0.81 in supermarkets and 0.73 in other gas stations. We can also observe that the variability in the pass through is lower for supermarkets (0.04) than for other gas stations (0.07). Among other gas stations, the pass through is lower in gas stations on motorways and more generally higher for gas stations with the lowest prices. For unleaded petrol prices, we obtain similar conclusions, the pass through is a little higher in supermarkets than in other gas stations (0.70 versus 0.64) but the difference is smaller.

Finally, the values of parmaters σ_1 are on average quite large 1.58% on average for diesel prices and 1.92% on average for unleaded petrol prices. We can interpret the impact of the market Rotterdam price as a common aggregate shock and ε_1 captures all firm and time-specific shocks. The large values of σ_1 reflects the importance of idiosyncratic shocks in triggering price changes; this feature was acknowledged by many studies of the recent literature on price rigidity (e.g. Golosov and Lucas, 2007), it can explain why we observe relative large price changes (compare to the aggregate fundamentals) and why we can observe the same day price increases and decreases.

The second part of Tables 5 and 6 reports the parameters associated with the adjustment thresholds.

In a standard constant adjustment threshold model, large values of the bands reflect large costs of price changes and all price changes are equal to the size of the inaction band. In our framework, adjustment thresholds are time-varying, allowing for variability in the size of price changes over time for a given gas station. However, as shown by Gautier and Le Bihan (2011), in that case, the mapping between those parameters and the adjustment cost is not trivial, and the mean and the variance of the threshold are positively related. In particular, when both the mean and the variance of adjustment thresholds are large, the price setting behaviour is very close to a Calvo price setting model. We compare our results obtained with a time-varying (S, s) model with results obtained from a standard (S, s) model and a Calvo model (see Tables B and C in appendix). First, as expected, the estimated adjustment thresholds in time-varying (S,s) models are larger than those obtained for a fixed menu cost model. On average, for diesel prices the time-varying adjustment thresholds are larger than 4.33% in absolute values whereas the average size of price changes is less than 2.5%. For unleaded petrol prices, the adjustment thresholds are a little larger more than 5.5% whereas the average price change in absolute values is around 3%.

Second, the variation over the week of the thresholds reflect variations in the price adjustment cost. The thresholds are larger on Monday and Saturday (the median value is larger than 5% for price decreases and price increases on Monday and Saturday for diesel prices and around 7% for unleaded petrol prices), the thresholds are on average lower on Tuesday and Friday (about 4% for diesel prices and 5% for unleaded petrol prices). This result is consistent with the variations in the frequency of price changes over the week (see above). Differences between supermarkets and other gas stations are not strong. Mean and variance of adjustment thresholds are a little larger for supermarkets than for other gas stations, this result suggests that if the pass through is larger for supermarkets, the decision of price change is less impacted by the aggregate shocks.

Finally, the variability of the idiosyncratic shock ε_2 associated with the adjustment threshold is quite large about 3.1% for diesel prices and 4.1% for unleaded petrol prices. This explains the gap between the average observed price change and the average adjustment threshold (see Gautier and Le Bihan 2011 for details). This large variability is necessary to replicate the large variability in the size of price changes for a given station.

To test the presence of asymmetry in the response of gasoline prices to shocks on the wholesale price, we use the estimates obtained for the adjustment thresholds. If there is some downward price rigidity, it would imply that on average, for a given value of the price gap $(p_{i,t-\tau} - p^*_{i,t})$, a firm would be more likely to hit the threshold trigerring price increases than the threshold triggering price decreases. In other words, it would imply that in absolute values, the threshold associated to price increases is smaller than the threshold associated to price decreases. If we examine the median values of the thresholds for price decreases and increases, we can note that on Monday, Tuesday and Wednesday there seems to be some asymmetry in price changes, the difference appears a little larger for unleaded petrol around 0.2 and $0.1 - 0.15$ for diesel prices. In other days, the difference is smaller (less than 0.1) but the direction of the asymmetry is also reversed. If we analyze estimation results obtained from a fixed menu cost model, we find a small downward asymmetry for unleaded petrol but not for diesel prices.

More formally, to assess the degree of asymmetry in price changes, we test that the difference between thresholds triggerring price increases and decreases are significant at each day and for every gas station, this test is a Wald test ($\gamma_s + \gamma_S > 0$). Table 7 summarizes the proportion of firms for which the sum of thresholds is significantly larger than zero. We detect for a small proportion of gas stations some asymmetry in price changes. At a 5%-level, we find that between 15 and 20% of gas stations selling diesel have asymmetric threshold on Monday, Tuesday or Wednesday. This proportion is a little higher for unleaded petrol (slightly above 20%). At a 1% level, the proportion is smaller for diesel prices. If we consider Thursday, Friday and Saturday, the proportion of asymmetric firms is lower close to 8% for diesel and 10% for unleaded petrol. We also find that asymmetric behaviour is more frequent in supermarkets than in other gas stations.

The proportion of gas stations which are downward asymmetric (at a 5% level significancy) for at least 3 days of the week is equal to 5.5% for diesel and 11.8% for unleaded petrol; if we consider four days of asymmetric behaviour those proportions are 1.1% and 4.4%. To compare those results, we run the same test on the standard fixed menu cost model and we find a little less than 6% of gas stations have an asymmetric behaviour for diesel prices and 7.1% for unleaded petrol.

4.3 Fit of the model

In this subsection, we assess the goodness of fit of our model by examining its ability to replicate some aggregate moments and the distribution of price changes. We run Monte Carlo simulations on the basis of our parameter estimates and explanatory variables are taken at their sample values. We simulate each price trajectory 150 times using our model. Then, we compute aggregate statistics like the frequency of price changes, the average price increase and decrease, we also display the whole distribution of price changes. Moreover, we compare the simulated statistics obtained with our time-varying (S, s) model with aggregate statistics obtained using estimates from two other models (Calvo and fixed (S, s) model).

Results are summarized in Tables 8 and 9 and on Figures 8 and 9. First, on the frequency of price changes, we find that the Calvo model does better in reproducing the average frequency of price changes than other models (between 11 and 10.5% of price changes versus 11% and 10% in the sample for diesel and unleaded petrol respectively). The two menu cost models overestimate the frequency of price changes but time-varying (S, s) model is closer than the fixed (S, s) model. On the average size of price changes, the Calvo model and the variable (S, s) model are closer to the sample average than the fixed (S, s) model which predict that almost a majority of price changes are larger than 5% in absolute values. If we examine more closely the simulated distributions of price changes, we can observe that the Calvo model is able to match quite correctly the distribution of actual price changes but cannot reproduce the small proportion of small price changes: between 2 and 3% of price changes are smaller than 0.5% in absolute values in our sample and the Calvo model predicts more than 15% of price changes samller than 0.5% in absolute values (see Figures 8 and 9). The variable menu cost model is better able to match this stylised fact, the fraction of small price changes is between 3 and 3.5% for diesel and unleaded petrol. Finally, Table 9 summarizes the main results on the proportion of price changes over the week, we find that the variable menu cost model is able to predict changes in frequencies of price changes over the week. More generally, the main drawback of the Calvo model is that it is unable to predict that the frequency of price changes will move with the Rotterdam market.

5 Aggregate dynamic response of gasoline prices

In this section, we run several simulation exercises to assess the speed and the aggregate response of gasoline prices to different shocks to the Rotterdam wholesale prices. For that, we simulate individual trajectories of prices for all gas stations using Monte Carlo simulations on the basis of our parameter estimates. Shocks $\varepsilon_{1i,t}$ and $\varepsilon_{2i,t}$are drawn from two independant i.i.d. normal distributions with mean 0 and variances σ_{1i} and σ_{2i}. We also assume Rotterdam wholesale price to be constant, price decisions are only driven by the idiosyncratic shock. Each trajectory is simulated for 55 days and the first 15 days to eliminate some possible initial conditions issues.

We simulate each trajectory 500 times. We then aggregate all individual price trajectories to obtain an aggregate price level. Finally, we run again the same experiment but introduce a permanent shock in the wholesale gas price. We consider different options: -1%, $+1\%$, $+2\%$ and $+5\%$ change in the wholesale Rotterdam prices. Finally, we compare the average inflation rate after the shock with the inflation rate without any shock. Moreover, we compare the simulated inflation response to shocks obtained with our variable (S, s) model with the inflation response obtained using estimates from our two other models (Calvo and constant (S,s) model).

Figure 10 displays the inflation response of diesel and petrol prices to a 1%-shock on Rotterdam prices in the three models. We first observe that in all three models the long-term impact of the shock is exactly equal to the average value of β (ie 0.77 for diesel and 0.67 for unleaded petrol), this result is very consistent with the degree of pass through of Rotterdam prices to retail prices. We also observe a rather short adjustment of retail prices to the shock. After 10 days, it seems that a full adjustment is achieved. Table 10 gives some details on the delay of adjustment of retail prices. This table gives the proportion of the shock absorbed in inflation after a certain duration in days. Using the variable (S, s) model as a DGP for the simulations and a 1%-shock, we find for example that around 40% of the total adjustment is achieved the day after the shock. We observe that 5 days after the shock about 90% of the total response of retail gasoline prices is observed and 95% of the total response is incoporated into prices after 2 weeks. There are some differences in the delay for the transmission of shock between the different models used as DGP in the simulation. On Figure 10, we observe that the transmission is shorter in the case of the constant (S, s) model and longer in the Calvo model. 95% of the total response to the shock is observed after 3 days in a constant (S, s) model whereas it takes 15 days in the Calvo model. The time-varying (S, s) model appears as an intermediate case. Those differences in the delay to incorporate shocks are rather well-known.

Figure 11 illustrates the response of the frequency of price changes to a 1%-shock on Rotterdam prices. In the Calvo model, the probability of price change is constant over time and exogenous, so it is not modified after a shock on Rotterdam price. Consequently, firms will change their prices gradually, the day after a shock 23% of firms will change their prices, at date 2, among 77% of firms which have not changed their prices, 23% of other firms will change their prices (i.e. 18% of total firms)...The cumulated proportion of prices modified at each date after the shock is exactly equal to the proportion of the shock incorporated into prices. However, for firms adjusting their prices after the shock the sizes of price changes are heterogenous. Firms that changed their prices the day before are more likely to change their prices by smaller amounts than firms that were allowed to change some weeks ago for instance. In our simulation exercise, the frequency of price changes does not respond to shock on Rotterdam market prices with the Calvo model (see Figure 11). In a standard menu cost, as explained by Caballero and Engel (2007), the reaction is quicker because of a selection effect: firms adjusting their prices are those the closest to the threshold and when they adjust they adjust by the size of the band either $-S$ if it is a price decrease and s if it is an increase. This implies a quick increase in the frequency of price changes driven by a drop in the frequency of price decreases and an increase in the frequency of price increase (see Figure 11). The random (S, s) model allows to reduce the selection effect and makes the adjustment delay longer. If σ_2 is extremly high, price changes are not driven any more by change in fundamentals but only by idiosyncratic shocks on the adjustment cost and in that case, the model is very close to the Calvo model. In our simulation exercise with a time-varying (S, s) model, we can observe that the frequency of price changes responds more slowly than in the case with a fixed (S, s) model. However, the difference is quite small implying that the estimated time-varying model behaves quite closely to the fixed menu cost model in terms of frequency of price changes.

Figure 12 shows the inflation response of retail fuel prices to different market price shocks using the time-varying threshold model. First, we observe that the long term response is perfectly proportional to the shock, in the diesel price case, after a 1%-shock we obtain a response of 0.77, with the 2%-shock a response equal to 1.54% and with the 5%-shock a response equal to 3.85%. Second, we also observe that a larger shock is incorporated more quickly (see Figure 12). In Table 10, for diesel prices, a 5%-shock on Rotterdam prices is almost fully incorporated in 5 days (95% of the shock) whereas 5 days after the shock less than 90% of the total response to the shock was incoporated in the case with 1 and 2%-shocks. For petrol prices, we obtain similar conclusions: 5 days after the shock, 91% of the total response to the shock is incoporated whereas only 86% and 87% of the total response to the shock is observe in the cases 1% and

2%-shocks. We can also note that shocks are slightly more quickly incoporated in diesel prices than in petrol prices. The fact that retail prices react more quickly to larger shocks can be rationalized by the selection effect: the proportion of firms adjusting in a menu cost model is equal to the proportion of firms closest to the threshold and when they adjust those firms fully incoporate the shock. So, when the shock is larger, the number of firms adjusting their prices is larger (see Figure 13 for an illustration in our simulation exercise). This implies that the shock is more quickly incoported into prices. On the contrary, in the Calvo model, the selection effect is null and the number of firms adjusting after a shock does not vary. So, the delay in reaction of retail prices to a market price shock will be exactly the same for all types of shocks.

Finally, we find no asymmetry in the aggregate response of retail gasoline prices to a market Rotterdam price shock. To test the presence of this asymmetry, we run simulations with a positive and a negative 1% shock on Rotterdam prices for diesel and petrol prices. As expected, Table 10 shows no difference in the speed of reaction of retail prices to a positive or a negative market price shock. In all cases and models we use we find the same delays in the transmission of shocks. There is however a very small exception for petrol prices at date +1 for time-varying threshold model. This result is very consistent with what we find when we test the presence of asymmetry in the thresholds. The proportion of firms with some asymmetries is rather limited and this aggregate result suggests that those assymmetries are very small.

6 Conclusion

In this paper, we examine the degree of price rigidity in French gas stations using a data set containing millions of price quotes collected at a daily frequency on the period between January 2007 and June 2009.

We first provide some new findings on the price setting behaviour of gas stations. Gasoline prices are modified very frequently, they are modified on average more than once a week. Price changes show some regular patterns over the week, firms are more likely to change their prices on Tuesday and Friday than on Saturday, Sunday or Monday. We also observe on the sample period that price decreases are as frequent as price increases. Prices changes are on average rather sizeable if we compare them with the average price changes of wholesale price changes. Moreover, the distribution of price change is M-shaped, ie the proportion of small and very small price changes is very low. This pattern of the distribution of price changes is fully consistent with menu cost predictions and is not present in most empirical studies on price rigidity using individual price quotes. Finally, we observe some heterogeneity in price setting behaviour of gas stations. Supermarkets change their prices more often but by larger amounts than other traditional gas stations.

In this paper, we also estimate price rigidity models and by using those price rigidity models we are able to better assess the degree of price rigidity and the degree of pass through of costs to gasoline prices. Our baseline model is a time-varying (S, s) model which allows us to be rather flexible to replicate the infrequency of price changes and the distributions of price changes. We estimate this model for every gas stations available in our data set. We find that the degree of pass through of wholesale market prices to retail gasoline prices is lower than 1 for most gas stations. This pass through is on average 0.77 for diesel prices and 0.67 for unleaded petrol prices. This pass through is somewhat larger in supermarkets than in other gas stations (on average 0.81 versus 0.73 for diesel prices and 0.70 versus 0.64 for petrol prices). Lastly we find that thresholds trigerring price changes are rather large on average but vary a lot over time (because of systematic variations over the week but also because of idiosyncratic shocks). Finally, using simulations, we simulate the aggregate response to shocks of gasoline retail prices. We find that the adjustment of fuel prices to market wholesale price shocks is quick, most of response of retail prices occurs in the first two weeks after the shock. We also compare response obtained with alternative models of price rigidity. The longest response is obtained with the Calvo model where the delay for a full response is close to 3 weeks.

We also test for the presence of asymmetry in the response of retail gasoline prices to market wholesale price shock. We assess whether thresholds trigerring price increases and decreases are different for every gas stations. A larger threshold for price decrease would imply that firsm would react more slowly to a decrease in costs. We find that a small proportion of gas stations show some asymmetry in their price setting behaviour and when their price setting behaviour is asymmetric, the asymmetry is small. All in all, in our simulation exercises, the speed of reactions of retail prices to a comparable positive or negative wholesale price shock is the same.

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Table 1: Price durations (in days) and frequency of price changes (in %)

	Nb obs.	Mean	Q25	Q50	Q75
Price duration					
- Diesel					
individual price trajectories	1,315,188	5.23	2.00	4.00	7.00
average by gas station	10,161	6.64	4.61	6.05	8.13
- Unleaded Petrol					
individual price trajectories	1,213,842	5.58	2.00	4.00	7.00
average by gas station	10,013	7.02	4.95	6.41	8.54
Frequency of price changes					
- Diesel					
Total	10,161	17.62	11.82	16.25	21.50
Increase	10,161	8.71	5.83	8.13	10.78
Decrease	10,161	8.91	5.84	8.15	10.91
- Unleaded Petrol					
Total	10,013	16.52	11.19	15.27	20.00
Increase	10,013	8.74	6.07	8.21	10.56
Decrease	10,013	7.78	5.00	7.06	9.55

Note: For statistics on price durations, for the line "individual price trajectories", we compute statistics on the duration of price changes considering all individual price trajectories. For the line "avergage by gas station" but also for the frequency results, we compute firstly the average duration and frequency of price changes for each retailer. Then we compute the statistics (mean, Q1, median, Q3) of these average durations and frequencies.

Table 2: Heterogeneity in price durations (in days) and frequencies of price changes (in %)

	Supermarkets	Other gas stations
Price duration		
- Diesel	6.01	7.14
- Unleaded Petrol	6.47	7.46
Frequency of price changes		
- Diesel	20.10	15.60
- Unleaded Petrol	18.54	14.86

Note: We compute firstly the average duration and frequency of price changes for each retailer. Then we compute the statistics (mean, Q1, median, Q3) of these average durations and frequencies.

Table 3: Frequency of price changes over the week (in %)

	Diesel			Unleaded Petrol		
	Total	Supermarkets	Other stations	Total	Supermarkets	Other stations
Monday	12.47	15.13	9.16	12.50	15.19	9.24
Tuesday	18.91	17.79	20.31	19.06	18.00	20.35
Wednesday	17.38	16.25	18.79	17.24	16.18	18.54
Thursday	16.80	15.78	18.08	16.74	15.60	18.13
Friday	21.02	22.14	19.62	21.23	22.33	19.89
Saturday	12.61	12.14	13.20	12.43	11.94	13.02
Sunday	0.80	0.77	0.84	0.80	0.76	0.84

Note: Frequencies are computed as the proportion of price changes (caluclated over all price changes) at each day of the week. All columns sum to 100%.

Table 4: Size of price changes (in %)

		Nb obs	Mean	Q25	Q50	Q75
Diesel prices						
Increases						
	Total	639,966	2.33	1.15	1.77	2.80
	Supermarkets	353,619	2.46	1.08	1.82	3.07
	Other gas stations	286,347	2.16	1.21	1.71	2.54
Decreases						
	Total	651,078	-2.41	-3.06	-1.87	-1.16
	Supermarkets	361,676	-2.50	-3.25	-1.91	-1.09
	Other gas stations	289,402	-2.30	-2.86	-1.85	-1.23
Unleaded Petrol prices						
Increases						
	Total	625,757	2.86	1.41	2.04	3.49
	Supermarkets	340,431	3.07	1.32	2.22	3.89
	Other gas stations	285,326	2.60	1.46	1.92	3.10
Decreases						
	Total	563,489	-2.93	-3.71	-2.16	-1.37
	Supermarkets	311,985	-3.08	-4.00	-2.22	-1.24
	Other gas stations	251,504	-2.75	-3.42	-2.10	-1.45

Note: Frequencies are computed as the proportion of price changes at each day of the week.

Table 5: Estimation results - Time-varying (S,s) model

		Diesel					Unleaded petrol				
		Q25	Q50	Q75	Mean	Stdc	Q25	Q50	Q75	Mean	Stdc
α		1.14	1.88	3.08	2.11	1.27	-3.29	-2.31	-1.24	-2.22	1.73
β		0.71	0.80	0.83	0.77	0.07	0.63	0.68	0.72	0.67	0.06
σ_1		1.42	1.55	1.71	1.58	0.28	1.68	1.88	2.11	1.92	0.41
	Mon.	-7.91	-5.71	-3.77	-7.71	8.00	-9.85	-7.08	-4.79	-9.16	8.44
	Tues.	-5.74	-4.09	-2.96	-4.56	2.67	-7.29	-5.16	-3.78	-5.74	3.19
γ_s	Wed.	-5.93	-4.35	-3.24	-4.76	2.55	-7.45	-5.50	-4.14	-6.03	3.13
	Thu.	-6.19	-4.57	-3.38	-5.02	2.97	-7.67	-5.72	-4.27	-6.31	3.79
	Fri.	-5.49	-4.01	-2.94	-4.39	2.48	-6.87	-5.10	-3.76	-5.56	3.30
	Sat.	-7.68	-5.46	-3.76	-7.51	7.75	-9.52	-6.99	-4.87	-9.11	8.39
	Mon.	3.89	5.81	8.38	8.52	8.76	4.99	7.29	10.51	10.28	9.61
	Tues.	3.09	4.24	5.89	4.72	2.97	3.98	5.41	7.56	6.14	4.50
γ_S	Wed.	3.31	4.46	6.08	4.93	2.88	4.29	5.71	7.77	6.39	4.18
	Thu.	3.29	4.52	6.18	5.03	3.16	4.29	5.79	7.88	6.56	4.61
	Fri.	2.82	3.94	5.46	4.33	2.55	3.70	5.07	6.97	5.58	3.24
	Sat.	3.69	5.36	7.58	7.50	7.97	4.88	6.97	9.68	9.38	8.89
σ_2		2.52	3.11	3.82	3.18	1.03	3.12	3.82	4.74	3.98	1.33

Note: We estimate for each individual gas station a time-varying (S,s) model and then compute statistics on the parameter estimates we obtained. We consider all gas stations with more than 400 individual observations of prices. For diesel prices, 7,917 values of parameters estimates are available and 7,211 for unleaded petrol prices. Observations on Sundays are excluded from the sample used for the estimation.

Table 6: Estimation results - Time-varying (S,s) model - supermarkets versus other gas stations

		Diesel prices				**Unleaded petrol prices**			
		Supermarkets		Others		Supermarkets		Others	
		Mean	Stdc	Mean	Stdc	Mean	Stdc	Mean	Stdc
α		1.47	0.89	2.75	1.27	-2.75	1.45	-1.70	1.82
β		0.81	0.04	0.73	0.07	0.70	0.04	0.64	0.07
σ_1		1.61	0.22	1.55	0.34	1.96	0.33	1.88	0.47
	Mon.	-5.80	5.63	-9.63	9.44	-7.12	5.76	-11.18	10.03
	Tues.	-4.59	2.72	-4.53	2.61	-5.83	3.24	-5.66	3.14
γ_s	Wed.	-4.83	2.54	-4.69	2.55	-6.17	3.15	-5.90	3.10
	Thu.	-5.06	3.06	-4.97	2.89	-6.47	3.77	-6.15	3.81
	Fri.	-4.17	2.64	-4.62	2.28	-5.32	3.33	-5.79	3.25
	Sat.	-6.44	5.81	-8.60	9.17	-8.14	6.54	-10.07	9.80
	Mon.	6.24	6.11	10.82	10.29	7.68	6.82	12.85	11.15
	Tues.	4.86	3.37	4.59	2.49	6.32	5.15	5.96	3.74
γ_S	Wed.	4.99	2.93	4.97	3.14	6.54	4.04	6.25	4.32
	Thu.	5.08	3.18	4.97	3.14	6.67	5.32	6.46	4.86
	Fri.	4.07	2.46	4.59	2.60	4.34	3.14	5.84	3.32
	Sat.	6.47	6.15	8.53	9.34	8.47	7.80	5.84	10.45
σ_2		3.19	1.11	3.17	0.93	4.01	1.36	3.94	1.30

Note: We estimate for each individual gas station a time-varying (S,s) model and then compute statistics on the parameter estimates we obtained. We consider all gas stations with more than 400 individual observations of prices. For diesel prices, 4,004 and 3, 913 values of parameters estimates are available for supermarkets and other stations respectively and 3,585 and 3,626 for unleaded petrol prices. Observations on Sundays are excluded from the sample used for the estimation.

Table 7: Proportion of gas stations with significant downward asymmetric reaction (Wald test $\gamma_s + \gamma_S > 0$)

		5%			1%		
		Total	Supermarkets	Other stations	Total	Supermarkets	Other stations
Diesel							
	Mon.	16.46	24.10	8.64	9.65	15.04	4.14
	Tues.	20.75	24.98	16.43	10.90	14.79	6.93
	Wed.	17.97	17.48	18.48	8.87	9.44	8.28
	Thu.	8.44	11.44	5.37	3.84	5.29	2.35
	Fri.	6.85	8.44	5.21	3.47	4.17	2.76
	Sat.	8.22	9.29	7.13	3.88	4.37	3.37
	Fixed Cost	5.87	8.50	3.35	1.99	3.03	0.99
Unleaded							
	Mon.	22.35	25.44	19.18	18.78	21.34	16.14
	Tues.	21.07	24.26	17.77	15.17	18.61	11.63
	Wed.	20.50	23.42	17.49	14.67	17.38	11.88
	Thu.	11.65	13.28	9.97	8.45	9.95	6.90
	Fri.	10.64	12.65	8.56	7.96	9.95	5.91
	Sat.	13.73	14.67	12.76	11.08	11.89	10.25
	Fixed Cost	7.14	10.10	4.25	2.32	3.37	1.28

Note: We compute the proportion of gas stations for which the hypothesis $\gamma_{s_i} + \gamma_{S_i} > 0$ is accepted at a 5%- and 1%-levels. for the time-varying threshold models, we compute this test day by day (i) and for the standard (S,s) model we test the hypothesis $\gamma_s + \gamma_S > 0$.Sundays are excluded from the analysis.

Table 8: Simulated aggregated statistics

	$F+$	$F-$	$dp-$	$dp+$	Prop. of $\lvert dp\rvert$		
					$< 0.5\%$	$< 1\%$	$> 5\%$
Diesel							
Sample	10.66	10.92	-2.40	2.38	8.86	23.94	8.96
Variable menu cost	13.08	13.11	-2.84	2.90	9.30	18.65	12.45
Fixed Menu Cost	14.37	14.76	-6.09	6.60	0.07	0.21	60.66
Calvo	11.23	11.18	-2.43	2.46	17.34	30.61	10.46
Unleaded Petrol							
Sample	10.27	9.15	-2.96	2.91	6.78	17.00	14.52
Variable menu cost	12.07	12.36	-3.39	3.51	7.71	15.20	21.83
Fixed Menu Cost	14.02	13.83	-7.63	8.22	0.04	0.09	80.07
Calvo	10.62	10.37	2.99	-2.87	14.52	25.78	17.07

Note: We compute simulated price trajectories using our parameter estimates and taking exogenous variables at their sample values. We then compute the frequency of price changes for each gas station and calculate the average frequency of price changes. The same procedure is followed to calculate the average size of price changes and the average proportion of small and large price changes. We use simulations from the time-varying threshold model, the fixed (S,s) model and the "Calvo" model. Sundays are not considered.

Table 9: Simulation results: share of price changes over the week

	Mon.	Tues.	Wed.	Thur.	Fri.	Sat.
Diesel						
Sample	13.12	19.12	17.34	16.78	20.90	12.72
Variable menu cost	15.30	18.24	16.86	16.39	19.40	13.82
Unleaded Petrol						
Sample	13.19	19.24	17.26	16.68	21.13	12.50
Variable menu cost	15.04	18.23	16.98	16.33	19.38	14.04

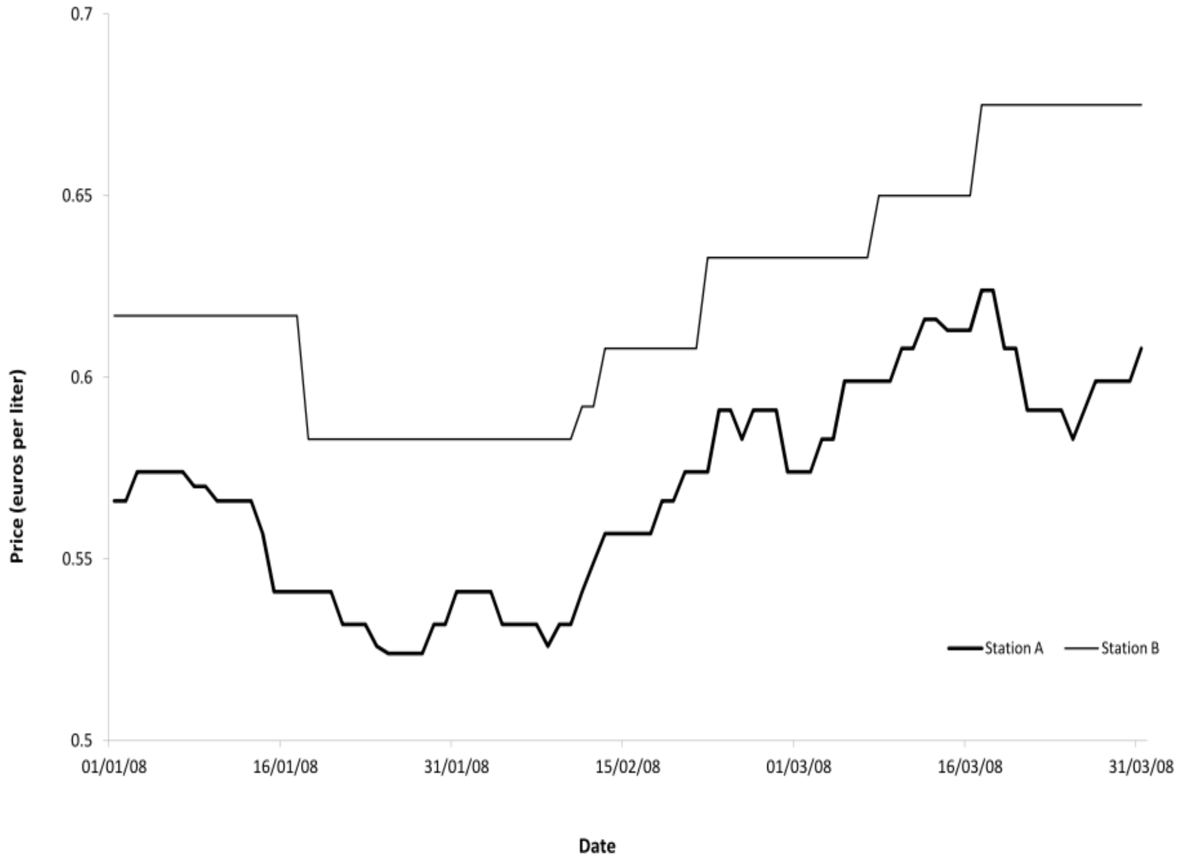
Note: We compute simulated price trajectories using our parameter estimates and taking exogenous variables at their sample values. We then compute the frequency of price changes for each gas station and calculate the average frequency of price changes by day. Sundays are not considered. We use simulations from the time-varying threshold model, the fixed (S,s) model and the "Calvo" model.

Table 10: Dynamic response of gasoline prices to shocks on wholesale market prices (Rotterdam)

		Fixed (S,s)				Time-varying (S,s)				Calvo	
	nb days	-1%	1%	2%	5%	-1%	1%	2%	5%	1%	-1%
Diesel											
	1	0.74	0.74	0.75	0.82	0.43	0.43	0.46	0.58	0.23	0.23
	2	0.90	0.90	0.91	0.95	0.63	0.63	0.66	0.77	0.40	0.40
	3	0.95	0.95	0.96	0.98	0.77	0.77	0.79	0.88	0.52	0.52
	5	0.98	0.98	0.98	1	0.87	0.87	0.89	0.95	0.69	0.69
	10	0.99	0.99	0.99	1	0.97	0.97	0.97	0.99	0.88	0.88
	15	0.99	0.99	0.99	1	0.99	0.99	0.99	1	0.95	0.95
Petrol											
	1	0.73	0.73	0.73	0.77	0.40	0.41	0.42	0.49	0.21	0.21
	2	0.89	0.89	0.89	0.92	0.61	0.61	0.62	0.70	0.37	0.37
	3	0.94	0.94	0.94	0.96	0.75	0.75	0.76	0.82	0.50	0.50
	5	0.97	0.97	0.97	0.99	0.86	0.86	0.87	0.91	0.67	0.67
	10	0.99	0.99	0.99	0.99	0.96	0.96	0.96	0.98	0.87	0.87
	15	0.99	0.99	0.99	1	0.99	0.99	0.99	0.99	0.94	0.94

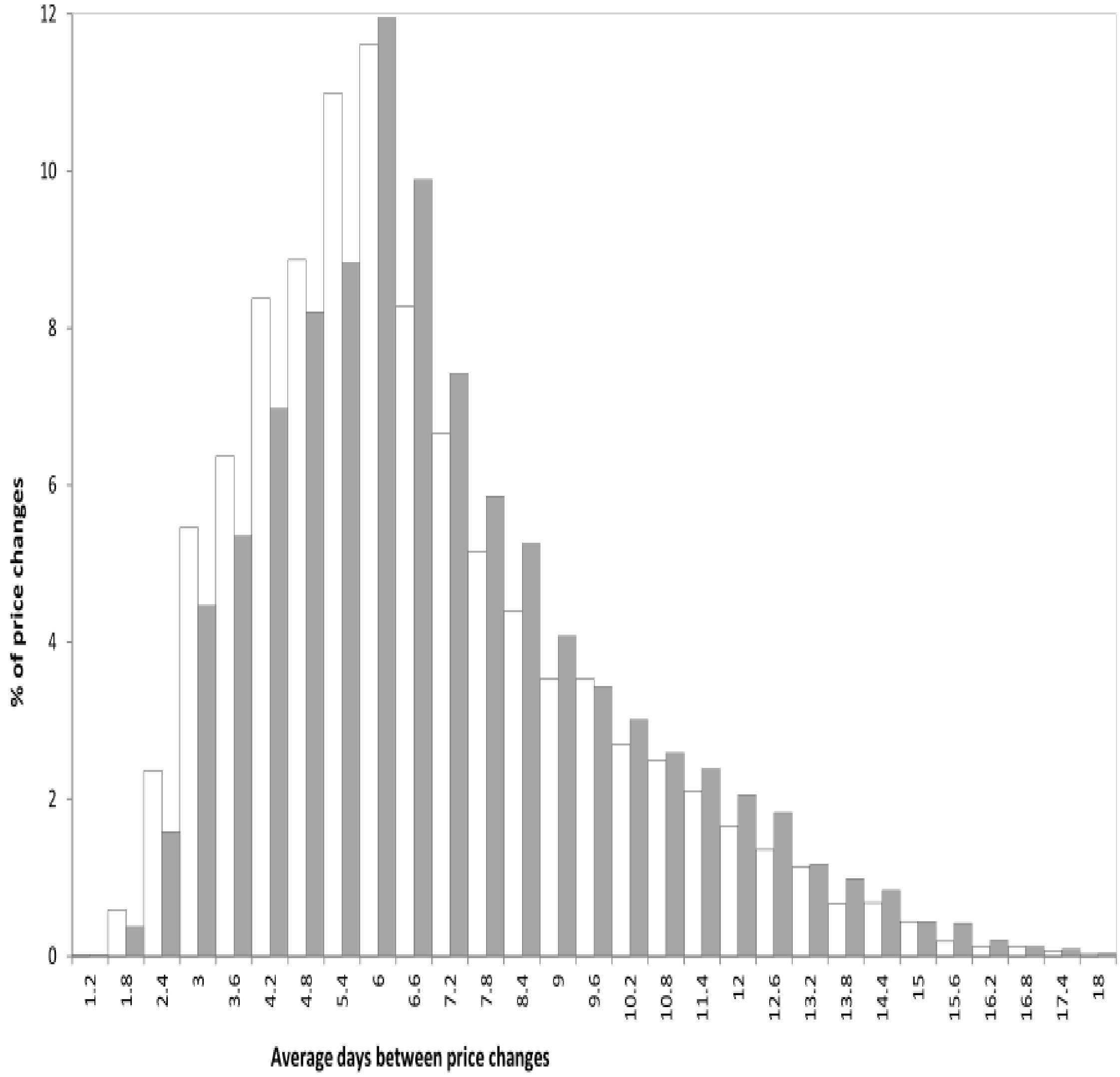
Note: We compute simulated price trajectories using our parameter estimates and aggregate those price trajectories. then we run the same exercise but adding a permanent shock on market prices. We compute the difference between the two aggregate price indices obtained. We then calculate the cumulated response of retail prices to a shock as the cumulated difference. Finally, we compute the ratio as the cumulated response after a certain duration frm the date of the shock on the total response measured as the cumulated response after 45 days. We use simulations from the time-varying threshold model, the fixed (S,s) model and the "Calvo" model.

Figure 1: Examples of price trajectories for two diesel retailers



Note: Prices are tax excluded.

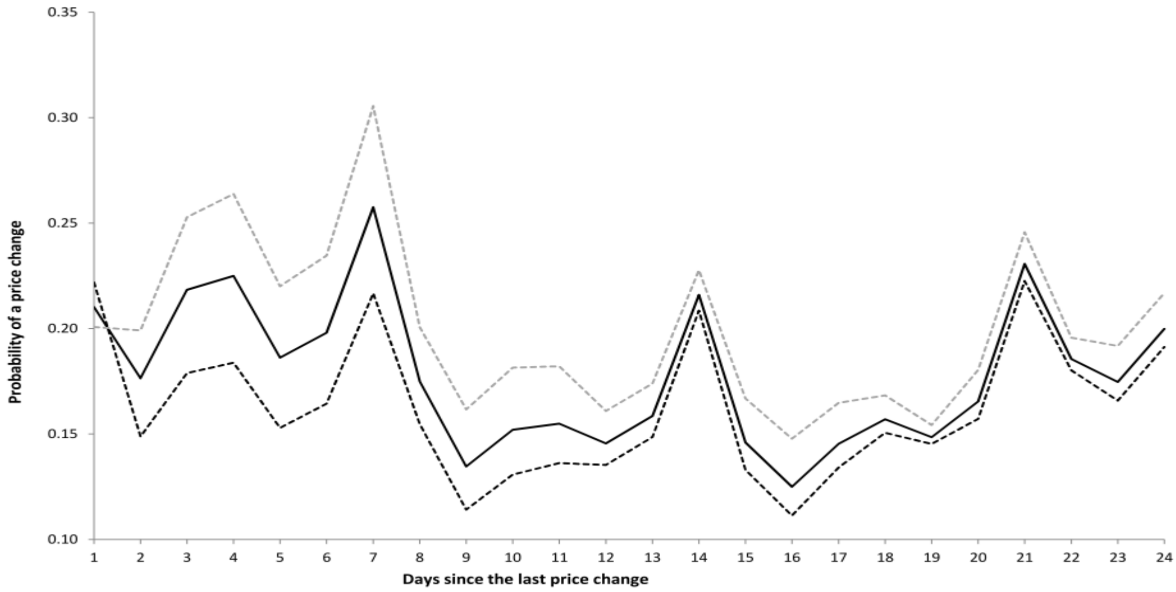
Figure 2: Distribution of firm-level average durations of prices (in days)



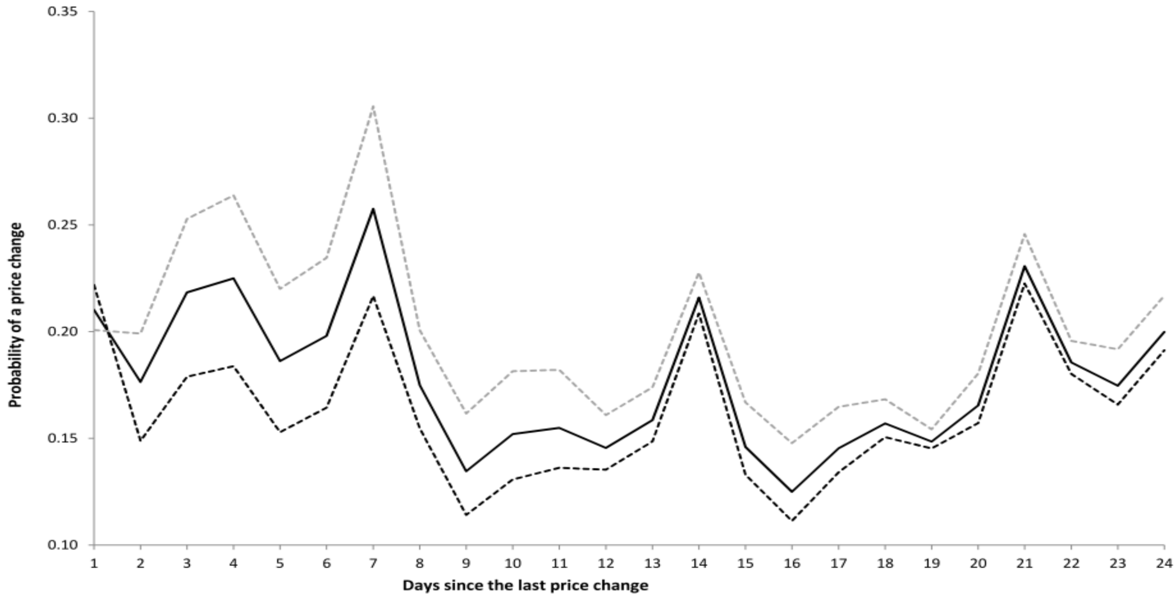
Note. Each observation is the average duration between two price changes calculated for every individual gas stations. Grey bars are for unleaded petrol prices and whitebars are for diesel prices.

Figure 3: Hazard rates for price changes

a) Diesel



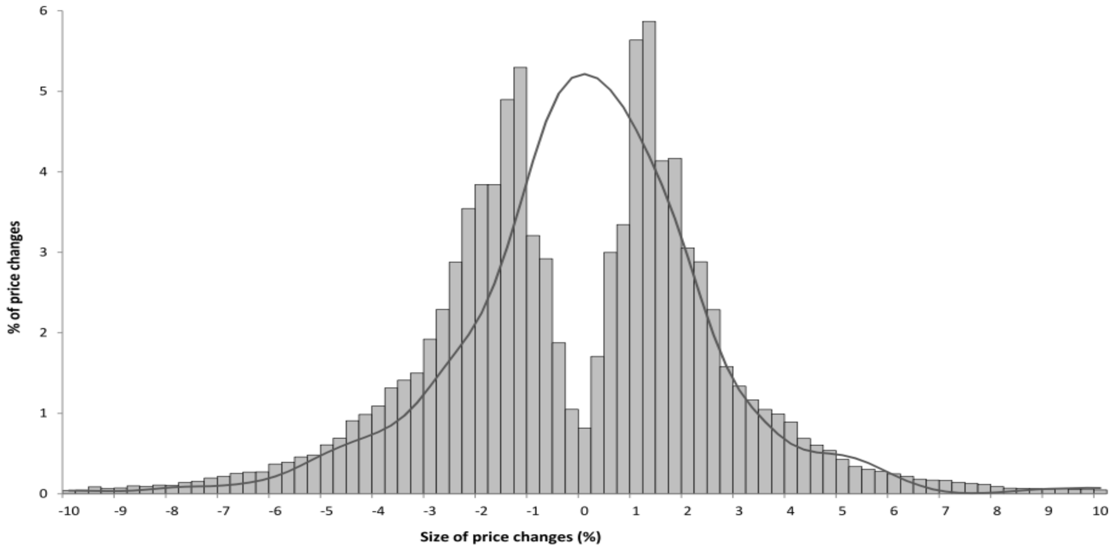
b) Unleaded petrol



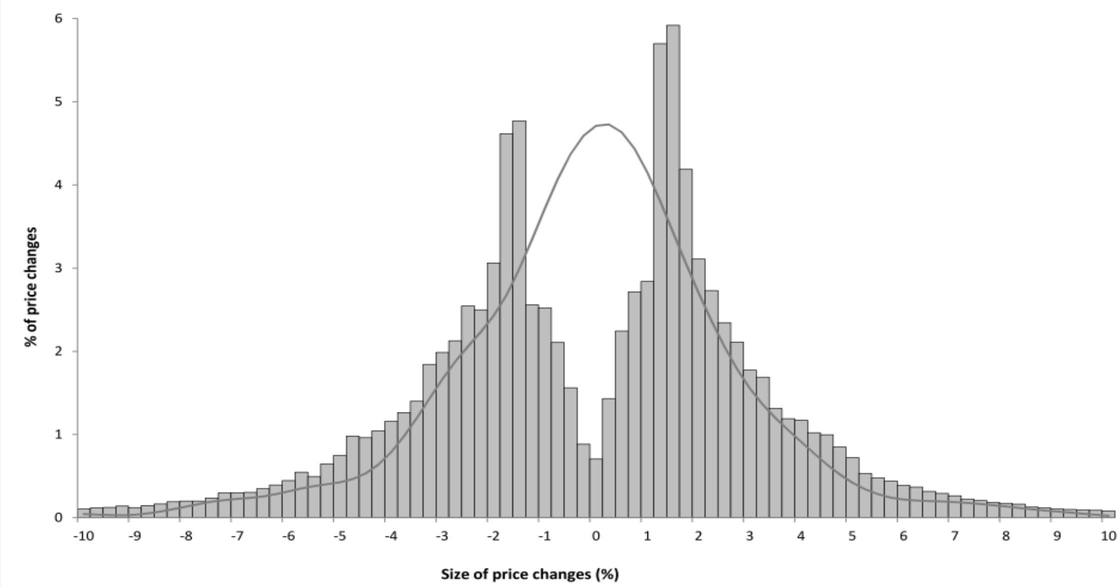
Note. Solid black line for all gas stations, dashed grey line for supermarkets, dashed black line for other gas stations. Left-censored price paths are excluded. All other price paths are taken into account.

Figure 4: Distributions of individual retail price changes (in %)

a) Diesel

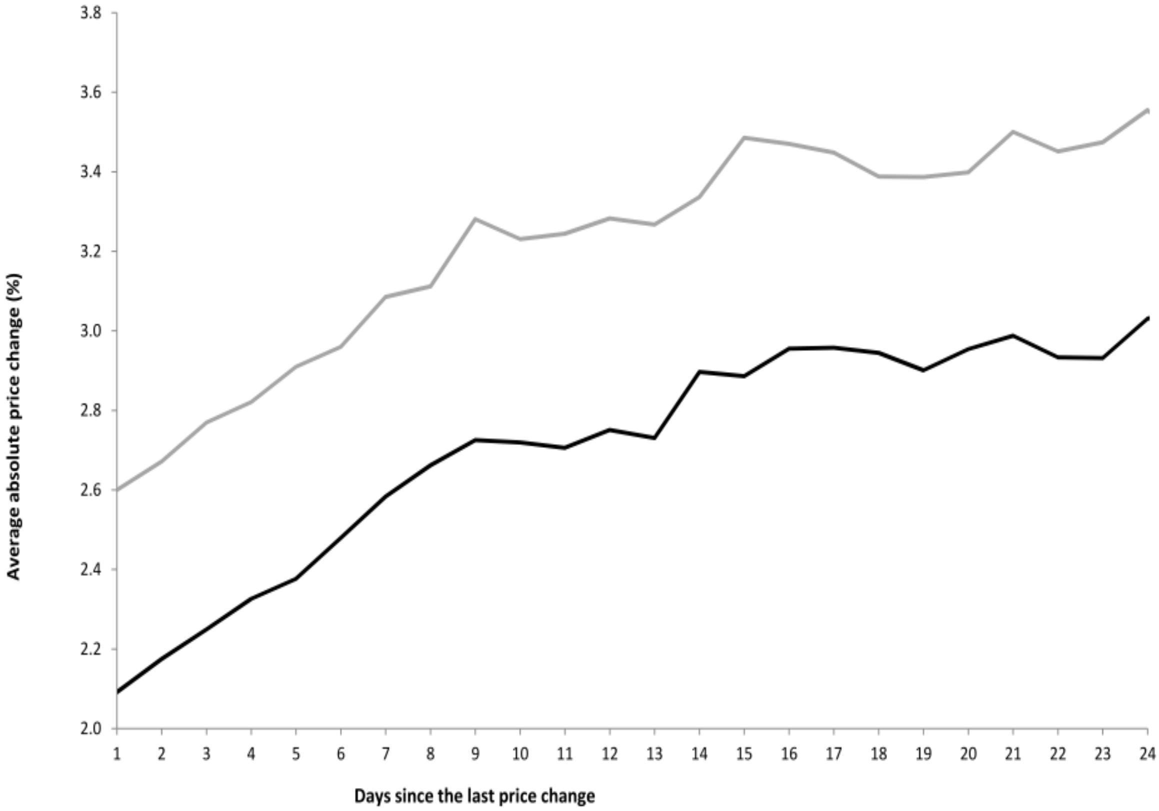


b) Unleaded petrol



Note. Observations are individual price changes when prices are actually changed. Grey bars respresent the distribution of retail price changes and grey lines are the kernel density estimators for distributions of Rotterdam price changes. Retail price changes are calculated using prices excluding taxes.

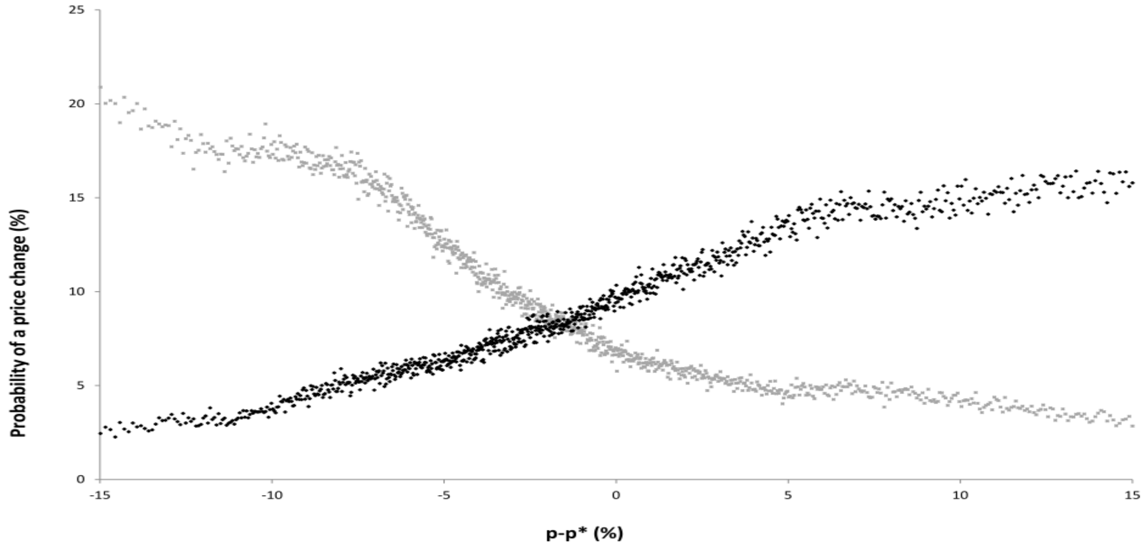
Figure 5: Average size of absolute price changes (in %) by duration of price change (in days)



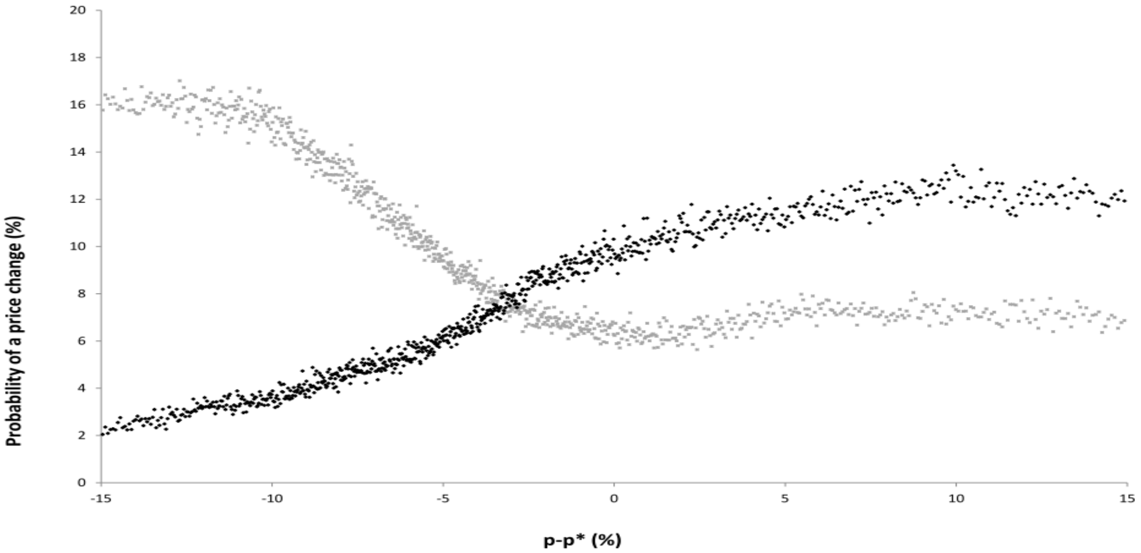
Note. Grey line for unleaded petrol prices and black line for diesel prices. We compute the average price change (in absolute terms) is computed for each duration of prices. Price changes are calculated using prices excluding taxes.

Figure 6: Adjustment hazard functions

a) Diesel

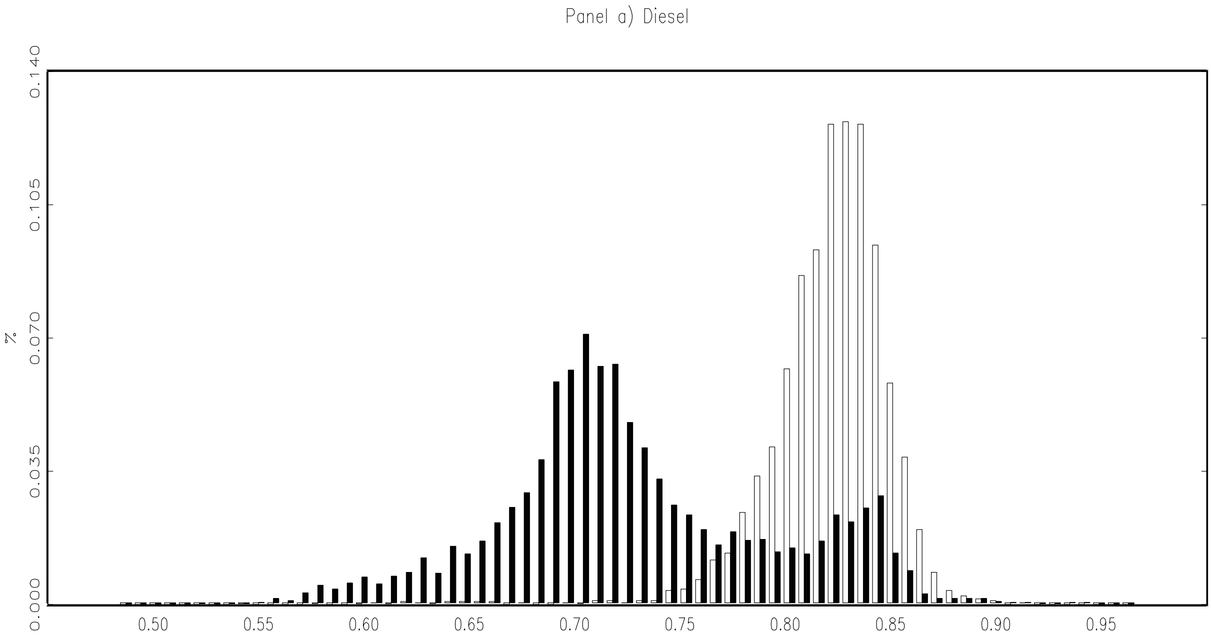


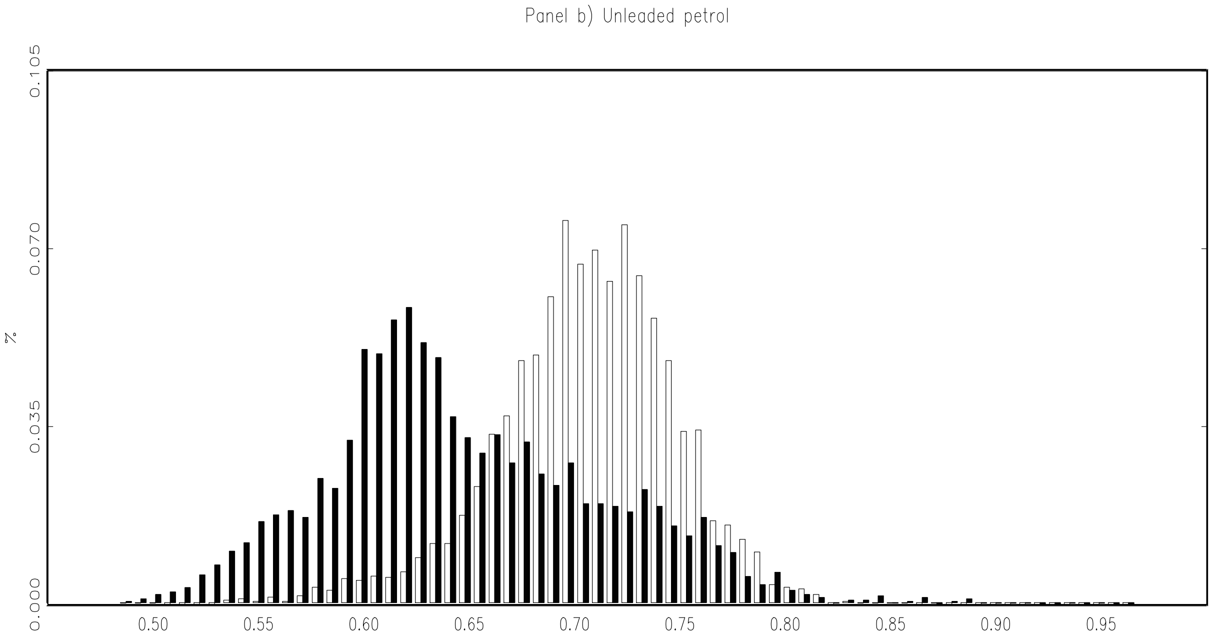
b) Unleaded petrol



Note. Adjustment hazard functions are computed as the probability of price increases or decreases as a function of the log difference between the observed nominal price and the frictionless price (the number of classes of $p - p*$ is chosen optimally). For each retailer, the difference $p - p*$ is centered. p is the log price of fuel in our microdata set. $p*$ is the log Rotterdam market price. Black points are for probability of price decreases. Grey points are for probability of price increases.

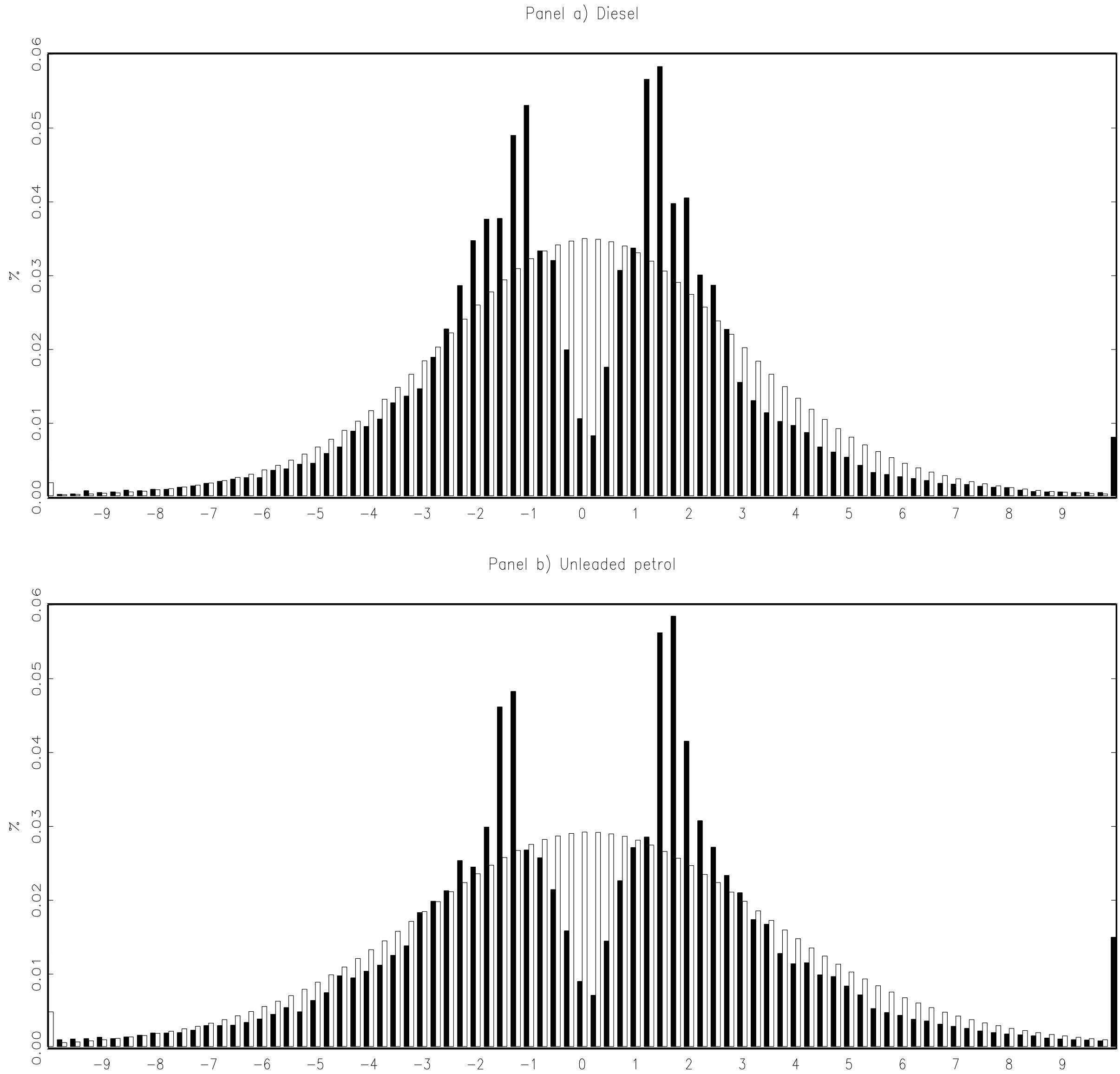
Figure 7: Distribution of β_i (degree of passthrough) using the time-varying threshold model





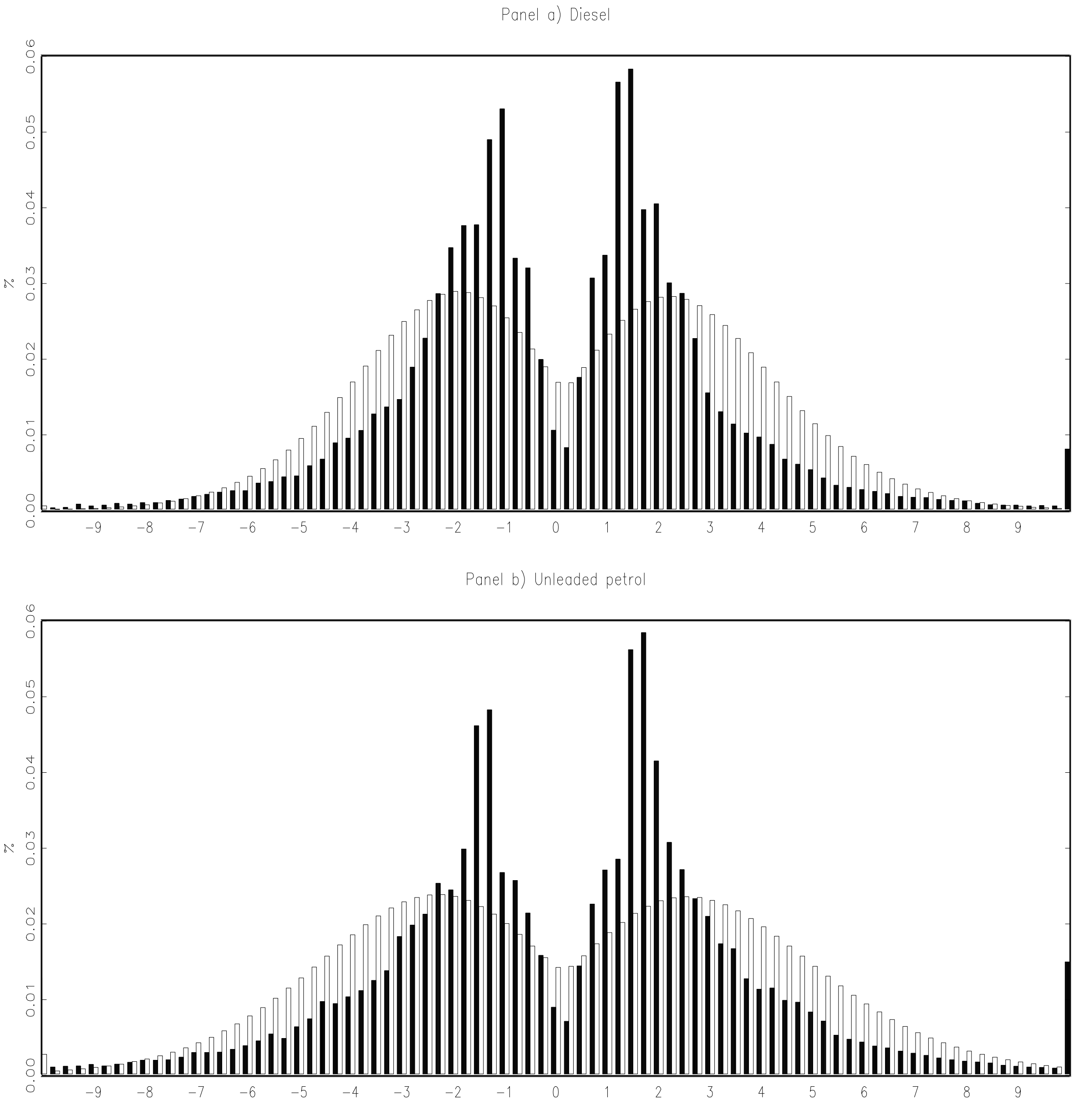
Note: Each observation is a value of β estimated for an individual gas station. White bars are for prices in supermarkets and black bars for prices in other gas stations.

Figure 8: Simulated and actual distributions of price changes (Calvo model versus actual data)



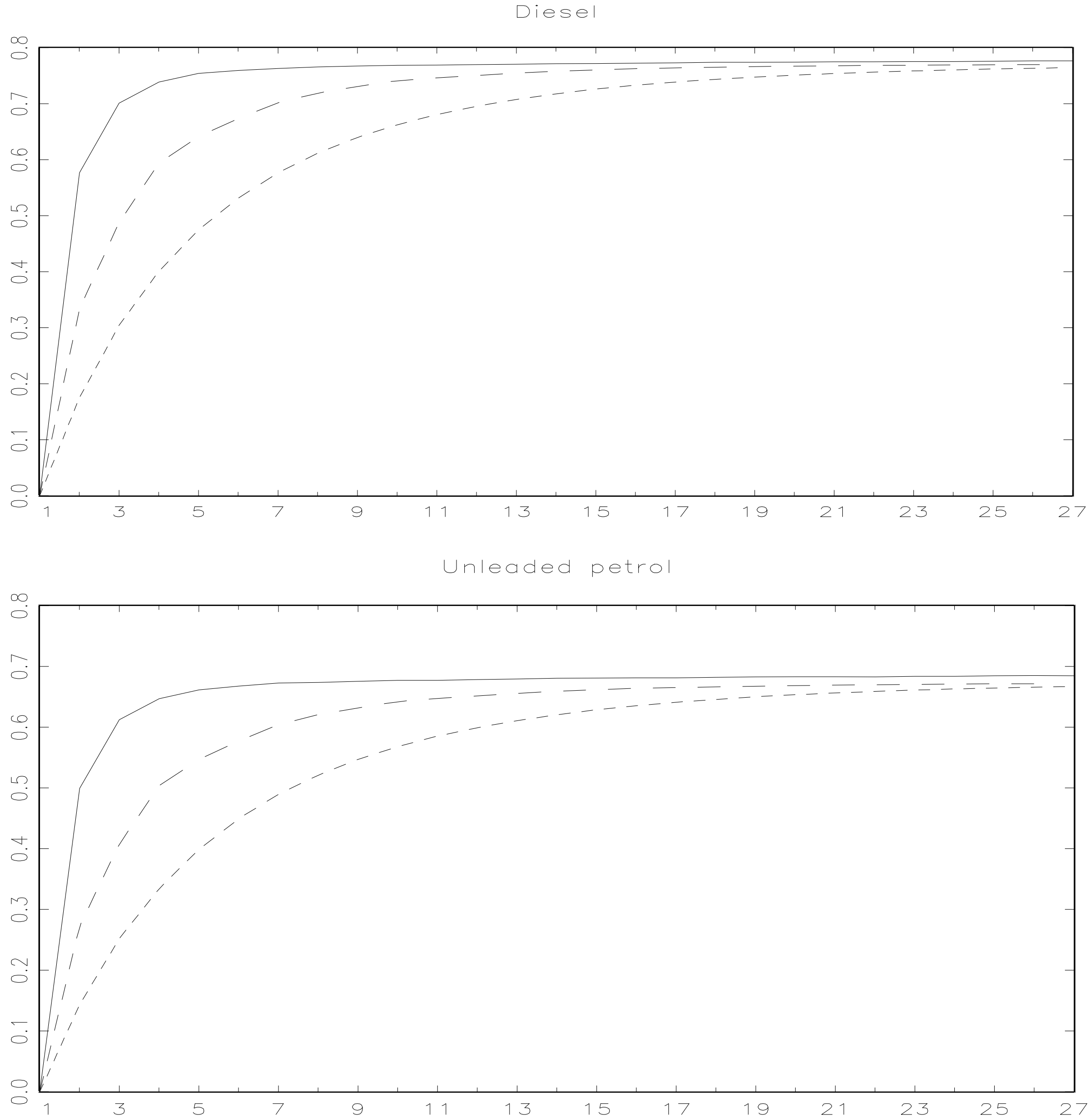
Note: White bars are for the distribution of simulated price changes using the Calvo model and black bars are for the actual distribution of price changes observed in the data.

Figure 9: Simulated versus actual distribution of price changes (time-varying (S,s) model versus actual data)



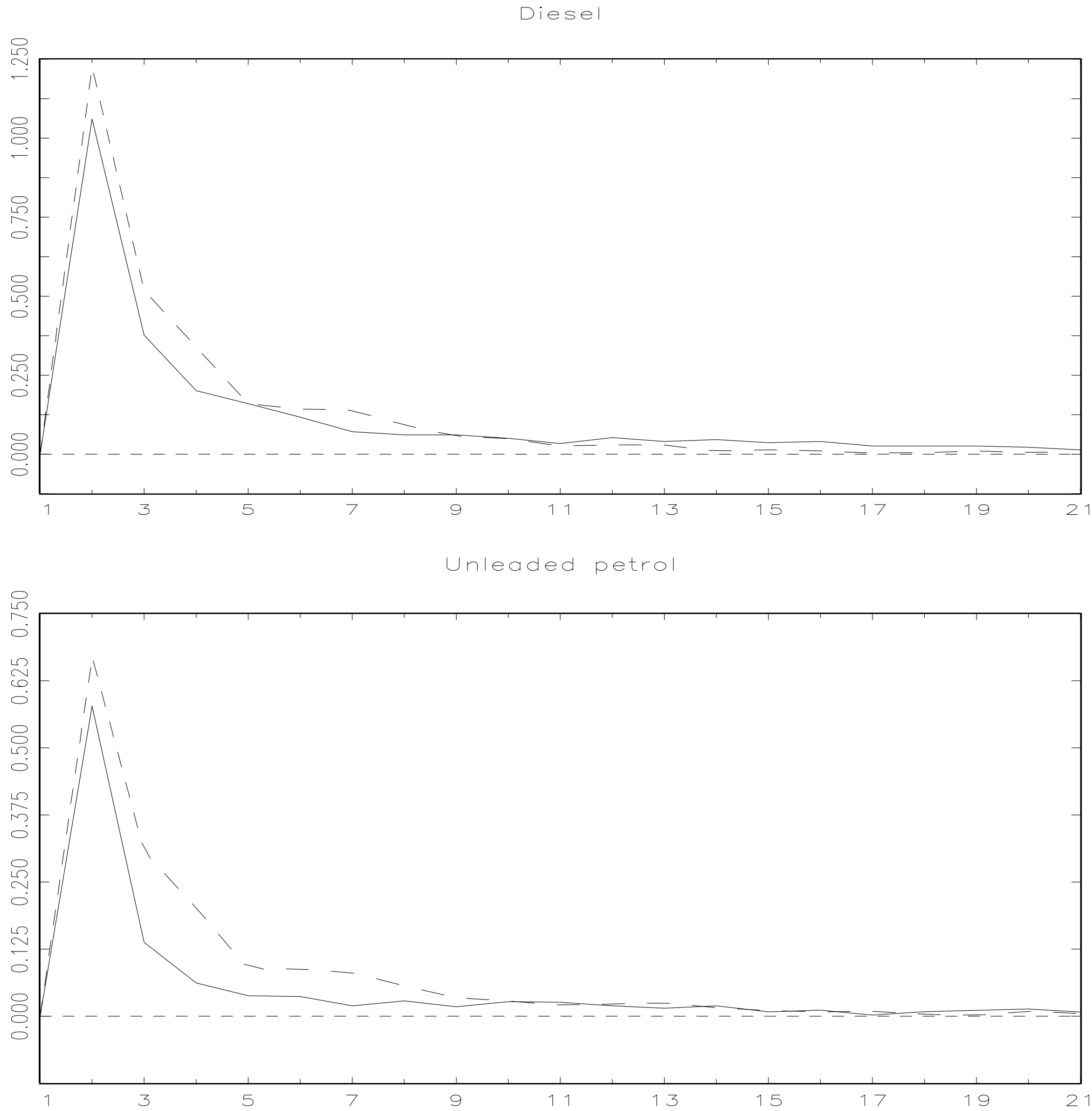
Note: White bars are for the distribution of simulated price changes using the time-varying threshold model and black bars are for the actual distribution of price changes observed in the data.

Figure 10: Aggregate responses of gasoline inflation to a 1%-shock on Rotterdam price for the fixed (S,s) model, Calvo model and time-varying (S,s) model



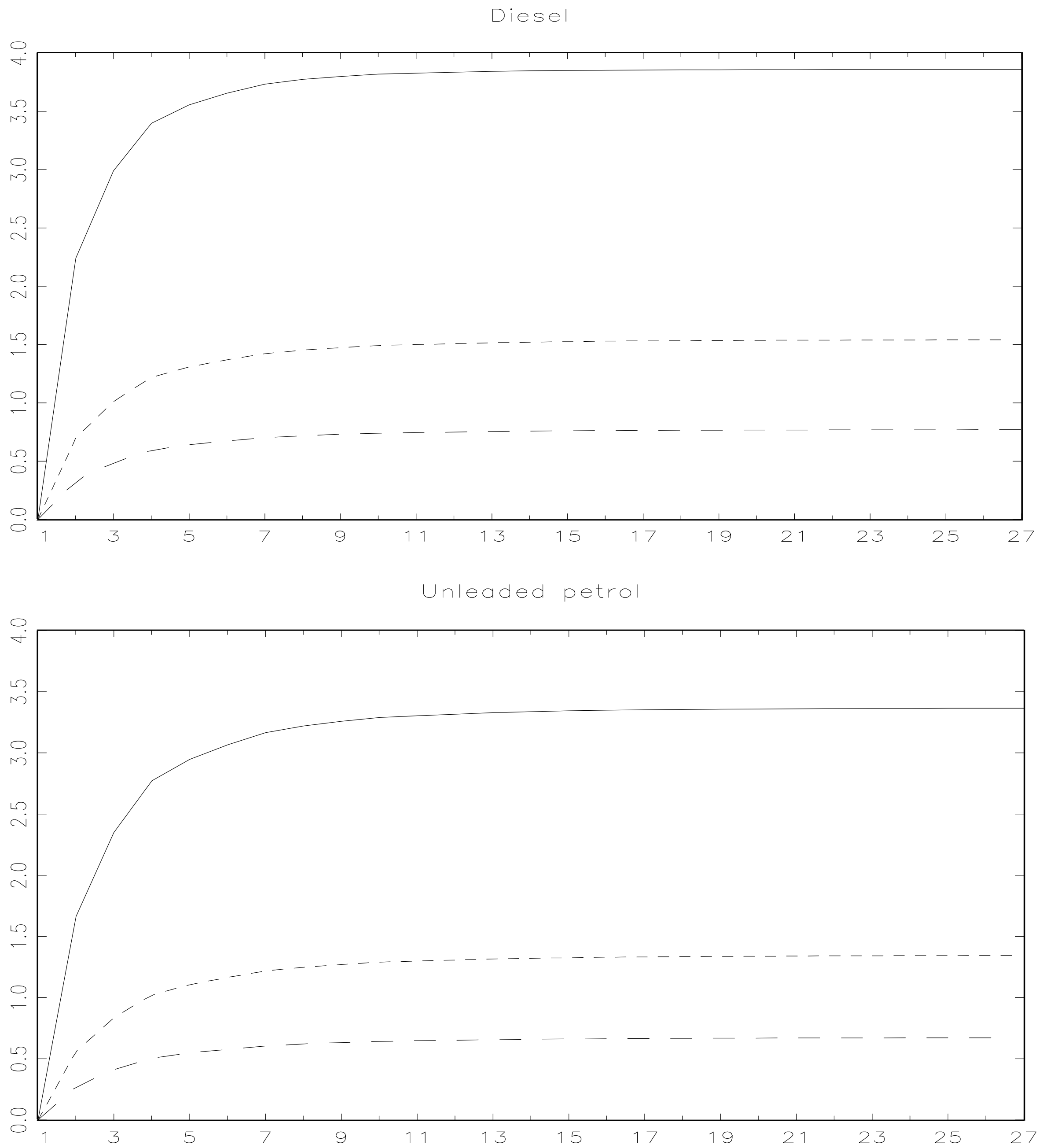
Note: dashed line for the time-varying (S,s) model, short dashed line for the Calvo model, solid line line for the fixed adjustment cost model.

Figure 11: Aggregate responses of the frequency of price changes to a 1%-shock on Rotterdam price the fixed (S,s) model, Calvo model and time-varying (S,s) model



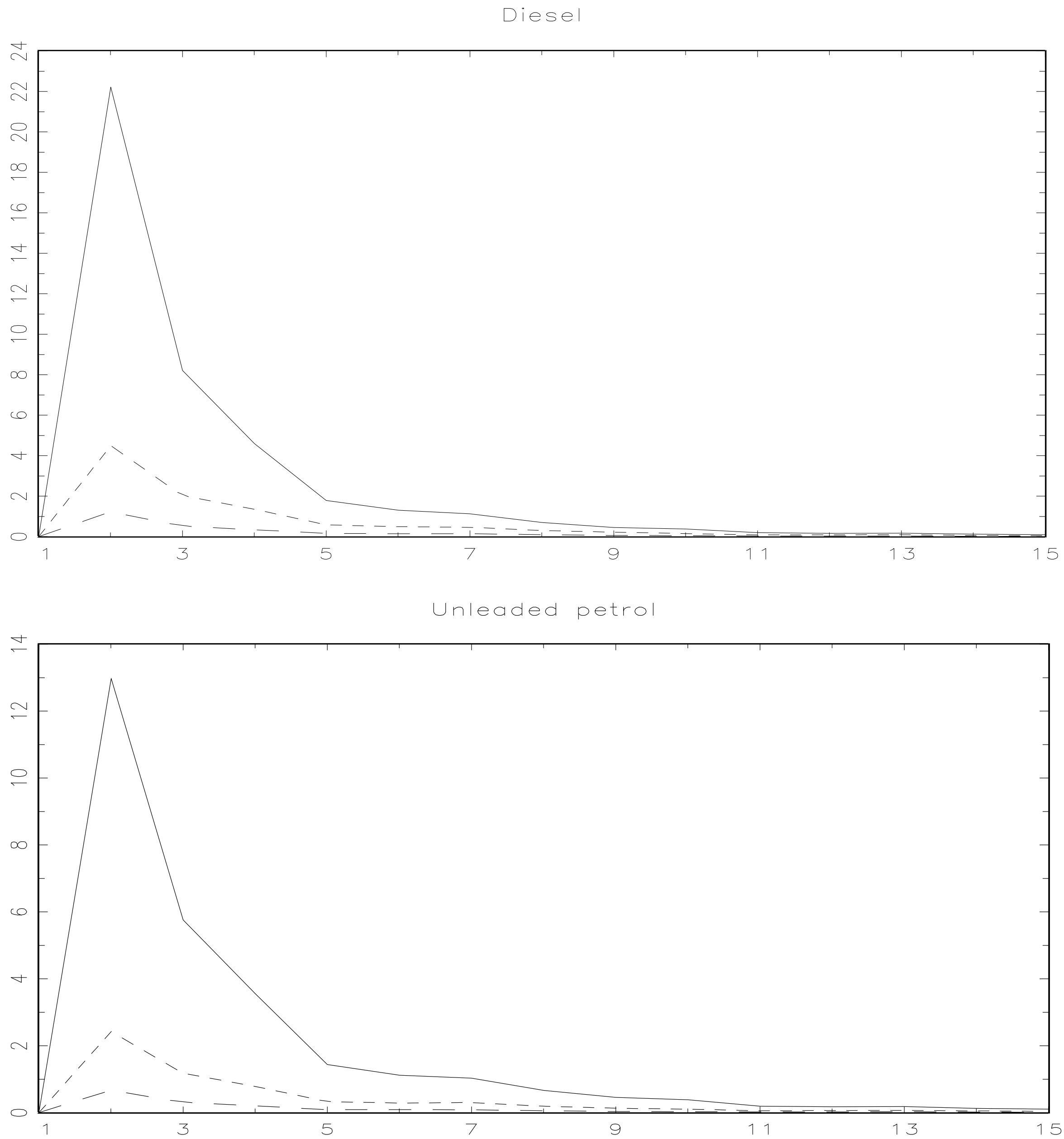
Note: dashed line for the variable adjustment cost model, short dashed line for the Calvo model, solid line line for the fixed adjustment cost model.

Figure 12: Aggregate response of gasoline inflation to shocks on Rotterdam price (time-varying (S,s) model)



Note: dashed line for the response to a 1% shock, short dashed line for the response to a 2% shock, solid line line for the response to a 5% shock.

Figure 13: Aggregate response of the frequency of price changes to shocks on Rotterdam price (time-varying (S,s) model)



Note: dashed line for the response to a 1% shock, short dashed line for the response to a 2% shock, solid line line for the response to a 5% shock.

APPENDIX

Likelihood function

The contribution to the likelihood function of price constancy in firm i at date t is :

$$
\begin{aligned}
l_{1i,t} &= \Pr(dp_{i,t,\tau} = 0 | p_{i,t-\tau}, X_{it}, p_t^o) \\
&= \Pr(s_{it} < p_{i,t-\tau} - p_{i,t}^* < S_{it}) \\
&= \Pr(\gamma_{is} X_{it} + \varepsilon_{2,it} < p_{i,t-\tau} - \alpha_i - \beta_i p_t^o - \varepsilon_{1,it} < \gamma_{iS} X_{it} - \varepsilon_{2,it}) \\
&= \Pr(\varepsilon_{1,it} + \varepsilon_{2,it} < p_{i,t-\tau} - \alpha_i - \beta_i p_t^o - \gamma_{is} X_{it}; p_{i,t-\tau} - \alpha_i - \beta_i p_t^o - \gamma_{iS} X_{it} < \varepsilon_{1,it} - \varepsilon_{2,it}) \\
&= \Phi \left[\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o - \gamma_{is} X_{it}}{\sqrt{\sigma_{1i}^2 + \sigma_{2i}^2}} \right] \\
&\qquad - \Phi_2 \left[\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o - \gamma_{is} X_{it}}{\sqrt{\sigma_{1i}^2 + \sigma_{2i}^2}}; \frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o - \gamma_{iS} X_{it}}{\sqrt{\sigma_{1i}^2 + \sigma_{2i}^2}}; \frac{\sigma_{1i}^2 - \sigma_{2i}^2}{\sigma_{1i}^2 + \sigma_{2i}^2} \right]
\end{aligned} \tag{5}
$$

where Φ is the c.d.f of the Gaussian distribution and $\Phi_2$is the bivariate c.d.f of the Gaussian distribution.

The contribution to the likelihood function of a price increase in firm i at date t is:

$$
\begin{aligned}
l_{2i,t} &= \Pr(dp_{i,t,\tau} > 0 | p_{i,t-\tau}, X_{it}, p_t^o) \\
&= \Pr\left(\varepsilon_{1,it} = p_{i,t} - \alpha_i - \beta_i p_t^0\right) \times \Pr\left[p_{i,t-\tau} - p_{i,t}^* \leq s_{it}, \quad p_{i,t-\tau} - p_{i,t}^* < S_{it} \mid \varepsilon_{1,it} = p_{i,t} - \alpha_i - \beta_i p_t^0\right] \\
&= \frac{1}{\sigma_{1i}} \phi \left(\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o}{\sigma_{1i}} \right) \\
&\times \Pr \left[\begin{array}{c} p_{i,t-\tau} - \alpha_i - \beta_i p_t^0 - \varepsilon_{1,it} \leq \gamma_{is} X_{it} + \varepsilon_{2,it}, \quad p_{i,t-\tau} - \alpha_i - \beta_i p_t^0 - \varepsilon_{1,it} < \gamma_{iS} X_{it} - \varepsilon_{2,it} \\ \mid \varepsilon_{1,it} = p_{i,t} - \alpha_i - \beta_i p_t^0 \end{array} \right] \\
&= \frac{1}{\sigma_{1i}} \phi \left(\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o}{\sigma_{1i}} \right) \times \Pr\left[-dp_{i,t,\tau} - \gamma_{is} X_{it} \leq \varepsilon_{2,it}, \quad dp_{i,t,\tau} + \gamma_{iS} X_{it} > \varepsilon_{2,it}\right] \\
&= \frac{1}{\sigma_{1i}} \phi \left(\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o}{\sigma_{1i}} \right) \times \left[\Phi \left(\frac{dp_{i,t,\tau} + \gamma_{iS} X_{it}}{\sigma_{2i}} \right) - \Phi \left(\frac{-dp_{i,t,\tau} - \gamma_{is} X_{it}}{\sigma_{2i}} \right) \right]
\end{aligned} \tag{6}
$$

where ϕ is the p.d.f of the Gaussian distribution and $dp_{i,t,\tau} = p_{it} - p_{it-\tau}$.

The contribution to the likelihood function of a price decrease in firm i at date t is:

$$
\begin{aligned}
l_{3i,t} \quad &= \Pr(dp_{i,t,\tau} < 0 | p_{i,t-\tau}, X_{it}, p_t^o) \\
&= \Pr\left(\varepsilon_{1,it} = p_{i,t} - \alpha_i - \beta_i p_t^0\right) \times \Pr\left[p_{i,t-\tau} - p_{i,t}^* > s_{it}, \quad p_{i,t-\tau} - p_{i,t}^* \geq S_{it} \mid \varepsilon_{1,it} = p_{i,t} - \alpha_i - \beta_i p_t^0\right] \\
&= \frac{1}{\sigma_{1i}} \phi\left(\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o}{\sigma_{1i}}\right) \\
&\times \Pr\left[\begin{array}{c} p_{i,t-\tau} - \alpha_i - \beta_i p_t^0 - \varepsilon_{1,it} > \gamma_{is} X_{it} + \varepsilon_{2,it}, \quad p_{i,t-\tau} - \alpha_i - \beta_i p_t^0 - \varepsilon_{1,it} \geq \gamma_{iS} X_{it} - \varepsilon_{2,it} \\ \mid \varepsilon_{1,it} = p_{i,t} - \alpha_i - \beta_i p_t^0 \end{array}\right] \\
&= \frac{1}{\sigma_{1i}} \phi\left(\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o}{\sigma_{1i}}\right) \times \Pr\left[-dp_{i,t,\tau} - \gamma_{is} X_{it} > \varepsilon_{2,it}, \quad dp_{i,t,\tau} + \gamma_{iS} X_{it} < \varepsilon_{2,it}\right] \\
&= \frac{1}{\sigma_{1i}} \phi\left(\frac{p_{i,t-\tau} - \alpha_i - \beta_i p_t^o}{\sigma_{1i}}\right) \times \left[\Phi\left(\frac{-dp_{i,t,\tau} - \gamma_{is} X_{it}}{\sigma_{2i}}\right) - \Phi\left(\frac{dp_{i,t,\tau} + \gamma_{iS} X_{it}}{\sigma_{2i}}\right)\right]
\end{aligned} \tag{7}
$$

where ϕ is the p.d.f of the Gaussian distribution and $dp_{i,t,\tau} = p_{it} - p_{it-\tau}$.

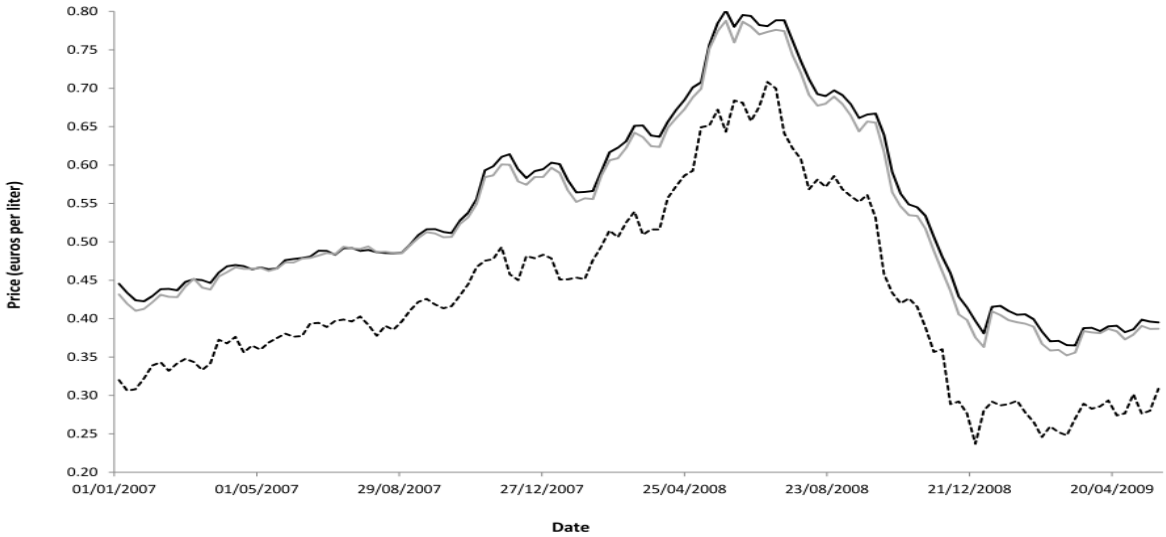
The likelihood function for an i.i.d. sample of a given firm i is thus:

$$
\ln L_i(\theta) = \sum_{t=1}^{T_i} (l_{1i,t} \times y_{1it} + l_{2i,t} \times y_{2it} + l_{3i,t} \times y_{3it})
$$

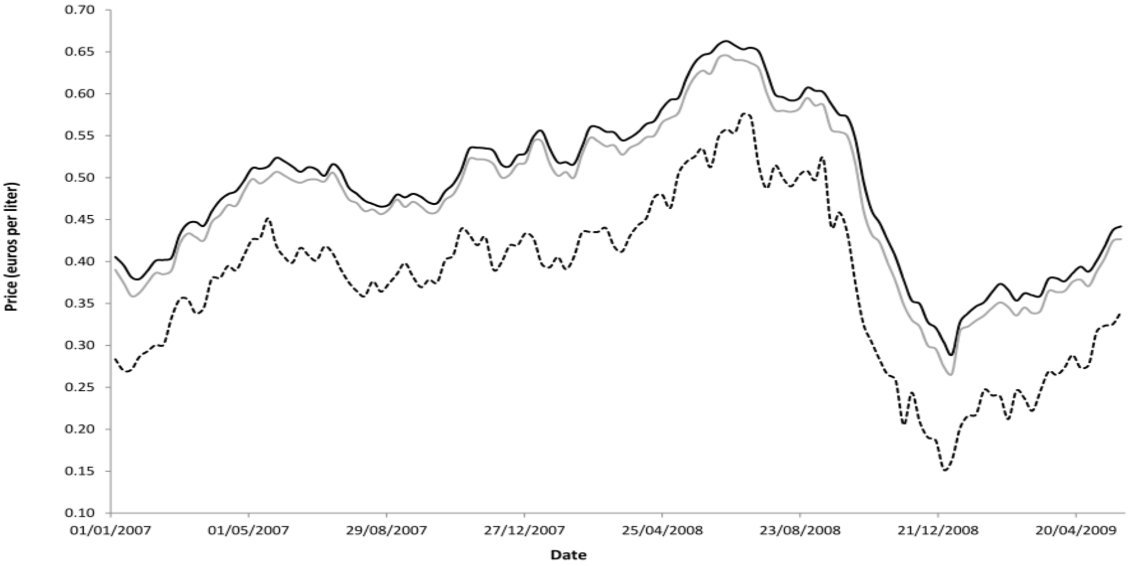
where $y_{1it} = 1$ if $dp_{i,t,\tau} = 0$ and 0 otherwise, $y_{2it} = 1$ if $dp_{i,t,\tau} < 0$ and 0 otherwise and $y_{3it} = 1$ if $dp_{i,t,\tau} > 0$ and 0 otherwise.

Figure A: Average retail prices (individual data set), weekly retail prices published by the Ministry of Economy and wholesale market prices (Rotterdam)

a) diesel



a) unleaded petrol



Note: dashed line is for Rotterdam prices, black line is for the average of individual prices collected in our data set and grey line is for the aggregate retail price series published by the Ministry of Economy each Friday.

Table A: Distribution of Price Changes and Average Duration by the Last Digit of Price

	Diesel		Unleaded Petrol	
	% of price trajectories	Average price duration (in days)	% of price trajectories	Average price duration (in days)
0	29.0	6.7	29.5	7.0
1	2.9	4.2	3.0	4.6
2	4.2	4.1	4.2	4.4
3	3.6	4.3	3.6	4.7
4	7.2	4.2	7.3	4.4
5	8.8	4.5	8.8	4.9
6	3.7	4.4	3.8	4.7
7	4.1	4.4	3.9	4.7
8	4.7	4.7	4.6	5.0
9	31.8	4.9	31.4	5.3

Note: We consider prices includeing all taxes, the proportion of price trajectories is computed as the ratio of number of price trajectories ending with one figure on all price trajectories and we compute the simple average duration. The last digit is the third one.

Table B: Estimation results - Fixed adjustment cost model

	Diesel					**Unleaded petrol**				
	Q25	Q50	Q75	Mean	Stdc	Q25	Q50	Q75	Mean	Stdc
α	1.56	2.39	3.68	2.62	1.39	-2.59	-1.51	-0.27	-1.34	1.91
β	0.72	0.80	0.84	0.78	0.07	0.64	0.69	0.73	0.69	0.06
σ_1	2.31	2.63	3.04	2.72	0.63	2.80	3.25	3.80	3.38	0.86
γ_S	3.22	4.02	5.17	4.31	1.65	4.13	5.21	6.68	5.56	2.03
γ_s	-5.21	-4.16	-3.39	-4.38	1.56	-6.39	-5.08	-4.11	-5.39	1.86

Note: We estimate for each individual gas station a fixed (S,s) model and then compute statistics on the parameter estimates we obtained. Observations on Sundays are excluded from the sample used for the estimation.

Table C: Estimation results - Calvo model

	Diesel					**Unleaded petrol**				
	Q25	Q50	Q75	Mean	Stdc	Q25	Q50	Q75	Mean	Stdc
α	1.21	1.96	3.15	2.19	1.31	-3.19	-2.19	-1.11	-2.11	1.75
β	0.71	0.80	0.83	0.77	0.07	0.63	0.68	0.72	0.68	0.07
σ_1	1.63	1.78	1.98	1.83	0.32	1.93	2.16	2.43	2.22	0.46
λ_1	-1.40	-1.27	-1.11	-1.25	0.27	-1.48	-1.35	-1.19	-1.32	0.29
λ_2	1.11	1.27	1.40	1.25	0.25	1.13	1.27	1.40	1.26	0.26

Note: We estimate for each individual gas station a "Calvo" model and then compute statistics on the parameter estimates we obtained. Observations on Sundays are excluded from the sample used for the estimation.