# A Conditional Markov Regime Switching Model to Study Margins: Application to the French Fuel Retail Markets

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**Abstract**

This paper uses a regime-switching model that is built on mean-reverting and local volatility processes combined with two Markov regime-switching processes to understand the market structure of the French fuel retail market over the period 1990-2013. The volatility structure of these models depends on a first exogenous Markov chain, whereas the drift structure depends on a conditional Markov chain with respect to the first one. Our model allows us to identify mean reverting and switches in the volatility regimes of the margins. In the standard model of cartel coordination, volatility can increase competition. We find that cartelization is even stronger in phases of high volatility. Our best explanation is that consumers consider volatility in prices to be a change in market structure and are therefore less likely to search for lower-priced retailers, thus increasing the market power of the oligopoly. Our findings provide a better understanding of the behavior of oligopolies.

**Keywords:** Regime switching; Markov chain; Cartels; Margins.
**MSC classification:** 60J10 91B25 91G30.
**JEL classification:** G10, G12, G15, D43.

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## Introduction

Recent market disruptions and oil price volatility have raised concerns about the evolution of retail gasoline prices. As noted by Smith [2009] [19], the last decade was characterized by increased volatility in the crude oil price. Multinational oil companies, embodied by producers, refiners or retailers, are regularly accused of unreasonably increasing their margins. The increasing margins significantly affected the budgets of consumers and increased the pressure from public opinion and political authorities on the actors in the oil industry.

Due to the structure of the gasoline market (demand and retail prices are highly predictable in the short term), the industry appears to be a natural candidate for a test of the level of collusion. This paper builds on two common ideas related to the retail fuel industry: The first is based on Borenstein et al. [1997] [4] and argues that an increase in the oil price triggers an immediate gasoline price adjustment because retail margins may otherwise become negative. In the case of declining oil prices, retailers decrease their prices slowly over time in an equilibrium response to the threat of price-cutting by competitors. As a result, retail prices adjust faster to oil price increases than they do to decreases. The asymmetric price transmission argument is based on the assumption that the observed asymmetry is evidence of oligopolistic coordination among retailers. This behavior leads us to our second common wisdom. There are numerous periods of cartelization (i.e., margins and asymmetric price transmission increase) and competition (i.e., margins and asymmetric price transmission decrease) because retail prices, crude oil prices and demand are easily observable and predictable.

Because margins are the subtraction of retail price and crude oil price, margin volatility provides information on the volatility of oil prices. The search behavior of consumers depends on the level of information they can access. When price volatility is high, consumers believe that price changes reflect movements in the market oil price and are not specific to their retailers. Consumers are less likely to search for lower-priced retailers because they expect prices to follow the market; therefore, retailers have increased market power and can increase their margins. This argument is somewhat opposed to the traditional oligopolistic coordination, which suggests that stability is the main determinant of the life cycle of a cartel. As Radchenko [2005] [17] noted, under oligopolistic coordination, we would thus expect that increased volatility would lead to a decline in gasoline asymmetry.

In this paper, we discuss the implications of oligopolistic coordination versus search theory on the relationship between margin volatility and levels in the French retail fuel market.

The volatility of margins provides information on the frequency of switches from competition and cartelization from a time-series perspective. High volatility in the margins can then be considered periods cumulating in cartelization (increasing margins and asymmetric price transmission) and price wars (decreasing margins and asymmetric price transmission). To accomplish this task, we use a Markov-switching model to identify regime changes in the volatility of margins in the French fuel retail market between 1990 and 2013. The use of Hamilton's Markov-switching models to study economic time series data, such as the business cycle, economic growth or unemployment, is not new. In his seminal paper [12], Hamilton noted that Markov-switching models are able to reproduce the different phases of the business cycle and capture the cyclical behavior of U.S. GDP growth data. More recently, Bai and Wang [2011] [3] went one step further by allowing for changes in variance and showed that their restricted model clearly identifies both short-run regime switches and long-run structural changes in the U.S. macroeconomic data. Goutte and Zou [2013] [11] compared the results from the best fit of the different regime switching models against the non-regime-switching diffusion in foreign exchange rate data. They proved that regime-switching models with both mean reverting and local volatility structures are the best choice to fit data well. Moreover, this modeling allows them to capture some significant economic behaviors well, such as crisis time periods or changes in the dynamic level of variance. Based on the above observations that Markov-switching models capture economic cycles and regime switching, we use the extended model stated by Goutte [2014] [10]. Since Oil price undergo alternating periods of calm and turbulence. Markov-switching models allow for more flexibility than linear models. We also use a mean reverting local volatility regime-switching model, where the volatility structure depends on a first Markov chain and the drift structure has a mean reverting effect that depends on a conditional Markov chain with respect to the first one.

Our results show that there were basically two periods over the last 20 years: the 1990s are characterized by low volatility and the 2000s by high volatility. In these regimes, it is possible to identify interesting sub-regimes: in the 1990s, cartelization occurs during the summer when demand peaks, and competition increases during the remainder of the year; in the 2000s, volatility is high, and margins are at their highest level showing an increase in the market power of retailers. Our results show that volatility can even increase the gains of oligopolistic coordination because consumers search less for reduced prices.

The remainder of the paper is organized as follows. Section 1 presents the economic problem. In section 2, we review the literature on the determinants of margins. Section 3 presents the model. The estimation results for the French retail gasoline market are presented in section 4. A conclusion and a discussion of the policy implications follow.

## 1 The Economic Problem

Three approaches are used to explain fuel retail margins. The first approach is the traditional asymmetric price transmission proposed by Borenstein et al. [1997] [4]. Because prices are a natural signal for oligopoly coordination, they are sticky but tend to adjust faster when marginal costs increase. When coordination breaks down, retailers lower prices to the marginal cost. It is then easy to measure oligopoly coordination: when margins are large, coordination is important, whereas it is the opposite in the other case. Clarke [1983] [8] perfectly summarized this argument by saying that firms may have difficulty in monitoring the policies of their rivals in complex situations.

The second approach is derived from Borenstein and Shepard [1996] [5], who exploited the insights from the theoretical background of the supergame models to test for collusive pricing in retail gasoline markets by focusing on retail margins in the industry.

In supergame models with repeated play, firms can sustain implicit collusion by adjusting their current margins in response to changes in expected demand. Haltiwanger-Harrington [1991] [14] shows that when demand increases firms have incentives to deviate from the implicit collusion because near-term profits are more valued than future profits. In the gasoline market, costs and prices move regularly and make collusion more difficult to sustain.

The third approach is based on consumer search models. The search behavior of consumers is based on the relative variability of idiosyncratic (retailer specific) and common oil shocks. When consumers know that the volatility of the shocks increased, they are less likely to search for lower-priced retailers, which could lead to an increase in the market power of the retailers.

Recent empirical evidence on margins and asymmetric price transmissions in France identified collusive behavior in the market. Porcher and Porcher [2014] [16] use OLS regressions and found two different results: on the one hand, the margins decrease when the expected demand increases, which is a standard prediction for non-cooperative models; on the other hand, evidence of tacit collusion is found as margins decline when the expected marginal cost increases as the potential loss from future punishment decreases. Another piece of research by Boroumand et al. [2014] [6] used a Markov-switching model on weekly observations of fuel price in France from 1990 to 2011 and found two different volatility regimes. The authors found an asymmetric price transmission of crude oil prices to retail prices, and they evaluate it in different volatility regimes. When the volatility is low, the transmittal of a price change from crude oil to retail fuel is higher than in periods of high volatility. Prices are stickier when there is more price volatility, thus confirming the argument that oligopolies can coordinate under high-volatility regimes.

Overall, the literature assumes that volatility can affect the degree of asymmetry in two competing ways. As Radchenko [2005] [17] summarizes it, on the one hand, in the oligopolistic coordination theory, an increase in the price volatility leads to a reduction in the degree of asymmetry in the gasoline price response. On the other hand, standard search theory implies that volatile crude oil prices encourage consumers to search less, thus increasing the market power of retailers.

To the best of our knowledge, there is only one paper relating asymmetric price transmission to oil price volatility. Radchenko [2005] [17] uses a VAR model and proxies of volatility that is constructed using the rolling standard deviation of oil prices and one that is based on GARCH. He finds that asymmetry in gasoline prices declines with an increase in oil price volatility, thus supporting the oligopolistic coordination theory. Our results differ from Radchenko [2005] [17]. Our results tend to prove that margins (and thus asymmetric price transmission) are increasing in phases of high volatility. Consumers consider volatility in prices to be a change in market structure and are therefore less likely to search for lower-priced retailers, thus increasing the market power of the oligopoly.

# 2 A Markov Switching Analysis

Let $T > 0$ be a fixed maturity time and denote by $(\Omega, \mathbb{F} := (\mathcal{F}_t)_{[0,T]}, \mathbb{P})$ an underlying probability space. In this paper, we will follow the Conditional Regime Switching model introduced by Goutte (2014) in [10].

Thus, we first recall the main points of this modeling.

## 2.1 Conditional Markov chain

Markov-switching (MS) models have been widely used in economics and finance since the seminal work of Hamilton [1989] [12]. Shortly afterwards, Cai [1994] [7] and Hamilton and Susmel [1994] [13] utilized this kind of methodology to capture highly volatile markets. Generally, in MS models, econometricians distinguish two or more regimes that are the outcome of a Markov chain whose realizations are unobserved. MS modeling is a major tool with which to better interpret market conditions by inferring the latent state of the market and of the economy.

The market structure of the French fuel retail market is clearly non-linear ... One of the objectives of this class of regime switching stochastic models is to capture various key features of the data such as mean trend gap or recession in a same economic level state of market volatility. In particular, in a possible high regime volatility state, our class of model will be able to capture different possible trends of the long mean average such as increasing or recession periods.

We begin with the construction of our Markov regime switching model. We will classify the states of the economy into exogenous and endogenous regimes characterizing long-run structure changes and short-run business cycles, respectively. The exogenous regime values will be given by a homogeneous continuous time Markov chain $X^2$ on finite state $\mathcal{K} := \{1, 2, \ldots, K\}$ and with transition matrix $P^{X_2}$ given by

$$P^{X_2} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1K} \\ p_{21} & p_{22} & \cdots & p_{2K} \\ \vdots & \vdots & \vdots & \vdots \\ p_{K1} & p_{K2} & \cdots & p_{KK} \end{pmatrix}. \tag{2.1}$$

**Remark 2.1.** *The quantity $p_{ij}$ represents the intensity of the jump from state $i$ to state $j$.*

The endogenous regime values will be given also by a homogenous continuous time Markov chain $X^1$ on finite state $\mathcal{L} := \{1, 2, \ldots, L\}$ but its transition matrix will depend on the value of the exogenous regime. Hence, the transition matrix of $X^1$ will be conditional on the value of the Markov chain $X^2$. The endogenous economic regime thus follows a conditional Markov chain, where the Markovian property applies only after conditioning on the exogenous state. Hence, the state of the endogenous regime $X^1$ will be determined by conditioning on the state of the exogenous regime $X^2$.

To define the transition matrix of $X^1$ we first construct a time grid partition of the time interval $[0, T]$. For this, we partition the time interval such that,

$$0 = t_0 < t_1 < \cdots < t_N = T \quad \text{with} \quad \Delta_t := t_{k+1} - t_k = 1 \quad \text{for all} \quad k \in \{0, \ldots, N\}. \tag{2.2}$$

For all $s \in \mathcal{K}$, we can now define the probability transition to state $i \in \mathcal{L}$ to $j \in \mathcal{L}$ with respect to the value of the Markov chain $X^2$ of the Markov chain $X^1$ as

$$p^s_{ij} = \mathbb{P}\left(X^1_{t_k} = j | X^2_{t_k} = s, X^1_{t_{k-1}} = i\right), \quad \forall k \in \{1, \ldots, N\}, \quad \forall s \in \mathcal{K}. \tag{2.3}$$

Hence we get $K$ possible transition matrix $P_s^{X_1}$, $s \in \mathcal{K}$ given by

$$P_s^{X_1} = \begin{pmatrix} p_{11}^s & p_{12}^s & \dots & p_{1L}^s \\ p_{21}^s & p_{22}^s & \dots & p_{2L}^s \\ \vdots & \vdots & \vdots & \vdots \\ p_{L1}^s & p_{L2}^s & \dots & p_{LL}^s \end{pmatrix}. \tag{2.4}$$

We assume in the what follows that

**Assumption 2.1.** *1. For all $k \in \{1, \dots, N\}$, $X_{t_k}^2$ is an exogenous Markov process. Hence, it satisifes*

$$\mathbb{P}\left(X_{t_{k+1}}^2 | X_{t_k}^2, X_{t_k}^1, X_{t_{k-1}}^2, X_{t_{k-1}}^1, \dots, X_{t_0}^2, X_{t_0}^1\right) = \mathbb{P}\left(X_{t_{k+1}}^2 | X_{t_k}^2\right). \tag{2.5}$$

*2. For all $k \in \{1, \dots, N\}$, $X_{t_k}^1$ is conditionally Markovian:*

$$\mathbb{P}\left(X_{t_{k+1}}^1 | X_{t_{k+1}}^2, X_{t_k}^1 X_{t_{k-1}}^2, X_{t_{k-1}}^1, \dots, X_{t_0}^2, X_{t_0}^1\right) = \mathbb{P}\left(X_{t_{k+1}}^1 | X_{t_{k+1}}^2, X_{t_k}^1\right). \tag{2.6}$$

Point 2 of Assumption (2.1) means that the value of the Markov chain $X^1$ at time $t_k$, $k \in \{1, \dots, N\}$ depends both on the value of the Markov chain $X^1$ at time $t_{k-1}$ and of the Markov chain $X^2$ at time $t_{k-1}$.

**Remark 2.2.** *In the particular case where $\mathcal{K} \equiv \mathcal{L} := \{1, 2\}$ and under Assumptions 2.1, this model can be defined by the joint distribution $Z_{t_k} = \left(X_{t_k}^1, X_{t_k}^2\right)$ in the space $\mathcal{S} := \{(1,1), (1,2), (2,1), (2,2)\}$. Hence, in this two-regimes case, the transition matrix of the Markov chains $X^1$ and $X^2$ is given by:*

$$P^{X_2} = \begin{pmatrix} p & 1-q \\ 1-p & q \end{pmatrix}$$

*and*

$$P_1^{X_1} = \begin{pmatrix} p_1 & 1-q_1 \\ 1-p_1 & q_1 \end{pmatrix}, \quad P_2^{X_1} = \begin{pmatrix} p_2 & 1-q_2 \\ 1-p_2 & q_2 \end{pmatrix}.$$

*Moreover, we have*

$$\mathbb{P}\left(Z_{t_{k+1}} | Z_{t_k}, Z_{t_{k-1}}, Z_{t_0}\right) = \mathbb{P}\left(Z_{t_{k+1}} | Z_{t_k}\right) = \mathbb{P}\left(X_{t_{k+1}}^1 | X_{t_{k+1}}^2, X_{t_k}^1\right).\mathbb{P}\left(X_{t_{k+1}}^2 | X_{t_k}^2\right) \tag{2.7}$$

*and so the $4 \times 4$ transition matrix of $Z$ is given by*

$$P^Z = \begin{pmatrix} p.P_1^{X_1} & (1-q).P_1^{X_1} \\ (1-p).P_2^{X_1} & q.P_2^{X_1} \end{pmatrix}. \tag{2.8}$$

In the special case of the previous Remark, we obtain $Z_{t_k} = \left(X^1_{t_k}, X^2_{t_k}\right)$ in the space $\mathcal{S} := \{(1,1),(1,2),(2,1),(2,2)\}$. This means that we have four different states which can be explain by the following Figure 2.1

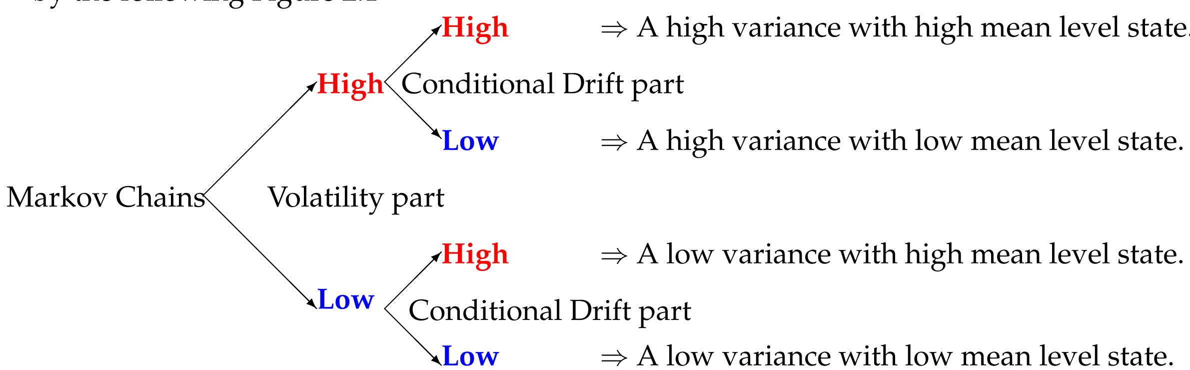



Figure 1: Contribution of the use of a conditional Markov chain for the drift component.

**Remark 2.3.** *If we assume that for all $i, j \in \mathcal{L}$ and $s_1 \neq s_2 \in \mathcal{K}$ that $p^{s_1}_{ij} = p^{s_2}_{ij}$, then the Markov chain $X^1$ is no longer a conditional Markov chain. Indeed, its transition matrix no longer depends on the values of the Markov chain $X^2$ and so the two Markov chains $X^1$ and $X^2$ are now independent. Hence, this regime switching model becomes an independent regime switching model studied, for example, by Goutte and Zou [2013] [11], applied to foreign exchange rate data.*

From an economic point of view, we can interpret the two-states case as mentioned in Remark 2.2 as a low/high mean and a low/high variance. Hence, whenever we know the variance level state we can determine whether we are in low or high mean level. Hence this model can capture a different level of mean in each level of variance. Indeed, with this modelling, an economic datum can be in a high variance regime but with a low mean trend and respectively in a low variance level but with a high mean level. Thus, this conditional regime switching model allows us to differentiate between these different possible states.

### 2.2 Regime switching diffusion

In what follows, we will work on a discretized version of the mean-reverting, heteroskedastic process given by the following stochastic differential equation

$$dY_t = \left(\mu\left(X^1_t, X^2_t\right) - \beta\left(X^1_t, X^2_t\right) Y_t\right) dt + \sigma\left(X^2_t\right) |Y_t|^{\delta} dW_t, \quad \delta \in \mathbb{R}^+.$$

Thus, we will work on the following observed data process $Y_{t_k}$, where time $(t_k)_{k\in\{0,1,\ldots,N\}}$ is defined by the construction (2.2), given by:

**Definition 2.1.** *Let $(Y_{t_k})_{k\in\{0,\dots,N\}}$ be our data process (i.e. a time series) and let $(X^1_{t_k})_{k\in\{0,\dots,N\}} \in \mathcal{L}$ and $(X^2_{t_k})_{k\in\{0,\dots,N\}} \in \mathcal{K}$ be two Markov processes. Then our general model is given by*

$$Y_{t_k} = \mu\left(X^1_{t_k}, X^2_{t_k}\right) + \left(1 - \beta\left(X^1_{t_k}, X^2_{t_k}\right)\right) Y_{t_{k-1}} + \sigma\left(X^2_{t_k}\right) |Y_{t_{k-1}}|^{\delta} \epsilon_{t_k}, \quad \delta \in \mathbb{R}^+. \tag{2.9}$$

*where $(\epsilon_{t_k})_{k\in\{0,\dots,N\}}$ follows a $\mathcal{N}(0,1)$.*

**Remark 2.4.**

- *The regime switching model (2.9) is a continuous time regime switching diffusion with drift $\mu\left(X^1_{t_k}, X^2_{t_k}\right) + \left(1 - \beta\left(X^1_{t_k}, X^2_{t_k}\right)\right) Y_{t_{k-1}}$ and volatility $\sigma\left(X^2_{t_k}\right) |Y_{t_{k-1}}|^{\delta}$, $\delta \in \mathbb{R}^+$.*
- *The drift factor ensures mean reversion of the process towards the long run value $\frac{\mu\left(X^1_{t_k}, X^2_{t_k}\right)}{\beta\left(X^1_{t_k}, X^2_{t_k}\right)}$, with speed of adjustment governed by the parameter $\beta\left(X^1_{t_k}, X^2_{t_k}\right)$. From an economic point of view, if the value of $\beta\left(X^1_{t_k}, X^2_{t_k}\right)$ is high then the dynamic of the process $Y$ is near the mean value, even if there is a spike at time $t \in [0,T]$. Then, for a small time period $\eta$, the value of $Y_{t+\eta}$ will be close to the value of the mean again.*
- *The two Markov chains can be seen as economic impact factors. Indeed, assume that our regime switching diffusion $Y$ models the spread of a firm A. Then, an economic interpretation of the regime switching model is that the exogenous Markov chain $X^2$ could be the credit rating of the firm A given by an exogenous rating company such as "Standard and Poors". And the endogenous regime $X^1$ is then an indicator of the potentially "good health" of the firm A given the value of its credit rating (i.e. the value of the exogenous regime $X^2$).*

The regime switching model (2.9) is thus a mean reverting model with local volatility.

Indeed, in (2.9), we use a model where the volatility component is on power $\delta$. This parametrization implies that our model has a local volatility structure.

Hence it is a regime switching mean reverting constant of elasticity variance model (CEV).[1] So our model is constructed to encompass most of the financial models stated in the literature. Indeed, we can obtain:

- a regime switching Cox-Ingersoll-Ross model (CIR) by taking $\delta = \frac{1}{2}$.
- a regime switching Vasicek model by taking $\delta = 0$.
- a regime switching mean reverting geometric Brownian motion by taking $\delta = 1$.

[1]This model was developed by Cox, J. in "Notes on Option Pricing I: Constant Elasticity of Diffusions." Unpublished draft, Stanford University, 1975.

**Remark 2.5.** *To highlight the usefulness of the suggested model from an economic point of view, we can remark that oil prices can change instantaneously. Hence these changes argue the use of those models with abrupt changes like the Markov-switching models.*

Regarding Remark 2.4, given $Y_{t_{k-1}}$, $Y_{t_k}$ has a conditional Gaussian distribution, we have:

$$Y_{t_k} \sim \mathcal{N}\left(\mu\left(X^1_{t_k}, X^2_{t_k}\right) + \left(1 - \beta\left(X^1_{t_k}, X^2_{t_k}\right)\right) Y_{t_{k-1}}, \sigma^2\left(X^2_{t_k}\right) |Y_{t_{k-1}}|^{2\delta}\right).$$

Let $\mathbf{Y_k} := \{Y_{t_0}, Y_{t_1}, \ldots, Y_{t_k}\}$ denote the history of Y up to time $t_k, k \in \{1, \ldots, N\}$. Therefore $\mathbf{Y_n} := \mathbf{Y_T}$ represents the full history of the data process Y. Assume, now, that we work with the bivariate Markov process $Z_t = (X^1_t, X^2_t)$ defined in Remark 2.2. Hence, it takes its values in the finite space $\mathcal{S} := \mathcal{K} \times \mathcal{L}$. Let $\Theta$ be the set of all parameters to be estimated. In fact, there are $K(2L+1)+6$ parameters in $\Theta$.

**Remark 2.6.** *If $\mathcal{K} = \mathcal{L} = \{1, 2\}$, then $\Theta$ contains 16 parameters to be estimated:*

$$\Theta := \{\mu(1,1), \mu(1,2), \mu(2,1), \mu(2,2), \beta(1,1), \beta(1,2), \beta(2,1), \beta(2,2), \sigma(1), \sigma(2), p, q, p_1, q_1, p_2, q_2\}.$$

Given the data process history information, the probability distribution function (pdf) of $Y_{t_k}$ is given by

$$f\left(Y_{t_k} | Z_{t_k} = (i,j); \mathbf{Y_{k-1}}; \Theta^{(n)}\right) = \frac{1}{\sqrt{2\pi}\sigma(j)|Y_{t_{k-1}}|^{\delta}} \exp\left\{-\frac{\left[Y_{t_k} - (1-\beta(i,j))Y_{t_{k-1}} - \mu(i,j)\right]^2}{2\sigma^2(j)|Y_{t_{k-1}}|^{2\delta}}\right\} \quad (2.10)$$

with $X^1_{t_k} = i$, $i \in \mathcal{L}$ and $X^2_{t_k} = j$ for $j \in \mathcal{K}$.

The estimation process is detailed in Goutte [2014] [10].

# 3 An Application to the French Fuel Retail Market

## 3.1 Data

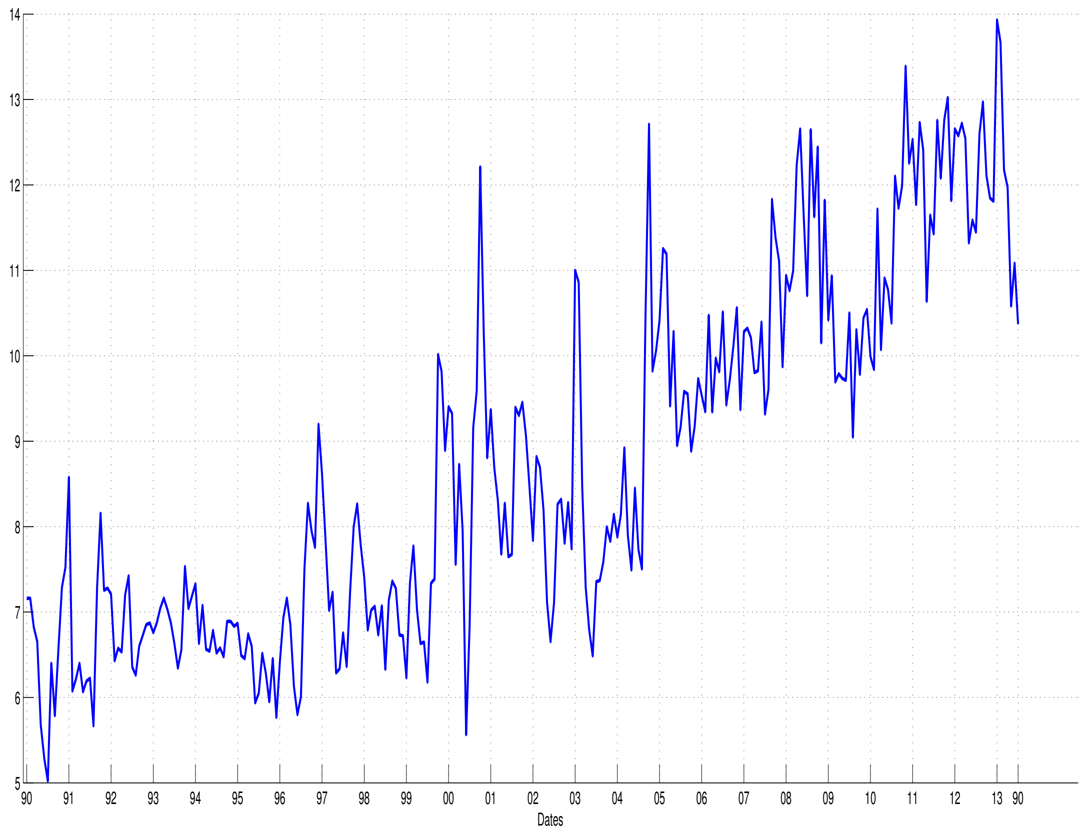
The data set used in this paper corresponds to the margins observed in the fuel retail industry, and it covers the period between April 1990 and September 2013. The data were extracted from the French National Institute for Statistics (INSEE) and the Environment Ministry. The retail margin (MARGIN) is defined as the retail price minus the refined oil price (Rotterdam price). The retail price and the refined oil price are the mean observed prices for a given month at the national level. Our data set does not allow us to control for the transportation costs between terminals and station operators because the prices for these transactions are not publicly available. For our purposes, the Rotterdam price is the best proxy for marginal costs. Figure 2 plots the evolution of margins in cents of euros for the entire period, and Table 1 gives the general descriptive statistics.

Figure 2 shows spikes and changes in the level of volatility of the price, which we hope to capture in our different regime states. It can be observed that the margins were far from stable in the short run but that overall, they tended to grow between 1990 and 2013. This increase in margins suggests that competition has not been as intense as it is sometimes argued by the majors. However, we observe strong changes in margins from month to month that could reflect price adjustments or strategic behaviors by firms when the demand and marginal costs vary. The difference between the lowest level of margins (5 cents per liter) and the highest level (close to 14 cents) is somewhat surprising. This result is even more surprising if we consider the margin rate (i.e., the margins to retail price ratio): it varies from 14% to more than 50%. Such high margins, even considering other regulated or monopolistic industries (see Porcher [2014] [15] for a literature review on the margins in the French water public service), confirm the suspicious cartelization of the market. The variations in the margins outline different phases of competition and cartelization of the market. Here, we focus on the margins in cents and not in percentages because we are considering the consumers' point of view of the volatility and cartelization interaction. Indeed, due to the volume exchanged on the market, each extra cent in the margin has a massive impact on the overall profit of the industry due to the volume of exchanges.

Table 1: Descriptive Statistics

| Statistics | Margin |
|---|---|
| Number of Obs. | 283 |
| Mean | 8.715242 |
| Minimum | 5.023399 |
| Maximum | 13.932600 |
| Variance | 4.418402 |
| Standard Deviation | 2.102000 |
| Skewness | 4.476678 |
| Kurtosis | 40.679010 |

Figure 2: **Margins in cents of euros between April 1990 and September 2013**



### 3.2 Estimation Results

We compare different version of the general model (2.9) which are given by different values of the parameter $\delta$. To measure the goodness of fit of these different models we give the Log likelihood values obtained by each model since the Expectation-Maximization estimation process maximizes this value. Furthermore, we calculate also the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) which are given by

$$AIC = -2\ln(L(\Theta^{(n)})) + 2 * k \quad \text{and} \quad BIC = -2 * \ln(L(\Theta^{(n)})) + k\ln(n), \tag{3.11}$$

where $L(\Theta^{(n)})$ is the log-likelihood value obtained with the estimated parameters $\Theta^{(n)}$ found by the (EM) procedure, $k$ is the degree of freedom of each model and $n$ the number of observations. We recall that the preferred model is the one with the minimum AIC or BIC value. Hence, upper is the Log likelihood value of a model better fit is it. Moreover, in the same way, lower are the BIC and AIC criteria better the fit of the model is. Nevertheless, even if the model with the best fit is the one yielding the highest log likelihood value, we have to weight these values with those given by regime switching classification indicator or measure. Indeed, even if a model could fit well data and obtain a high log likelihood value if it doesn't cut, classify well the data in two different statically significant states then it is not a good model to fit our data in a non-linear way.

#### 3.2.1 Good Classification Measures

An ideal model is one that classifies regimes sharply and has smoothed probabilities which are either close to zero or one. In order to measure the quality of regime classification, we propose two measures:

(1) The **regime classification measure (RCM)** introduced by Ang and Bekaert (2002) [1] and generalized for multiple states by Baele [2] (2005). Let $K(>0)$ be the number of regimes, the RCM statistic is then given by

$$\text{RCM}(K) = 100.\left(1 - \frac{K}{K-1}\frac{1}{T}\sum_{k=1}^{N}\sum_{Z_{t_k}}\left(P\left(Z_{t_k}|\mathbf{Y_T};\Theta^{(n)}\right) - \frac{1}{K}\right)^2\right), \tag{3.12}$$

where the quantity $P\left(Z_{t_k}|\mathbf{Y_T};\Theta^{(n)}\right)$ is the well-known smoothed probability and $\Theta^{(n)}$ is the vector parameter estimation result (see Goutte (2014) [10] for more details). The constant serves to normalize the statistic to be between 0 and 100. Good regime classification is then associated with low RCM statistic value: a value of 0 means perfect regime classification and a value of 100 implies that no information about regimes is revealed.

(2) The **smoothed probability indicator** introduced by Goutte and Zou (2013) [11]. A good classification for data can be also seen when the smoothed probability is less than 0.1 or greater than 0.9. This then means that the data at time $t \in [0, T]$ is, with a probability exceeding 90%, in one of the regimes for the 10% error.

Thus, even if a model has a higher log likelihood value, it is important that its RCM be close to zero and its smoothed probability indicator be close to 100%, to insure we have significantly different regimes.

#### 3.2.2 Estimation results

We now give the log-likelihood, RCM, AIC and BIC values obtained by our estimation procedure for different regime switching models.

| $\delta$ | LogL | AIC | BIC | RCM(K=4) | $P^{10\%}$ |
|---|---|---|---|---|---|
| 0 | -320.1906 | 608.3812 | 730.7083 | 7.248168 | 90.957447% |
| 0.5 | -172.6274 | 313.2549 | 435.5820 | 15.723725 | 83.156028% |
| 1 | -20.1687 | 8.3374 | 130.6645 | 32.031286 | 62.588652% |
| 1.5 | 120.6861 | -273.3722 | -151.0451 | 26.708315 | 62.943262% |
| 2 | 268.3155 | -568.6310 | -446.3039 | 29.693809 | 58.244681% |

Table 2: Log likelihood value, AIC, BIC, RCM statistics and smoothed probability indicator given by the (EM) procedure for different values of $\delta$.

All the results are stated in Table (2). If we look at the log likelihood value alone, we can see that the highest value is obtained for the regime switching model with parameter $\delta = 2$. But if we also look at the RCM values or the smoothed probability indicators, we can see that this model provides a very poor classification of the data. Indeed, we can show that the model with $\delta = 0$ obtains an RCM of $7.25$ while the model with $\delta = 2$ obtains only an RCM of $29.69$. Moreover, this model classifies only 58.24% of the data well while the model with $\delta = 0$ classifies 90.96% of it well.

To conclude, the choice of the regime switching model with $\delta = 0$ seems to be a good choice to fit this data since it obtains a good log likelihood value and it yields significantly the best results in the state classification of the data than any other.

We can give now the values of each parameters of the model with $\delta = 0$ obtained by our estimation process. These results are stated in Tables 3 and 4

Table 3: Parameters estimated for the regime switching models (standard deviations in parentheses obtained by taking the square root of the inverse of the Hessian matrix).

| State $(X^1, X^2)$ | $\mu$ | $\beta$ | $\sigma$ | Long Mean value | Speed of Adjustement |
|---|---|---|---|---|---|
| $(1,1)$ | 5.10 (0.72) | 0.62 (0.10) | 0.126 (0.01) | 8.19 | 0.62 |
| $(2,1)$ | 3.45 (0.33) | 0.52 (0.05) | 0.126 (0.01) | 6.65 | 0.52 |
| $(1,2)$ | 3.23 (1.83) | 0.51 (0.28) | 0.942 (0.10) | 6.38 | 0.51 |
| $(2,2)$ | 2.28 (0.46) | 0.22 (0.04) | 0.942 (0.10) | 10.39 | 0.22 |

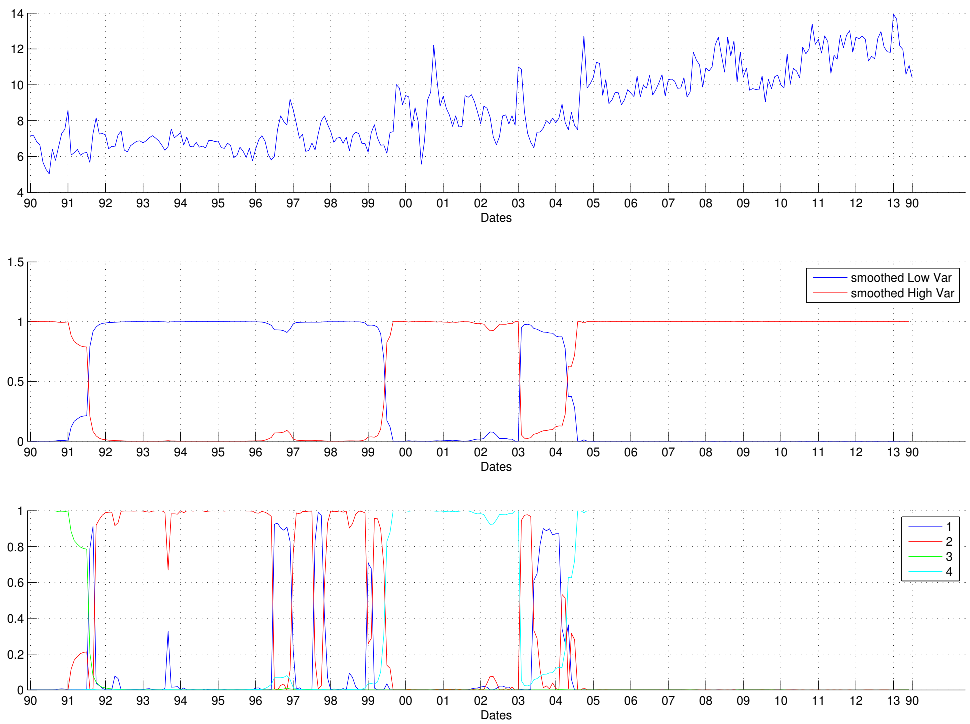
Table 4: Parameters estimated for the regime switching probabilities transition.

| Probability | Value |
|---|---|
| $p_1$ | 0.74 |
| $q_1$ | 0.94 |
| $p_2$ | 1 |
| $q_2$ | 1 |
| $p$ | 0.98 |
| $q$ | 0.99 |

The close to one values obtained for the transition probabilities estimated parameters in Table 4, demonstrate that each regime or enough significant and reflet a real economic dynamic.

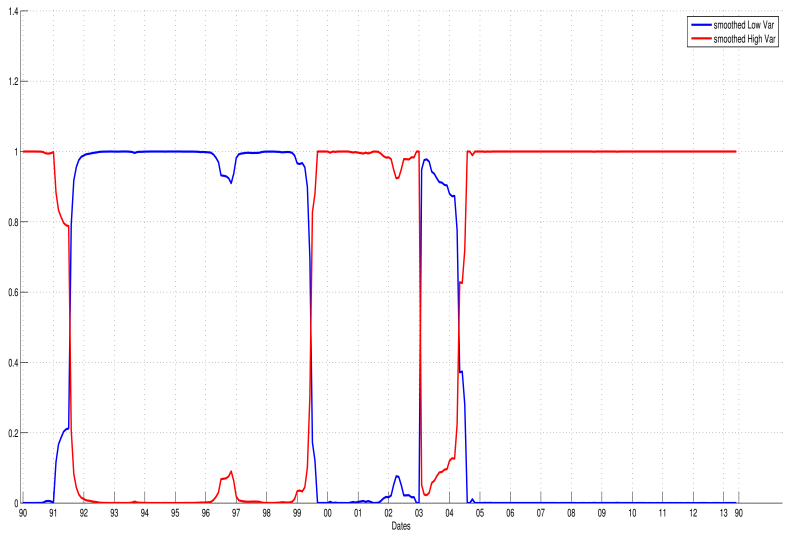
## 3.3 Comments

Figure 3: **Resume**




The results summarized in Figure 4 show that there are two different volatility regimes. In the first regime (blue on the graph, State 1), volatility is low ($\sigma_1 = 0.126$). This corresponds to two different periods: August-September 1991 to August-September 1999 and then January 2003 to May-June 2004. In the second regime (red on the graph, State 2), volatility is high ($\sigma_2 = 0.942$). This regime appears between April 1990 and August-September 1991, August-September 1999 to December 2002 and finally May-June 2004 to September 2013. Using another data set on France and a traditional Markov-switching analysis, Boroumand et al. [2014] [6] show that there are two distinct volatility regimes for fuel retail prices: the 1990s are characterized by low price volatility, whereas the 2000s show high volatility in fuel retail prices. Because retail margins are the difference between the retail price and the marginal cost, periods with stable margins, i.e., the retail prices closely follow the evolution of costs, are characterized by a phenomenon of cartelization when margins are high and competition when margins are low.

Figure 4: **Smoothed Variance plot**




In each of these volatility regimes, there are two different long-term mean levels and a disparate velocity of return to the mean described in Table 5.

Table 5: Drift parameters

| State | Volatility level | Color in Figure 5 | Long Mean value | Speed of Adjustement |
|---|---|---|---|---|
| State (1,1) | Low volatility $\sigma_1 = 0.126$ | Blue Line | 8.19 | 0.62 |
| State (2,1) | Low volatility $\sigma_1 = 0.126$ | Red Line | 6.65 | 0.52 |
| State (1,2) | High volatility $\sigma_2 = 0.942$ | Green Line | 6.38 | 0.51 |
| State (2,2) | High volatility $\sigma_2 = 0.942$ | Cyan Line | 10.39 | 0.22 |

The first two lines of Table 5 depicts two regimes - State (x,1) with *i=1,2* - in which the volatility of margins is low. Using the results reported in Table 5, we can compare the two sub-regimes of the low-volatility regime. State (1,1) in blue in Figure 5 has an average long-term mean value that is higher than State (2,1) in red in Figure 5 ($8.19$ vs. $6.65$). Under low-volatility, State (1,1) would be considered more cartellized than State (2,1). The speed of adjustment towards the long-term mean is also more important in State (1,1) than in State (2,1), i.e. $0.62$ versus $0.52$. State (1,1) does not last for more than a few months.

In our dataset, this corresponds to the following periods:

- August-September 1991;
- June-November 1996;
- June-October 1997;
- December 1998 to February-March 1999;
- March-April 2003 to May-June 2004.

As predicted in supergame models that study cartels (e.g., Haltiwanger and Harrington, [1991]), when the demand is increasing, the margins respond positively because the near-term profits are weighed more heavily than future profits by firms. For this reason, the speed of adjustment is higher than in State (2,1) around the summer: firms adjust their prices upstream because demand is increasing and tend to adjust their price quickly to match the average. From this point of view, State (2,1) in red in Figure 5 is a recessive regime in which the margins are lower and adjust less rapidly than in State (1,1). In our dataset, this sub-regime corresponds to the following time periods:

- October 1991 to May 1996;
- December 1996 to May 1997;
- November 1997 to November 1998;
- March 1999 to July 1999;
- January 2003 to March 2003.

In the high-volatility regime, there is a first sub-regime in green in Figure 5, which corresponds to a low average long-term mean value of $6.38$ against $10.39$ in the other regime with a speed of adjustment that is higher than the other sub-regime with high volatility, i.e., $0.51$ versus $0.22$. This sub-regime corresponds to April 1990 to September 1991. The second sub-regime in the high-volatility regime, depicted in cyan in Figure 5, has a slower speed of adjustment and a higher volatility than the former one. In this regime, margins tend to deviate from their equilibrium and are unstable. However, this cyan regime has the highest mean of all of the sub-regimes, indicating that this regime has margins that tend to increase. This regime corresponds to the two following periods of high volatility: August-September 1999 to December

2002 and May-June 2004 to September 2013.

Overall, we observe that the speed of adjustment is higher when margins are important in the low-volatility regime, whereas the opposite is observed in the high-volatility regime. When the volatility is high, the margins seem to be more stable. Because margins are simply the difference between the retail price and the marginal costs, a possible interpretation is that those prices remain at a given level when the marginal costs increase. The risk premium of volatility is thus paid by consumers. This result is also supported by Boroumand et al. [2014] [6], who showed that asymmetric price transmissions of crude oil to retail prices can be higher when the price volatility is high.

In Figure 4, the low-volatility regime depicted in (in blue) is overall stronger in terms of speed adjustment to the mean but with a lower average compared with the high-volatility regime (in red). The sub-regimes depicted in red and green in Figure 4 can be considered recessive regimes.

Figure 5: **Regime Switching Segmentation in the 4 states**

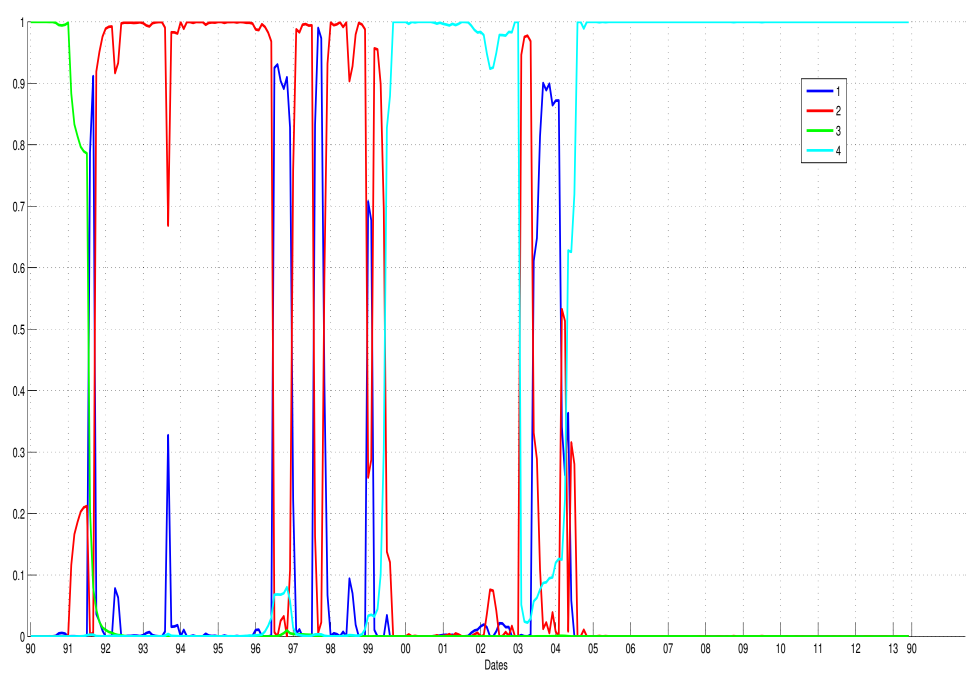


Figure 6: **Smoothed Recession plot**

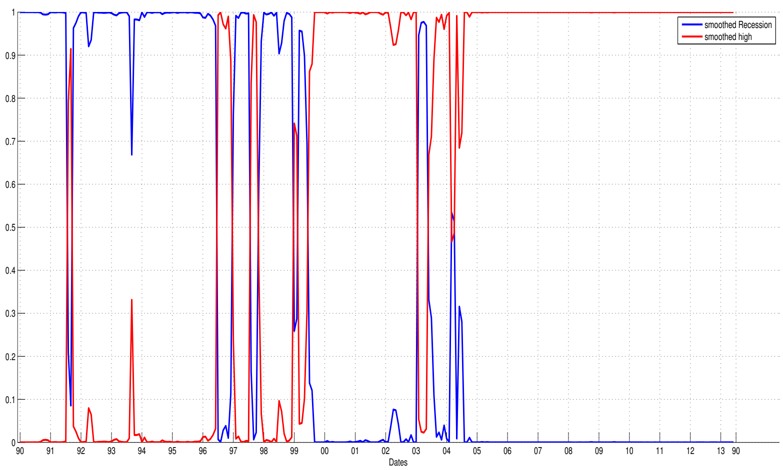



Figure 7: **Regime Switching segmentation with respect to the variance level.**

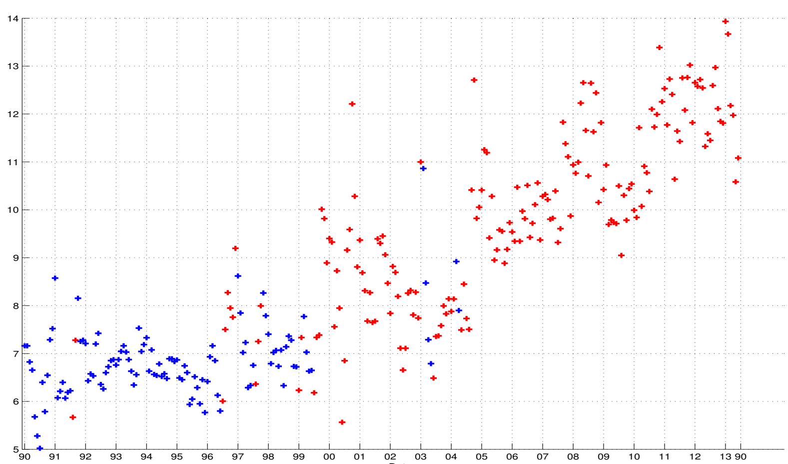
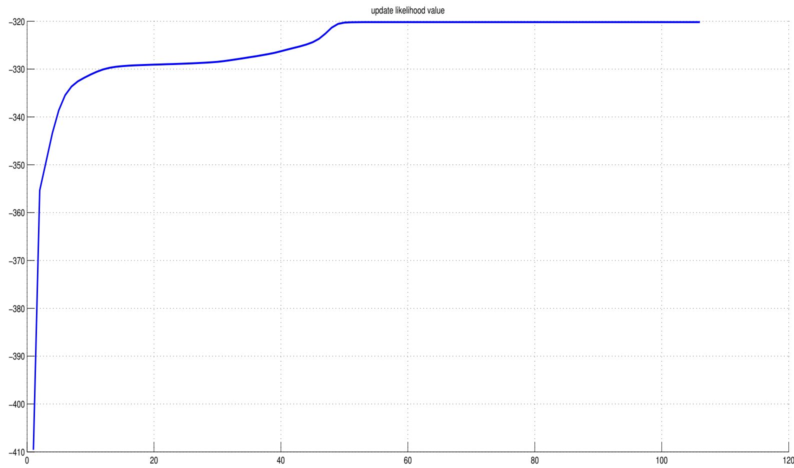


Figure 8: **Log Likelihood values at each iteration of the estimation process**




# 4 Conclusion and policy implications

This paper uses a regime-switching model built on mean-reverting and local volatility processes combined with two Markov regime-switching processes to understand the market structure of the French fuel retail market in the period 1990-2013. Our model allows us to identify mean reverting and switches in the volatility regime of the margin. In the standard model of cartel coordination, volatility can increase competition; however, we find that cartelization is even stronger in phases of high volatility. Our best explanation is that consumers take volatility in price as a change in the market structure and are less likely to search for lower-priced retailers, thus increasing the market power of the oligopoly.

The issue of margins in the fuel retail industry is crucial for consumers, policy makers and actors in the oil industry for several reasons. First, we are facing a period characterized by the fact that oil price volatility results from demand volatility and speculation. Higher prices and market volatilities of oil and gasoline make protecting consumer welfare against external shocks difficult for policy makers. Due to the asymmetric price transmissions, which lead to excess margins, increasing consumer information on the daily price of fuel could be a solution. Second, it seems that oil retailers are aware of their margins and tend to act strategically to increase their margins when they expect the demand to peak (see Porcher and Porcher, [2014] [16] and Borenstein and Shepard [1996][5]). Our results, which are similar to Boroumand et al. [2014] [6], show that during periods of high volatility, retailers have sticky prices, thus coordinating with other retailers, a behavior that is interesting in an industry where there are no menu costs (pump prices can be changed easily). When volatility is important, the shortsightedness of consumers increases, and the coordination of the oligopoly is easier. Our results contribute to the literature on cartels and asymmetric price transmissions by showing that during periods of high volatility, cartels are not less stable but seem to be even more powerful.

## References


[1] Ang, A. and Bekaert, G. (2002), *Regime Switching in Interest Rates*. Journal of Business and Economic Statistics 20 (2), 163-182.

[2] Baele, L. (2005), *Volatility Spillover Effects in European Equity Markets*. Journal of Financial and Quantitative Analysis, Vol. 40, No. 2.

[3] Bai, W. and Wang, P. (2011), *Conditional Markov chain and its application in economic time series analysis*. Journal of applied econometrics, 26, 715-734.

[4] Borenstein S., Cameron, A.C. and Gilbert, R. (1997). *Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes ?*. The Quarterly Journal of Economics, 112(1), 305-39.

[5] Borenstein, S. and A. Shepard (1996). *Dynamic Pricing in Retail Gasoline Markets*, The Rand Journal of Economics, 27(3), 429-451.

[6] Boroumand, R.H., Goutte, S., Porcher, S. and Porcher, T. (2014), *Asymmetric evidence in gasoline price responses in France: a Markov switching approach*. Working Paper.

[7] Cai (1994), *A Markov model of switching-regime ARCH'*. Journal of Business & Economic Statistics, 12, 309-316.

[8] Clarke, R. (1983), *Collusion and the Incentives for Information Sharing*. Bell Journal of Economics, 14, 383-394.

[9] Elliott, R.J., Aggoun, L. and Moore, J.B. (1994). *Hidden Markov Models: estimation and control*. Springer-Verlag, Berlin-Heidelberg- New York.

[10] Goutte, S. (2014). *Conditional Markov regime switching model applied to economic modelling.* Economic Modelling, 38, 258-269.

[11] Goutte, S. and Zou, B (2013), *Continuous Time Regime Switching Model Applied to Foreign Exchange Rate*. Math. Financ. Lett. 2013, 2013:8.

[12] Hamilton J. (1989), *A new approach to the economic analysis of non stationary time series and the business cycle*. Econometrica, 57 (2), 357- 384.

[13] Hamilton J., Susmel R. (1994), *Autoregressive Conditional Heteroskedasticity and Changes in Regime*. Journal of Econometrics, 64(1-2), 307-33.

[14] Haltiwanger J. and Harrington,J.J. (1991), *The Impact of Cyclical Demand Movement on Collusive Behavior*, The Rand Journal of Economics, 22(2), 89-116.

[15] Porcher, S. (2014), *Efficiency and Equity in Two-Part Tariffs: the Case of Residential Water Rates*. Applied Economics, 46(5), 539-555.

[16] Porcher, S. and Porcher, T. (2014), *The Determinants of Margins in French Retail Gasoline Markets*. Applied Economics Letters, 21(15), 1050-1053.

[17] Radchenko, S., (2005) *Oil Price Volatility and the Asymmetric Response of Gasoline Prices to Oil Price Increases and Decreases*. Energy Economics, 27(5), 708-730.

[18] Rotemberg, J.J. and Saloner,G., (1986) *A Supergame-Theoretic Model of Price Wars During Booms*. The American Economic Review, 76(3), 390-407.

[19] Smith, J. L., (2009). *World oil: Market or mayhem?* Journal of Economic Perspectives 23 (3), 145-164.