Citation for published version:

Martín-Moreno JM, Pérez R, Ruiz J. Rockets and feathers behaviour in the Spanish gasoline and diesel market: New evidence. Bull Econ Res. 2019; 71: 657–683. https://doi.org/10.1111/boer.12202

Peer reviewed version

Link to published version: https://doi.org/10.1111/boer.12202

Rockets and feathers behavior in the Spanish gasoline and diesel market: New evidence

José Mª Martín-Moreno* **Rafaela Pérez**** **Jesús Ruiz*****

Universidad de Vigo and rede

Universidad Complutense de Madrid and ICAE

Universidad Complutense de Madrid and ICAE

Abstract

In this paper we analyze the potential asymmetric response of retail prices for gasoline and diesel-fuel to changes in oil prices for the Spanish economy and its relation with the so-called 'rockets and feathers' behavior. We show that the assumption made by previous studies, which use as the key explanatory variable the sign –positive or negative- of the change in international oil prices, is inadequate for the Spanish case and the magnitude of the change in international oil prices is also relevant. For small changes in international oil prices there is neither price asymmetry nor rockets and feathers behavior in the retail markets. However, price asymmetries in line with rockets and feathers behavior in retail gasoline and gasoil markets are present when these changes exceed a certain threshold. Following Martín-Moreno et al. (2018) we first apply an Auto-regressive Error Correction Model and endogenously estimate the threshold triggering the rockets and feathers behavior. A time-varying nature for the dynamic response of retail prices to oil price shocks is revealed when we estimate the TAR-ECM model using rolling windows. Hence, in a second stage, we use a Markov-switching estimation of the model to test the robustness of the results given its suitability to changing environments. This study could have relevant policy implications for the Spanish gasoline and gasoil retail markets due to the ongoing debate on the existence of a rockets and feathers behavior in gasoline and gasoil retail markets between the Spanish regulatory body and the oil companies.

JEL Classification: C51, D43, Q43

Keywords: price asymmetries, crude oil prices, TAR-ECM, Markov-switching estimation

* **Corresponding author**. Departamento de Fundamentos del Análisis Económico. Facultad de CC.EE.EE. Universidade de Vigo. e-mail: jmartin@uvigo.es

** Departamento de Fundamentos del Análisis Económico I and ICAE. Universidad Complutense de Madrid. e-mail: rmperezs@ccee.ucm.es

*** Departamento de Fundamentos del Análisis Económico II and ICAE. Universidad Complutense de Madrid. e-mail: jruizand@ccee.ucm.es

We are grateful to Jorge Blázquez for their comments and suggestions that have helped to considerably improve the paper. Pérez and Ruiz would like to thank the Spanish Ministry of Economy and Competitiveness for the financial support provided through grant ECO2015-67305-P. Martín-Moreno thanks Spanish Ministry of Economy and Competitiveness and the Xunta de Galicia for financial support through grants ECO2015-68367-R and "Programa de Consolidación e Estructuración de Unidades de Investigación Competitivas do Sistema Universitario de Galicia 2014, de la Consellería de Cultura, Educación e Ordenación Universitaria (referencia GRC2014/021)". The authors also thank the participants at the 6th Atlantic Workshop on Energy and Environmental Economics (AWEEE) and the 14th IAEE European Energy Conference (Sustainable Energy Policy and Strategies for Europe) for their helpful comments.

1. Introduction

Standard economic theory claims that increases or decreases in input prices translate into symmetric changes in retail prices. However, there is wide-spread evidence of markets in which the transmission mechanism is asymmetric depending on whether prices increase or decrease. Academic literature has documented evidence of price asymmetries at a general level. Thus, Peltzman (2000) finds extensive evidence of asymmetric price transmission when analyzing 282 different products. The results show that, on average, the instantaneous response to a cost increase is at least twice the response to a cost decrease. These adjustments, which differ according to direction, are known as price asymmetries (Bettendorf et al., 2003). This asymmetric price transmission has been coined as *rockets and feathers behavior*.

In 2014 a bitter debate took place among the Spanish oil companies, the Ministry of Industry and Energy, and the regulatory body on the "rockets and feathers behavior" in the domestic markets of gasoline and diesel. In other words, the Ministry of Industry and Energy and the regulatory body accused oil companies of, intentionally, delaying the transmission of the international oil price plunge to domestic prices of oil related products. In March 2014, the National Commission of Markets and Competence (CNMC) published that the gross margin grew by 25% annually for gasoline and 11% for diesel. This remarkable increase happened in a context of a large decrease in international oil prices. Besides the increase in margins, retail prices without taxes for these fuels exceed the average for the Euro area. Spain was the EU-28 country with the fourth highest price for gasoline and the sixth highest for diesel. The regulatory body pointed out that international oil prices increases were transmitted to domestic retail prices in the same way as it was in the rest of the European Union, but oil price decreases were delayed and did not completely transmitted into retail prices. (See also El Pais 2014[1] and Expansion 2014[2]). In 2015, again, emerged a virulent debate among the oil companies and the regulatory body on the same topic (El Economista 2015[3]). The existence of a "rockets and feathers behavior" was pointed out by the regulatory body in a report June 2015, suggesting that the lack of competiveness of the Spanish market could be the reason behind this behavior (see Comisión Nacional de los Mercados y la Competencia, June 2015[4]). This debate is alive in Spain. In March 2017, BP suggested that the "rockets and feathers behavior" in the Spanish market was an only a "perception", not a reality. In this context, in our opinion the analysis of this phenomenon deserves a specific and in-depth study for the Spanish economy, with new econometric techniques. So, this study sheds light on the "rockets and feathers behavior" in Spanish oil-products markets, using a state-of-the-art methodology: the TAR-ECM and Markov-Switching models.

There are some papers that explore the existence the "rockets and feathers behavior" in the Spanish retail markets (see the Literature review section). However, following Martín-Moreno et al. (2018) our study is innovative in four different ways: i) The methodological approach is different. All the papers focused on Spanish retail markets assumes exogenous zero threshold in the variation rate of oil prices to test for asymmetric responses. However, we estimate a model that allows for possible changes in response when surpassing a non-zero threshold rather than the common zero threshold. We are interested in determining whether the transmission of oil price changes on retail prices is faster or slower depending on the size of such variation in the price of crude oil, which may be above or below zero. This technical change allows us to study whether the oil price

[1] https://economia.elpais.com/economia/2014/12/05/actualidad/1417809825_816390.html.
[2] http://www.expansion.com/2014/12/03/economia/1417608667.html
[3] http://www.eleconomista.es/economia/noticias/6493284/02/15/Las-petroleras-niegan-el-efecto-cohete-y-pluma-en-los-carburantes.html.
[4] https://www.cnmc.es/sites/default/files/1114748_0.pdf.

transmission depends on the size of the price variation. We find that the standard zero-threshold is not an adequate assumption. Asymmetric retail price responses takes place with international oil prices shift strongly (-2.5% in the case of gasoline market and -2% in the case of diesel market). ii) Second, another methodological difference is connected to the robustness test of the results obtained with the TAR-ECM estimation. As a first simple test, we carry out TAR-ECM estimations using rolling windows (one-year data size), and find evidence that the dynamic response seems to have a time-varying feature. Then, we test our results by developing a two-regime Markov-switching model as an alternative for estimating the non–linear dynamic relationship between the crude oil price and the retail price for gasoline and diesel-fuel. We propose this methodology because this type of model has never been used to characterize asymmetric price responses for the Spanish fuel market and this methodology improves the previous econometric analysis applied to Spanish fuel market[5]. iii) We use forward prices for crude oil instead of spot prices given that, in general terms, refineries use forward oil contracts to hedge against crude oil volatility. Moreover, we also use a longer future because the oil refining process and the subsequent distribution of oil products to gas stations takes time. For the sake of illustration, a cargo from Saudi Arabia to a Spanish refinery takes 3-4 weeks and, then, it takes 3-4 weeks more to refine the crude oil and deliver oil products to the gas station. A three-month future captures this temporal lag. And iv) we explore the asymmetric retail price response for the gasoline and diesel-fuel markets. Most of the current literature for the Spanish markets has only focused on gasoline[6]. We want to highlight that this is not a marginal development. Diesel market amounted 52.2% of total oil products consumption in 2016 (See CORES, 2017[7]) while gasoline amounted only for 8.2% of total consumption.

The main conclusion of this study is that gasoline and diesel prices respond asymmetrically to short-term changes in the international oil price. These asymmetries confirm that there is rockets and feathers behavior in Spanish retail market of gasoline and diesel.

The rest of the paper is organized as follows. Section 2 explores the most relevant literature applied to Spanish gasoline and diesel market. Section 3 describes the data used for the study. Section 4 introduces the two modeling approaches we used and presents the results obtained. Section 5 concludes.

2. Literature Review

In addition to the aforementioned evidence, more attention has been paid to price asymmetry in other markets. The gasoline market is one of the most extensively analyzed. Bacon (1991)[8] is considered a seminal paper in this

[5] This methodology improves the previous analysis in several dimensions. In this sense, TAR models are subject to the following restrictions: i) the regimes are determined by observable variables, so it is up to the researcher to select the variable or set of variables that determines the outcome in one or another regime; ii) the regime is determined by the value of the selected variable relative to a threshold value, which is constant for the entire sample; this restriction may be important when the sample includes structural breaks. By contrast, in the Markov-Switching models the state of the regime is unobservable; the data and procedures for non-linear maximum likelihood estimation are the only ones that identify the different regimes, without having been imposed by the researcher one a priori hypothesis regarding the driving forces behind the regime-switching, i.e. in our case, no a priori hypothesis on asymmetric price responses has been imposed. From this point of view, these models are less restrictive even though the estimated regimes may sometimes be difficult to identify and interpret. Different unobservable Markov processes, regardless of whether or not they are independent, may be incorporated so that, for example, the model parameters can follow the same process and the variance of model disturbances may follow a different one (also a different number of regimes can be assumed for parameter and error variance).

[6] Karaganis et al. (2015) explores the Spanish diesel markets. Nevertheless, they use oil spot prices and an ECM model with exogenous zero threshold, achieving different conclusions. They find no evidence of price asymmetries and do not provide evidence to support the "rockets and feathers" hypothesis.

[7] http://www.cores.es/en/publicaciones.

[8] This author uses biweekly data to find evidence of an asymmetric price adjustment process in the British gasoline market.

issue and Borenstein et al. (1997)[9] is, probably, the most cited paper regarding the rockets and feathers behavior in this market. However, there are a relevant number of papers addressing the issue with diverse econometric approaches for different countries and time spans[10], achieving different conclusions. Shin (1994) points out that the contradictory results found in these papers could be explained by the lack of homogeneity in the data, rather than the different models used.

To the best of our knowledge, the main papers that have analyzed the existence of asymmetric price transmission for the Spanish retail fuel market are Galeotti et al. (2003), Grasso and Manera (2007), Polemis et al. (2013), Karagiannis et al. (2015), Contín-Pilar et al. (2009), Balaguer and Ripollés (2012), Bagnai et el. (2016), Clerides (2010) and Venditti (2013).

Galeotti et al. (2003) examines asymmetries in the transmission of crude oil shocks to gasoline retail prices, considering the exchange rate as an element contributing to the asymmetries. For their analysis they use an asymmetric error-correction model and consider different stages for the transmission mechanism (refinery stage, distribution stage or single stage), finding asymmetries at different stages.

Grasso and Manera (2007) analyze price asymmetries in the gasoline market. They focus on the sensitivity of the empirical results to alternative econometric specifications. They estimate three different econometric models (namely asymmetric ECM, autoregressive threshold ECM, and ECM with threshold cointegration) and consider three different stages (in line with Galeotti et al., 2003), finding inconclusive results. The markets and countries with rockets and feathers behavior depend on the type of model. They estimate endogenous thresholds for TAR-ECM models, similar to our methodological approach, finding large differences among France, Germany, Italy, Spain and the UK.

Polemis et al. (2013) estimates a panel data error-correction model with exogenous zero threshold and concludes the existence of asymmetric responses in the retail and wholesale markets. Karagiannis et al. (2015), using the same approach, do not find evidence of the "rockets and feathers" phenomenon.

Contín-Pilar et al. (2009) examine the pricing behavior of the retail gasoline market using multivariate error-correction models with exogenous zero threshold and spot prices. Their results suggest that gasoline retail prices respond symmetrically to shifts of oil spot prices in a price regulated scheme and in a free market environment.

Balaguer and Ripollés (2012) use daily data to examine price asymmetries. Using an asymmetric error-correction model with exogenous zero threshold, this paper finds no evidence of asymmetries.

[9] This article is one of the most influential papers on the topic. The authors argue that gasoline retail price asymmetry may be triggered by the existence of tacit collusion in the market using econometric time series analysis. The empirical results are in line with rockets and feathers behavior. Among the possible sources of this asymmetry are production/inventory adjustment lags and the market power of some sellers.

[10] Other papers applied to the US economy using alternative econometric specifications are Balke, Brown and Yucel (2001), Radchenko (2005a), Al-Gudhea, Kenc and Dibooglu (2007) and Pal and Mitra (2015), among others. By contrast, the papers of Bachmeier and Griffin (2003) and Douglas (2010) find no evidence of asymmetries in the US economy. For European countries, in addition to the seminal paper of Bacon (1991), we should mention the paper of Reilly and Witt (1998) that finds rockets and feathers behaviour. Kirchgassner and Kübler (1992) focus on gasoline and fuel oil in Germany, but their results are non conclusive. The results of Asplund et al. (2000) are also non conclusive for the Swedish gasoline market. Lik Bettendorf et al. (2003) find the same conclusion for the Dutch gasoline market. Lamotte et al. (2013) and Boroumand et al. (2016) find an asymmetric gasoline price response in the French market.

Bagnai and Ospina (2016) use nonlinear autoregressive distributed lag (NARDL) with zero threshold and spot prices to investigate the asymmetries in gasoline pricing for twelve Eurozone countries. In their paper Eurozone countries display asymmetric long-run gasoline price adjustment and short-run gasoline price adjustment is symmetric.

Clerides (2010) using a ECM with zero threshold and spot prices proposed by Borenstein et al. (1997) finding a very weak evidence of asymmetric price responses in European retail gasoline markets

Finally, Vendetti (2013) using nonlinear impulse response functions and forecast accuracy tests based in ECM model with zero threshold and using spot prices, obtain that the results for the U.S. economy point to the presence of asymmetries in the adjustment of retail prices while for the euro area the evidence is mixed.

In conclusion, mixed evidence has been found given that Contín-Pilar et al. (2009), Balaguer and Ripollés (2012), Clerides (2010) and Karagiannis et al. (2015) encounter no evidence of asymmetric behavior, while the other three papers do encounter such evidence.

Following Martín-Moreno et al. (2018) our article contributes to filling a gap in the recent literature applied to Spanish fuel markets in the following way: we first use forward price data for crude oil because fuel dealers use forward contracts to cover against the changes in oil prices. Secondly, we endogenize the rise or fall of oil prices for which these price changes are transmitted asymmetrically to the prices of gasoline and diesel. We think that studing asymmetries for Spanish fuel market assuming positive or negative oil price growth could be inaccurate in some circumstances, making it difficult to obtain the asymmetry result. Finally, in a second stage of the analysis, we check the results found with the endogenous threshold TAR-ECM approach using the Markov-Switching model. To the best of our knowledge, this type of methodology has not been applied to detect asymmetric responses of retail prices to oil price shocks in Spain.

3. Data used for the analysis

A number of choices must be made in terms of the data when analyzing the asymmetric response of the retail fuel market to changes in the price of crude oil. We use weekly data for: i) Crude Oil-Brent price, 3 Months Forward (free on board) US Dollar per barrel, which is conveniently transformed into Euros by using the Dollar to Euro 3 month forward exchange rate, ii) price before taxes, in Euros, of gasoline per 1000 liters, iii) price before taxes, in Euros, of diesel per 1000 liters. The complete sample covers the period January 2009 to December 2017. The sources of the data are DataStream for oil price and exchange rate, and European Weekly Oil Bulletin for gasoline and diesel-fuel prices.

Forward oil prices are used instead of spot prices because fuel dealers use forward contracts to buy crude oil, so forward prices seem to be relevant when fixing the retail price of gasoline and diesel. On the other hand, the survey conducted by Grasso and Manera (2007) shows that “66.7% of the studies which support the presence of asymmetric price behavior employ net-of-tax gasoline prices, that is, asymmetries emerge more easily once the fiscal veil is removed”. We use this evidence to choose the pre-tax retail data. Moreover, taxes are out of the retailers’ control.

A look at the data shows that from 2014 onwards the variability of data displays volatility clusters. In particular, the volatility during 2014 to 2015 is below average, while from 2015 onwards it is above average and significantly higher than it was before 2014 (see figures 1a and 1b). To prevent results from being masked by this heterogeneity in the whole sample, we have analyzed the causal relationship from oil to gasoline (as well as from oil to diesel-fuel) prices for a period in which it is homogeneous, April 2009 to November 2013.[11] During that period, the data reflect that an upward trend in oil prices prevails along with occasional periods of maintenance or mild decreases in prices; so the information contained in the data is rich enough to capture potential regime switching.

[Insert Figures 1a and 1b]

4. Methodology: Econometric Models

4.1 TAR-ECM model

As a first approach we estimate a "Threshold autoregressive Error Correction Model" (TAR-ECM), in which retail fuel prices are explained through their own lags and the crude oil forward price is an exogenous variable. Our objective is to study possible asymmetric effects triggered by oil price shocks on retail prices of gasoline, or alternatively on retail prices of diesel (in Spain). Given this and the exogenous nature of crude oil for an economy such as Spain, which does not produce oil, we may use one univariate model for each market (gasoline and diesel) to undertake this analysis.

Furthermore, prices for crude oil, gasoline and diesel are I(1); so the price of Oil and gasoline could present a stationary linear combination, on the one hand, as could the price of Oil and diesel on the other. These possible cointegration relations, jointly with the possible asymmetric effects, lead us to a generalized ECM by Granger and Lee (1989), which incorporates a TAR mechanism because we assume that asymmetric effects surpassing a certain threshold could arise for changes in oil price. Such a specification is akin to the one shown in (2).

According to Grasso and Manera (2007), "the presence of short-run price reactions should be investigated with models designed to account for non-linear short-run price dynamics, such as the TAR-ECM specification", whilst "the simpler asymmetric Error Correction Models is indicated for capturing long-run (cointegration-based) asymmetries". We chose the TAR-ECM specification because our analysis focuses on potential asymmetries in the short-run and long-run price dynamics.

We formulate two causality regimes and allow the estimation procedure to endogenously estimate the threshold value for the variation rate of crude oil price that determines the jump from the first to the second regime.

As a previous step we check the cointegration relationship that exists between the retail prices of gasoline and diesel-fuel and the price of crude oil. The cointegration test consists in rejecting the non-stationary

[11] The analysis of this type of volatility cluster behaviour requires the use of models of the GARCH family.

hypothesis of the residuals of the level regressions between the endogenous and the explanatory variable (so we use the Engle-Granger two-step procedure):

$$x_{jt} = a + b\, p_t + \varepsilon_t \text{, for } j\text{= gasoline, diesel-fuel,} \tag{1}$$

where x_{jt} is the logarithmic transformation of the retail price and p_t is the logarithmic transformation of the Crude Oil-Brent forward price. Following Bermingham and O'Brien (2011), the standard cointegration model is not rich enough to capture the underlying dynamics if there is asymmetry in the way changes in the price of crude oil are transmitted to retail prices. Then, the econometric model we estimate is the following:

$$\begin{aligned}\nabla x_{jt} = \beta + \sum_{i=1}^{p} \rho_i \nabla x_{jt-i} + \left[\delta^{(1)}\hat{\varepsilon}_{t-1} + \sum_{l=0}^{q} \gamma_l^{(1)} \nabla p_{t-l}\right] \cdot Ind\left(\nabla p_t > \overline{c}\right) + \\ \left[\delta^{(2)}\hat{\varepsilon}_{t-1} + \sum_{l=0}^{q} \gamma_l^{(2)} \nabla p_{t-l}\right] \cdot \left(1 - Ind\left(\nabla p_t > \overline{c}\right)\right) + \zeta_{j,t}\ ,\end{aligned} \tag{2}$$

for j={gasoline, diesel}, where $\{\beta, \rho_i\}$ characterize the part of retail price variations that are not explained by the variations of crude oil price, $\{\delta^{(1)}, \gamma_1^{(1)}, \ldots, \gamma_q^{(1)}\}$ are the parameters that capture the effect of oil shocks on retail prices corresponding to the first regime, and $\{\delta^{(2)}, \gamma_1^{(2)}, \ldots, \gamma_q^{(2)}\}$ the ones corresponding to the second regime; finally, $\hat{\varepsilon}_t$ are the residuals of the cointegration equation. ∇ denotes first differences and $\overline{c}$ is the threshold parameter that will be estimated together with the remaining parameters of the dynamic equation.

This latter parameter, $\overline{c}$, is very interesting from an economic perspective, because it allows us to assess the behavior of fuel distributors: in particular, it will allow us to determine the threshold from which they decide to 'wait and see' before translating variations in cost into consumer price.

As is well known (see Grasso and Manera, 2007), plausible thresholds are the exogenous variables in first differences or the error correction term because the original series are not stationary. Oil Price is an exogenous variable for the Spanish economy and our interest is to study the effects of shocks in crude oil price on fuel retail prices. In our opinion, the relevant threshold variable should be the logarithmic first difference of such oil prices.

4.1.1 Interpreting the TAR-ECM Model

The specification presented through equation (2) is the basic approach to specifying asymmetry within a cointegration framework.

With respect to the economic interpretation of the model we will find evidence of long-run asymmetries if we can conclude that the parameters for the error correction term in equation (2), denoted by $\delta^{(1)}$ and $\delta^{(2)}$, are statistically different; analogously, we will find evidence of short-run asymmetries if the parameters that capture the direct effect of shocks in crude-oil price on the retail prices of fuel, denoted by $\gamma^{(1)}$ and $\gamma^{(2)}$, are statistically different. Furthermore, if the parameters for regime 1 are larger (in absolute value) than they are for the regime two, we can speak of a rockets and feathers behavior.

More precisely, if we first focus on the long-run asymmetries, positive equilibrium errors typically correspond to a period of falling crude prices (see Figures 2 and 3, in which we jointly represent the variation rate for crude oil price and the residuals of the cointegration equations (1)).

[Insert Figure 2 and 3]

If the rockets-feather hypothesis holds, we will find a smaller coefficient on the positive ECM term relative to the negative, meaning that there is less downward pressure on retail prices to restore the equilibrium margin after a period of falling refined prices as compared to the upward pressure on retail prices following a period of increasing crude prices. On the other hand, as shown in the next section, we find that the speed of adjustment coefficients, $\delta^{(1)}$ and $\delta^{(2)}$, are always negative; this indicates that they are working to bring the system back to equilibrium.

With respect to the short-run asymmetries, we will find evidence of the rockets-feathers hypothesis if the direct effect from crude oil to retail prices is stronger under the first regime, associated to a variation rate for crude oil price exceeding the threshold.

4.1.2. TAR-ECM estimation

As specified in Hansen (1997), following is the way to proceed to jointly estimate the parameters $\Phi = \left\{\beta, \rho_1, \dots, \rho_p, \delta^{(1)}, \delta^{(2)}, \gamma_0^{(1)}, \dots, \gamma_q^{(1)}, \gamma_0^{(2)}, \dots, \gamma_q^{(2)}\right\}$ and $\{\bar{c}\}$:

Step 1: We obtain estimates of Φ by OLS conditioned upon $\bar{c}$, that is, $\widehat{\Phi}(\bar{c})$.

Step 2: We obtain residuals $\zeta_{j,t}(\bar{c}) = \nabla x_{j,t} - Z_t\widehat{\Phi}(c)$, with Z_t being the vector of the explanatory variables of the regression (2), in order to compute residual variance: $\hat{\sigma}_j^2(\bar{c}) = \frac{1}{T}\sum_{t=1}^{T}\left[\hat{\zeta}_{j,t}(\bar{c})\right]^2$.

Step 3: We obtain the least square estimate of $\bar{c}$ by minimizing this residual variance, that is:

$$\hat{\bar{c}} = \underset{\bar{c}\in C}{\arg\min}\ \hat{\sigma}_j^2(\bar{c})$$

where C denotes the set of all allowable threshold values.

This minimization problem can be solved by means of direct search, i.e., using a grid of all allowable threshold values.

Step 4: The final estimates of parameters of regression (2) are given by $\widehat{\Phi} = \widehat{\Phi}(\bar{c})$, and the residual variance is given by $\hat{\sigma}_j^2 = \hat{\sigma}_j^2(\hat{c})$.

4.1.3. TAR-ECM estimation results and discussion

Augmented Dickey–Fuller (ADF) tests conclude that all the price series are I(1) as may be seen in table 1.The ADF and Phillips-Perron Tests for the log transformation of the series are lower in absolute value than the critical values at 5%, so we cannot reject the null hypothesis of unit root. Contrarily, the ADF tests for the first-differences of the series are more negative than the critical value is, so we reject the null hypothesis of unit root.

Using the Engle-Granger two-step approach, we reject the null hypothesis of non-stationarity for the residuals of the cointegration equations between retail (gasoline on the one side and diesel-fuel on the other) and crude oil prices given by (1), hence supporting the existence of common long-run trend. See table 2, which includes the ADF and Phillips-Perron tests for the residuals: because the tests are more negative than the critical values are, we can reject the null hypothesis of unit root.

[Insert Tables 1 and 2]

We have specified and estimated five different TAR-ECM models depending on the number of lags of the endogenous and exogenous variables (ranging from one to three lags). The results, including the AIC and BIC tests, are summarized in tables 3 and 4.

[Insert Tables 3, 4 and 5]

AIC and BIC tests joint with R^2 seem to indicate that the most desirable models are the simplest ones, with one lag for the endogenous variable and two terms for the exogenous variable, corresponding to the contemporaneous effect and the effect after one week of the shock in the oil price. In terms of the model described in equation (2), the selected model corresponds to the case p=q=1 (the shaded column in the tables, M.1 model). We can conclude that adding lags does not provide more information given that this information is generally statistically insignificant. Consequently, we will focus on the subsequent discussion in the M.1 columns of tables 3 and 4.

In table 5 we include the tests we have carried out to check if the parameters corresponding to one regime are statistically different to the homologous parameter of the other regime. We will use these results throughout the following discussion.

We start by analyzing the results corresponding to the gasoline market. Concerning the long-run asymmetries, the estimation suggests that the adjustment speed towards the long-run equilibrium is greater under the first regime (which corresponds to the case $\nabla p_t > \overline{c}$). According to the statistical test in the first column of table 5 we can conclude that $\delta^{(1)} > \delta^{(2)}$, in absolute value. This means that the correction of short-run disequilibrium is faster under the first regime. Thus it matches the so-called rockets behavior, with a stronger translation of crude oil price changes into fuel retail prices.

The results corresponding to the short-run asymmetries are not so readily interpretable. The contemporaneous effect is stronger for the second regime, $\gamma_0^{(1)} < \gamma_0^{(2)}$, while the one-week delayed effect is stronger under the first regime, $\gamma_1^{(1)} > \gamma_1^{(2)}$. Hence, with respect to the short-run effects, the asymmetry cannot be directly interpreted as being in line with the rockets and feathers hypothesis.

In the diesel-fuel market, we obtain results that in qualitative terms are similar to the ones found for gasoline in the sense that: i) the adjustment speed towards long-run equilibrium is greater under the first regime (in line with the rockets-feathers hypothesis); ii) the short-run asymmetries also point to a greater instantaneous effect in the second regime and a greater delayed effect under the first regime. The slight difference comes from the fact that the formal test in table 5 does not reject the null hypothesis stating that the parameters for the error correction term $\delta^{(1)}$ and $\delta^{(2)}$ are equal. However, the point estimation is greater for the first regime.

Other conclusions are:

a) The estimated parameters are very robust throughout the different models specified. Such is the case for those that capture the effect of oil price as well as for those corresponding to the error correction term.

b) The negative value obtained for the coefficients of the error correction term, $\delta^{(1)}$ and $\delta^{(2)}$, has also been found for other countries and its statistic significance means that the ECM mechanism is working to bring the system back to equilibrium.

c) Finally, we obtain negative estimated values for the threshold not only for the gasoline market (around -2.5%), but also for the diesel market (around -2.0%). Those values suggest that the standard zero threshold assumed by most of the papers analyzing the issue for the Spanish economy might be an inadequate assumption. The confidence intervals of these parameter estimations are obtained by inverting the likelihood ratio test-statistic (see Graphs 1 and 2).

[Insert Graphs 1 and 2]

In conclusion, we obtained evidence of price asymmetry in the short-run as well as in the adjustment to the long-run equilibrium for both markets: gasoline and diesel. The long-run asymmetries fall in line with the rockets and feathers behavior for both, although the statistical significance is mild in the case of diesel. The results are not conclusive in terms of the rockets-feathers behavior for short-run asymmetries.

4.1.4. TAR-ECM model using rolling windows

In the next exercise, we intend to explore whether the non-conclusive results corresponding to the short-run asymmetries (stronger instantaneous effect for regime 2 and stronger delayed effect for regime 1) are due to the time varying nature of the relationship between crude oil price and the retail prices of fossil fuels.

In order to unravel this hypothesis, we carry out rolling windows estimations for the TAR-ECM model described above, with the window size corresponding to one year (49 data). Roller windows are overlapping, so that every window eliminates the first observation of the previous window and includes a new observation at the end. That is, two consecutive windows share 47 observations out of the 49 weeks used for the estimation. The results are displayed in graphs 3.A to 3.C for the gasoline market and graphs 4.A to 4.C for the diesel market.

The main conclusions for the <u>gasoline market</u> are:

1. The estimated threshold parameter is negative in a major percentage of the periods, 66%, supporting the negative value estimated for the whole sample.
2. Regarding the short-run asymmetries, the instantaneous effect of crude oil price shocks is slightly larger for regime 2 during the first part of the sample. Yet the relative sizes invert in the last part of the sample, in which the instantaneous effect of regime 1 is remarkably larger. Taking into account only the periods for which the difference between parameters is statistically significative (95% degree of significance), we find that the instantaneous effect for regime 1 is larger ($\gamma_0^{(1)} > \gamma_0^{(2)}$) in 60% of the cases (52 times, versus 34 times in which the effect for regime 2 is larger).
3. With respect to the delayed effect of crude oil shocks, it is stronger for regime 1 in 58% of the cases and, if we only take into account the periods for which the difference between parameters $\gamma_1^{(1)}$ and $\gamma_1^{(2)}$ is statistically different from zero, the percentage of cases in which $\gamma_1^{(1)} > \gamma_1^{(2)}$ increases to 90%.
4. Finally, the adjustment speed towards the long-run equilibrium is stronger (larger absolute value for the δ parameter) in 60% of the cases; 100% of the significative cases.

The major conclusions for the <u>diesel market</u> are:

1. The estimated threshold parameter is also negative in 62% of the cases, similar to the gasoline market and consistent with the result for the complete sample.
2. The instantaneous short-run effect in regime 1 is larger ($\gamma_0^{(1)} > \gamma_0^{(2)}$) in 46% of the cases and, if we consider significative cases, the percentage is 52%. So, in this case, the result is more in line with a fifty-fifty percent for each regime, which does not support the existence of asymmetry in this specific parameter.

3. Contrarily, the results are much more supportive of the rockets-feathers hypothesis regarding the delayed short-run effect, $\gamma_1^{(i)}$ parameter as follows: in 81% of cases, the delayed effect is stronger under the first regime; the percentage rises to 97% of the cases in which the difference between parameters $\gamma_1^{(1)}$ and $\gamma_1^{(2)}$ is statistically different from zero.
4. With respect to the adjustment speed towards the long-run equilibrium, the results are in line with the difficulty in finding evidence of asymmetry in the complete sample. The δ parameter is larger in absolute value for the first regime only in 54% of the cases, while the difference is statistically different from zero using a significance of 95% only in three cases.

In our opinion, these detailed results seem to support the rockets-feathers behavior response in the gasoline market and, with some nuances, also in the diesel market.

Notwithstanding, our main conclusion is that the dynamic relationship between crude oil prices and the retail prices of fossil fuels seems to have a time-varying feature.

Then, our following strategy is to test previous results by implementing a procedure which is particularly suitable for capturing time-varying behaviors due to its flexibility.

4.2 The Markov-switching approach

Unlike the TAR-ECM approach, Markov-switching methodology assumes that the regime that occurs at time *t* cannot be observed, given that it is determined by an unobservable process denoted as S_t.

The general specification of the model is quite similar to the one formulated in the previous section:

$$\nabla x_{jt} = \beta + \sum_{i=1}^{p} \rho_i \nabla x_{jt-i} + \sum_{l=0}^{q} \gamma_l^{(S_t)} \nabla p_{t-l} + \delta^{(S_t)} \hat{\varepsilon}_{t-1} + \zeta_t, \zeta_t \sim N\left(0, \sigma_{S_t}^2\right)$$

where $S_t = 1, 2$ reflects the two possible states of nature or regimes. To complete the model, the properties of the process S_t need to be specified, and we assume it is a first-order Markov process. This assumption implies that the current regime S_t only depends on the regime in the last period, S_{t-1}. The model is completed by defining the transition probabilities of change from one state to the other: $P(S_t = i \mid S_{t-1} = j) = p_{ji}$, for *i j* = 1, 2[12].

Unlike the first estimation approach, we now consider that the auto-regressive part of the model is invariant to regime changes while the effect of crude oil prices on fuel retail prices (either gasoline or diesel-fuel) as well as the coefficient of the error correction term, might change with the regime. However, we use a gradual generalization of the model: 1) First, we allow only the effect of oil prices on retail prices (γ) to be regime-switching while the remaining parameters are regime-invariant. 2) In the second model we also allow the variance of the innovation term, σ, to be regime-switching. 3) The third model considers that both the coefficient

[12] For a detailed description of this methodology, see appendix.

of the error correction term, δ , and the variance for the innovation change with the regime. In models 4) and 5), the parameters capturing the effect of crude oil on retail prices as well as the coefficient for the error correction term are allowed to be regime-switching, and they differ with respect to the regime-switching characterization for the variance of innovations.

4.2.1 Estimation results using the Markov-switching methodology

The results obtained are displayed in tables 6 and 7 which respectively correspond to the gasoline and diesel models. We would like to focus our attention on the last column, M.5, given that it is the model that captures both the short-run and long-run asymmetries in which all the parameter estimations are statistically significant[13].

[Insert Tables 6 and 7]

When we analyze the gasoline market we find evidence of asymmetries in the behavior of prices in the short-run: there is a stronger contemporaneous effect of crude-oil price shocks on retail prices in regime 1 and similar delayed effects in both regimes. We also find evidence of asymmetries in the speed of adjustment towards the long-run equilibrium, which is faster in regime 1. Note that, as expected, we obtained the same negative sign for the coefficient of the error correction term as we did using the TAR-ECM estimation. Hence, both short and long-run asymmetries are in line with the rockets-feathers hypothesis. Furthermore, the volatility of the noise term is larger in regime 1 and the probability of staying in one given regime for two consecutive periods is also larger for regime 1 (it corresponds to upward trends in oil prices that are more frequent and persistent within the sample).

As an additional interpretation of the results, it is possible to analyze the expected duration of each regime, i.e., the expected length the system in state j, which can be calculated from the transition probabilities p_{11} and p_{22}, according to the formula in appendix 1. From the estimations for p and q in the most general model (M5), it is possible to infer an average duration of 16 weeks for the first regime (associated to the upward trend in crude oil price) in the sample, while the average duration of the second regime is 2 weeks.

For the diesel market our results were qualitatively similar to those found using the TAR-ECM methodology: i) in regime 1 the adjustment in long-run asymmetries is faster, so it falls in line with the rockets-feathers hypothesis, and ii) in regime 2 the contemporaneous effect of crude-oil price shocks on retail prices is stronger in short-run asymmetries; but the delayed effect is stronger in regime 1 in the short run. These results therefore support those found using the TAR-ECM methodology with endogenous threshold.

On the other hand, the volatilities for the noise term were in fact similar and the likelihood of staying in regime 1 for two consecutive periods was greater; this was akin to the results found for the gasoline market.

[13] Model 5 is the most efficient in the econometric sense, because the standard deviations of the parameters are the lowest, in particular, regarding the parameters γ_0 and γ_1 corresponding to regime 2. Thus, we focus the interpretation of the results on this latter model.

Finally, when we applied the same computations used for the gasoline model, we discovered that the average duration was 16 weeks for the first regime and 4 weeks for the second regime (see third and fourth column Table 7).

5. Conclusions and Policy Implications

The CNMC has stated in its report on the supervision of fuel distribution throughout Spanish petrol stations for January 2014 that the gross margin (i.e., the price before taxes minus the international price) has increased by 25% (annual growth rate) in the case of gasoline and 11% in the case of diesel-fuel. Additionally, prices before tax in Spain continue to be above the Euro zone average and have ranked fourth in the EU-28 classification in terms of the price of gasoline 95 and sixth in terms of the price of diesel-fuel. Furthermore, this report highlights that the three dominant firms in the Spanish sector (Repsol, Cepsa and BP) "show similar prices that are two or three cents (Euro) per liter above the price established by independent petrol stations."

In this sense, the perception is that the fuel market in the Spanish economy may not be fully competitive. Consumers are rapidly burdened with rises in crude oil prices while they hardly benefit from price falls. A rigorous in-depth analysis of this problem could help formulate better policies that would benefit consumers.

In this paper we analyze the potential asymmetric response of retail prices for gasoline and diesel-fuel to changes in oil prices for the Spanish economy, and their relation with the so-called 'rockets and feathers' behavior. Our approach differs from previous literature in two major aspects. Most previous work has analyzed the different causality channels depending on the negative or positive sign of the variation rate for the oil price. That is, the previous analysis separated the periods corresponding to increases in the price of oil from those corresponding to decreases. The standard hypothesis is that an increase in oil price will translate quickly into an increase in the gasoline price, whilst a decrease in oil price will pass on slowly and will have a lower magnitude on the price of gasoline. We use a different approach, a Threshold Auto-regressive Error Correction Model, to endogenously estimate the threshold in the variation rate of the price of oil that makes the difference. In a second stage, we test the robustness of the results by using a Markov-switching estimation of the model. We find evidence of an asymmetric response of gasoline and diesel-fuel prices to changes in the price of crude oil, both in the short-run as well as in terms of the adjustment towards the long-run equilibrium. Our results generally support the rockets-feathers hypothesis for the Spanish retail fuel market.

In view of our results, the Spanish government should analyze and implement policies aiming at alleviating this fuel price asymmetry. To this end, policymaker strategy in the national market could focus on different aspects. On the one hand, the Spanish economy has lacked price convergence over the last decades with respect to the rest of Europe. This may be explained by the behavior of sectors not subject to international competition, which produces the phenomenon known as dual inflation. The hydrocarbon sector is among the most important of these sectors. Therefore, it is essential to introduce greater competition for goods and services in the market in order to alleviate this problem. This policy directly influences the market under study and has a direct impact on the decrease of the asymmetry in diesel and gasoline prices. These types of policies should prioritize either the regulation of the market or the suppression of existing entry barriers to these markets. This would slow down the loss of welfare to Spanish consumers and avoid possible oligopolies. That is to say, the entry of new players into the Spanish market should be strengthened and intensified by introducing, for example, new gas stations at supermarkets; this policy was established a few years ago but continues to have important restrictions. This could help improve aspects like the lack of competition in the distribution of fuel and would thus reduce the market power of certain companies mentioned herein.

On the other hand, the fiscal policy of different Spanish autonomous communities can also explain this asymmetry. In some Spanish autonomous communities the relaxation or suppression of taxes is completely transferred to consumers, even though declines in international prices are not always transferred to them at the same speed.

Finally, we know that effective competition in the market relies heavily on the information available to consumers. Therefore, government policies aimed at informing consumers about the different prices of gas stations in real time would be a good measure to influence price asymmetry in this market.

References

Al-Gudhea, S., Kenc, T. and Dibooglu, S. (2007). “Do retail gasoline prices rise more readily than they fall?: A threshold cointegration approach”. *Journal of Economics and Business,* 59(6), 560-574.

Asplund, M., Eriksson, R. and Friberg, R. (2000). “Price adjustments by a gasoline retail chain”. *The Scandinavian Journal of Economics* 102(1), 101-121

Bachmeier, L.J. and Griffin, J.M. (2003). “New evidence on asymmetric gasoline price responses”. *Review of Economics and Statistics,* 85(3), 772-776.

Bacon, R.W., (1991). “Rockets and feathers: the asymmetric speed of adjustment of UK retail gasoline prices to cost changes”. *Energy Economics* 13 (July), 211–218.

Bagnai, A. and Ospina, C.A.M., (2016). “Asymmetric asymmetries in Eurozone markets gasoline pricing”. *The Journal of Economic Asymmetries* 13, 89-99.

Balaguer, J. and Ripollés, J. (2012), “Testing for price response asymmetries in the Spanish fuel market. New evidence from daily data”. *Energy Economics* 24, 2066-2071.

Balke, N.S., Brown, S.P. and Yücel, M. (2001). “Crude oil and gasoline prices: an asymmetric relationship?”. *Economic and Financial Policy Review* (Q1), 2-11.

Bermingham, C. and O’Brien, D. (2011). “Testing for Asymmetric Behaviour in Irish and UK Petrol and Diesel Markets”. *Energy Journal* 32(3), 1-26.

Bettendorf, L., Van der Geest, A., Verkevisser, M. (2003). “Price Asymmetry in the Dutch retail gasoline market”. *Energy Economics* 25, 669-689.

Borenstein, S., A.C. Cameron and R. Gilbert (1997). “Do Gasoline Prices Respond Asymmetrically to Crude Oil Prices?, *Quaterly Journal of Economics*, February, 112, 305-339.

Boroumand, R.H., Goutte, S., Porcher, S. and Porcher, T. (2016). “Asymmetric evidence of gasoline price responses in France: A Markov-switching approach”. *Economic Modelling*, 52, 467-476.

Brown S.P.A. and Yücel M.K. (2000). "Gasoline and crude oil prices: why the asymmetry?," *Economic and Financial Policy Review*, Federal Reserve Bank of Dallas, Q3, 23-29.

CNMC (2014). “ IS-Distribución de carburantes en estaciones de servicio”. Comisión Nacional de los Mercados y la Competencia. IS/DE/010/14.

CNMC (2015). " Estudio sobre el mercado mayorista de carburantes de automoción en España". Comisión Nacional de los Mercados y la Competencia. Junio 2015.

Contín-Pilart, I., Correljé, A.F., Palacios, M.B. (2009). "Competition, regulation, and pricing behavior in the Spanish retail gasoline market". *Energy Policy* 37, 219-228.

Douglas, C.C. (2010). "Do gasoline prices exhibit asymmetry? Not usually!". *Energy Economics* 32(4), 918-925.

Galeotti, Ml, Lanza, A., Manera, M. (2003). "Rockets and feathers revisited: an international comparison on European gasoline markets". *Energy Economics* 25, 175-190.

Grasso, M., Manera, M. (2007). "Asymmetric error correction models for the oil-gasoline price relationship". *Energy Policy* 35, 156-177.

Hamilton, J.D (1994). Time Series Analysis. Princeton University Press.

Hansen, B.E. (1996). "Sample splitting and threshold estimation". Working paper 319, Chestnut Hill, Massachusetts: Boston College.

Hansen, B.E. (1997). "Inference in TAR models". *Studies in Nonlinear Dynamics and Econometrics* 2, 1–14

Informe mensual de supervisión de la distribución de carburantes en las estaciones de servicio. *Comisión Nacional de los Mercados y la Competencia* (CNMC).Enero 2014.

Karagiannis, S., Panagopoulos, Y. And Vlamis, P. (2015). "Are unleaded gasoline and diesel price adjustments symmetric? A comparison of the four largest EU retail fuel markets". *Economic Modelling* 48, 281-291.

Kim, C. (1994). "Dynamic linear models with Markow-switching". *Journal Econometrics*, vol. 60, Issues 1-2. January-February, 1-22.

Kirchgässner, G. and Kübler, K. (1992). "Symmetric or asymmetric price adjustments in the oil market: an empirical analysis of the relations between international and domestic prices in the Federal Republic of Germany, 1972-1989". *Energy Economics*, 14(3), 171-185.

Lamotte, O., Porcher, T., Schalck, C. and Silvestre S. (2013). "Asymmetric gasoline price responses in France". *Applied Economics Letters*, 20, 457-461.

Martín-Moreno, J.M., Pérez, R. and Ruiz, J. (2018). "Evidence about asymmetric price transmission in the main European fuel markets: from TAR-ECM to Markov-switching approach". *Empirical Economics*. Forthcoming

Pal, D. and Mitra, S.K (2015). "Asymmetric impact of crude price on oil product pricing in the United States: An application of multiple threshold nonlinear autoregressive distributed lag model". *Economic Modelling*, 51, 436-443.

Peltzman, S. (2000)."Prices rise faster than they fall". *Journal of Political Economy*, 108(3), 466:501.

Polemis, L.M., Fotis, P.M. (2013). "Do gasoline prices respond asymmetrically in the euro zone area? Evidence from cointegrated panel data analysis". *Energy Policy* 56, 425-433.

Reilly, B. and Witt, R. (1998). "Petrol price asymmetries revisited". *Energy Economics,* 20(3), 297-308.

Venditti, F. (2013). "From oil to consumer energy prices: how much asymmetry along the way?. *Energy Economics*, 40, 468-473.

Figure 1a

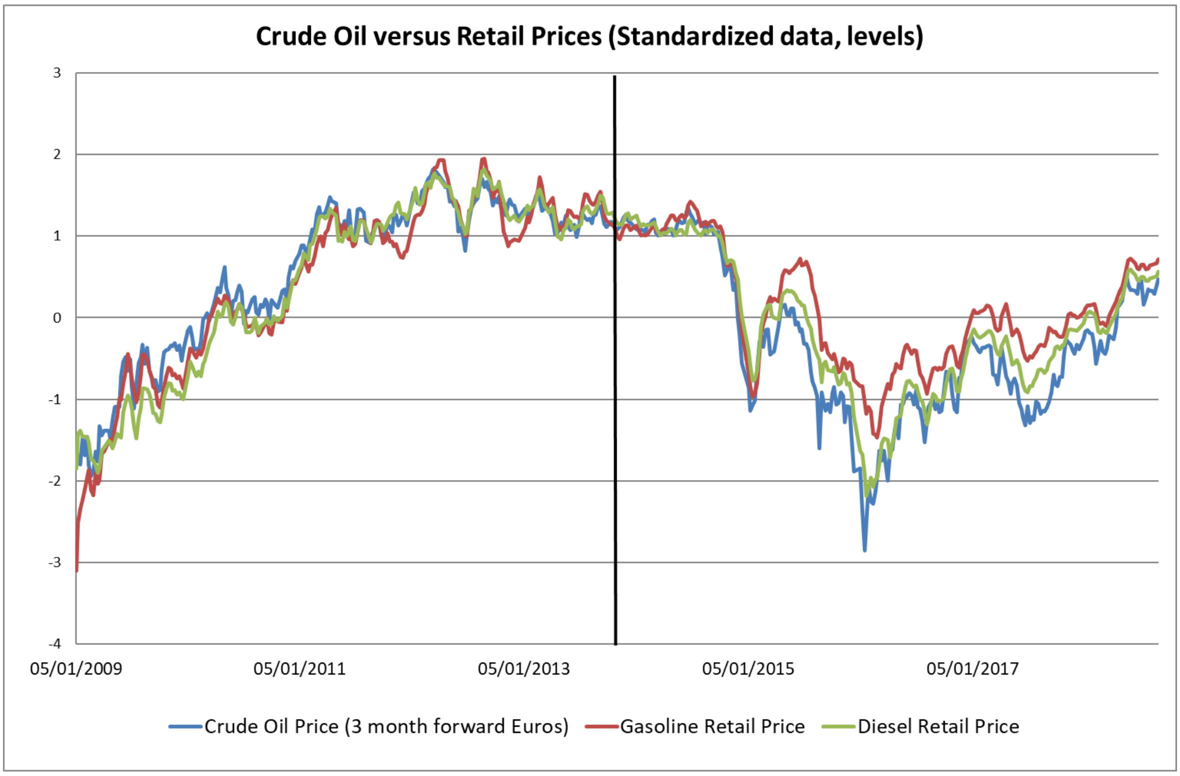


Figure 1b

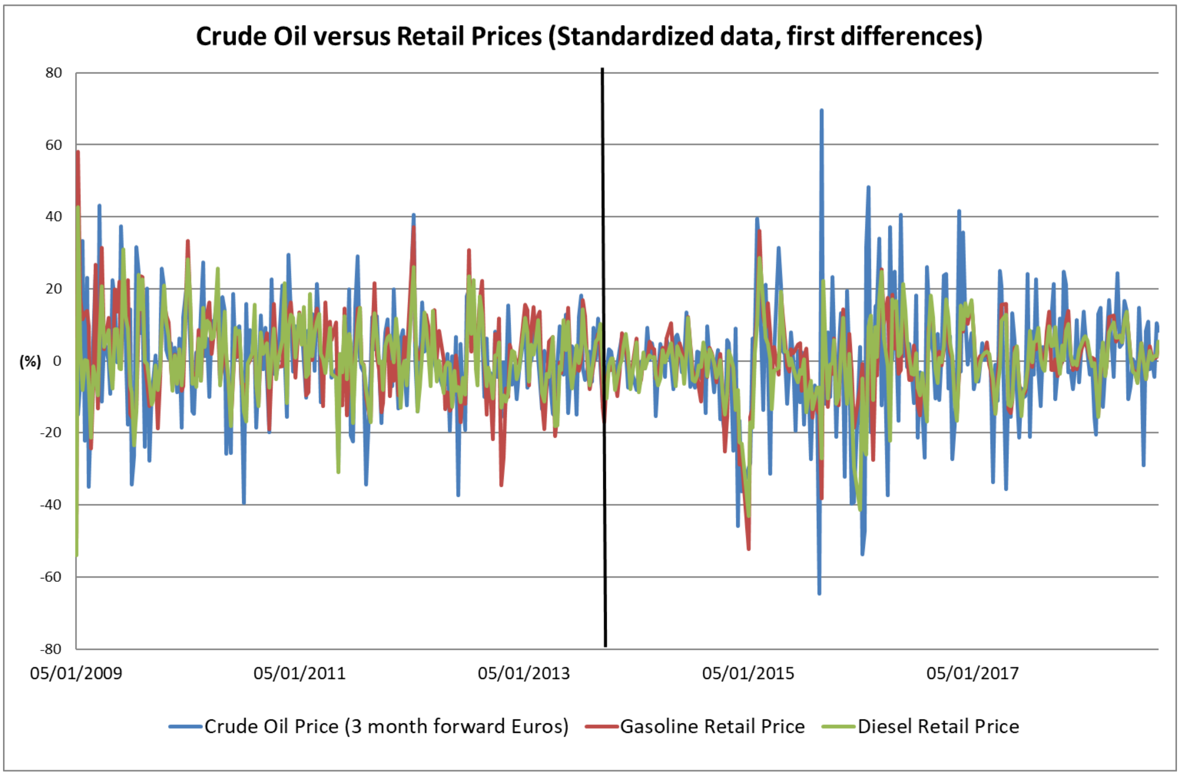


Figure 2: Residuals of the cointegration equation gasoline-crude oil vs. variation rate of crude oil Price

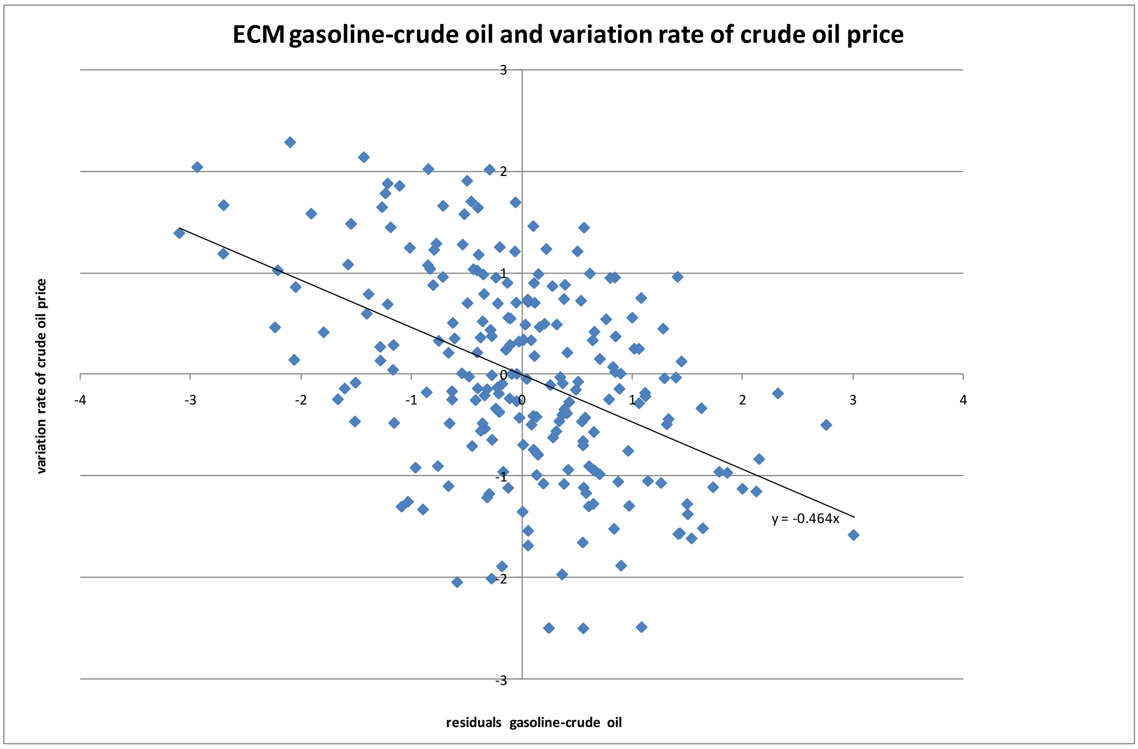


Figure 3: Residuals of the cointegration equation gasoil-crude oil vs. variation rate of crude oil Price

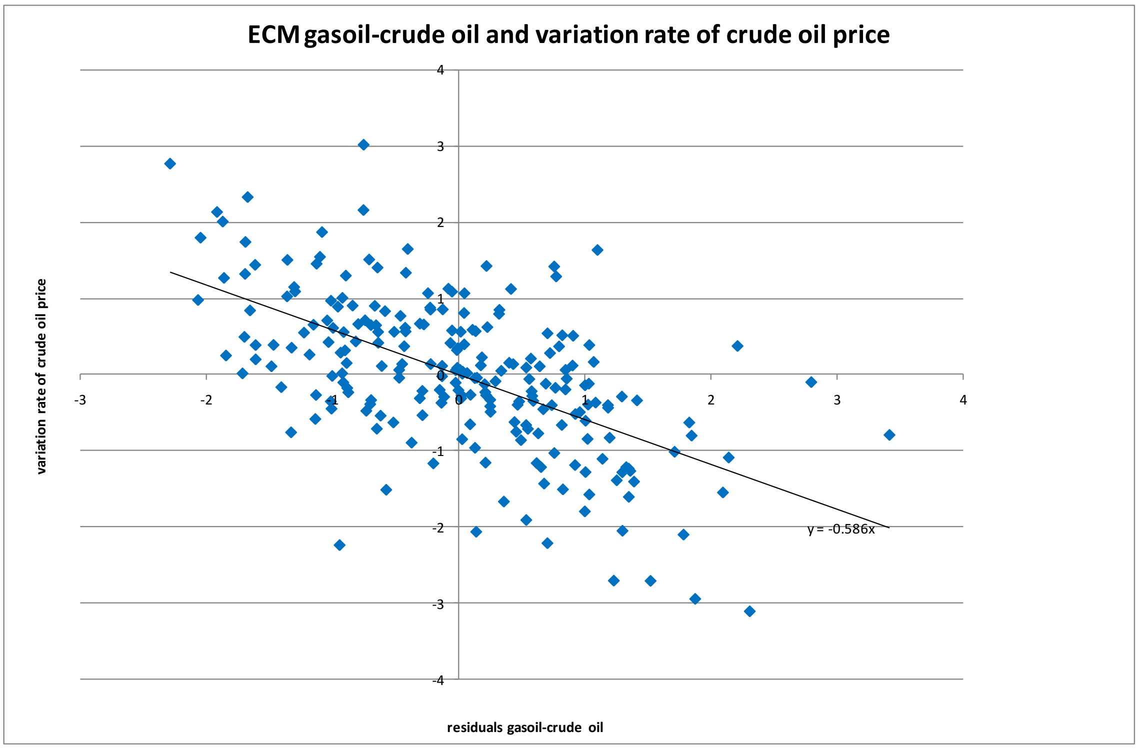


Table 1: Unit root tests

	ADF Test	Phillips-Perron Test
$\log(v_t)$		
v=Gasoline	-2.393	-2.551
v=Gasoil	-2.090	-2.313
v=Petrol	-2.568	-2.651
Test critical values		
1% level	-3.45910	-3.45897
5% level	-2.87409	-2.87403
10% level	-2.57353	-2.57350
$\nabla\log(v_t)$		
v=Gasoline	-11.011	-10.824
v=Gasoil	-11.476	-11.187
v=Petrol	-15.007	-15.185
Test critical values		
1% level	-2.575189	-2.575189
5% level	-1.942230	-1.942230
10% level	-1.615768	-1.615768

Table 2: Cointegration equations

$$\log(x_t) = a + b\log(p_t) + \varepsilon_t$$

***x*=Gasoline**	Coefficient	Std.Error	t-statistic	Prob.
a	3.050	0.050	61.050	0.0000
b	0.798	0.012	68.050	0.0000
Residuals ADF test	-5.823			
Residuals Phillips-P test	-5.741			
***x*=Gasoil**	Coefficient	Std.Error	t-statistic	Prob.
a	2.689	0.039	68.507	0.0000
b	0.894	0.009	97.010	0.0000
Residuals ADF test	-8.158			
Residuals Phillips-P test	-8.074			
ADF and Phillips-Perron Tests critical values				
1% level	-2.575			
5% level	-1.942			
10% level	-1.616			

Table 3. Gasoline-crude Oil TAR-ECM Models

	Parameters	M.1 (p=q=1)	M.2 (p=2,q=1)	M.3 (p=q=2)	M.4 (p=3,q=2)	M.5 (p=q=3)
	□	**0.0029 (0.0014)**	**0.0027 (0.0014)**	**0.0026 (0.0013)**	**0.0028 (0.0014)**	**0.0028 (0.0014)**
	ρ_1	-0.0158 (0.0573)	-0.0376 (0.0604)	-0.0786 (0.0646)	-0.0719 (0.0645)	-0.0723 (0.0651)
	ρ_2		0.0483 (0.0483)	0.0202 (0.0504)	0.0403 (0.0534)	0.0370 (0.0632)
	ρ_3				-0.0463 (0.0489)	-0.0506 (0.0510)
Regime 1	$\gamma_0^{(1)}$	**0.2319 (0.0328)**	**0.2340 (0.0328)**	**0.2381 (0.0327)**	**0.2385 (0.0330)**	**0.2380 (0.0334)**
	$\gamma_1^{(1)}$	**0.3593 (0.0351)**	**0.3657 (0.0355)**	**0.3749 (0.0356)**	**0.3709 (0.0356)**	**0.3707 (0.0358)**
	$\gamma_2^{(1)}$			0.0586 (0.0428)	0.0524 (0.0430)	0.0532 (0.0466)
	$\gamma_3^{(1)}$					-0.0024 (0.0433)
	$\delta^{(1)}$	**-0.2293 (0.0464)**	**-0.2303 (0.0463)**	**-0.2146 (0.0480)**	**-0.2157 (0.0479)**	**-0.2157 (0.0495)**
Regime 2	$\gamma_0^{(2)}$	**0.3913 (0.0612)**	**0.3933 (0.0611)**	**0.4072 (0.0617)**	**0.4028 (0.0616)**	**0.3987 (0.0621)**
	$\gamma_1^{(2)}$	**0.2599 (0.0684)**	**0.2687 (0.0686)**	**0.2834 (0.0687)**	**0.2779 (0.0686)**	**0.2852 (0.0701)**
	$\gamma_2^{(2)}$			0.0922 (0.0668)	0.0796 (0.0675)	0.0798 (0.0686)
	$\gamma_3^{(2)}$					0.0345 (0.0631)
	$\delta^{(2)}$	-0.0556 (0.0470)	-0.0576 (0.0469)	-0.0344 (0.0528)	-0.0290 (0.0527)	-0.0239 (0.0534)
Threshold	$\overline{c}$	-0.0248 [-0.0338,-0.0223]*	-0.0248 [-0.0338,-0.0223]*	-0.0248 [-0.0343,-0.0223]*	-0.0248 [-0.0343,-0.0223]*	-0.0248 [-0.0343,-0.0220]*
	AIC test BIC test	236.47 -1.85*10^3	237.46 -1.84*10^3	241.45 -1.83*10^3	242.44 -1.82*10^3	246.39 -1.82*10^3

Note: Standard deviations of the parameters between brackets; Bold typo for significative parameters.

(*)The 90 per cent confidence region for the threshold $\overline{c}$

Table 4. Diesel-crude Oil TAR-ECM Models

	Parameters	M.1 (p=q=1)	M.2 (p=2,q=1)	M.3 (p=q=2)	M.4 (p=3,q=2)	M.5 (p=q=3)
	□	**0.0014 (0.0010)**	**0.0014 (0.0010)**	**0.0013 (0.0010)**	**0.0014 (0.0010)**	**0.0015 (0.0010)**
	ρ_1	-0.1086 (0.0557)	**-0.1398 (0.0584)**	**-0.2067 (0.0648)**	**-0.1959 (0.0651)**	**-0.2034 (0.0655)**
	ρ_2		0.0401 (0.0417)	0.0093 (0.0437)	0.0329 (0.0467)	0.0074 (0.0621)
	ρ_3				-0.0549 (0.0412)	-0.0677 (0.0439)
Regime 1	$\gamma_0^{(1)}$	**0.2683 (0.0252)**	**0.2732 (0.0252)**	**0.2717 (0.0249)**	**0.2729 (0.0249)**	**0.2725 (0.0248)**
	$\gamma_1^{(1)}$	**0.4205 (0.0290)**	**0.4325 (0.0296)**	**0.4447 (0.0298)**	**0.4416 (0.0300)**	**0.4430 (0.0302)**
	$\gamma_2^{(1)}$			0.0779 (0.0362)	0.0664 (0.0375)	0.0739 (0.0407)
	$\gamma_3^{(1)}$					0.0089 (0.0360)
	$\delta^{(1)}$	**-0.2100 (0.0444)**	**-0.2276 (0.0458)**	**-0.1991 (0.0482)**	**-0.1939 (0.0506)**	**-0.1953 (0.0510)**
Regime 2	$\gamma_0^{(2)}$	**0.3680 (0.0426)**	**0.3664 (0.0423)**	**0.3612 (0.0421)**	**0.3569 (0.0421)**	**0.3548 (0.0420)**
	$\gamma_1^{(2)}$	**0.2926 (0.0474)**	**0.3089 (0.0482)**	**0.3259 (0.0488)**	**0.3180 (0.0489)**	**0.3133 (0.0491)**
	$\gamma_2^{(2)}$			0.0588 (0.0515)	0.0440 (0.0524)	0.0647 (0.0571)
	$\gamma_3^{(2)}$					0.0502 (0.0460)
	$\delta^{(2)}$	**-0.1382 (0.0487)**	**-0.1385 (0.0487)**	**-0.1272 (0.0592)**	**-0.1289 (0.0589)**	-0.1020 (0.0636)
Threshold	$\overline{c}$	-0.0201 [-0.0229,-0.0079]*	-0.0201 [-0.0229,-0.0079]*	-0.0201 [-0.0229,-0.0079]*	-0.0201 [-0.0229,-0.0079]*	-0.0201 [-0.0229,-0.0079]*
	AIC test BIC test	235.86 -1.99*10^3	236.84 -1.98*10^3	240.80 -1.97810^3	241.79 -1.96*10^3	245.79 -1.96*10^3

Note: Standard deviations of the parameters between brackets; Bold typo for significative parameters

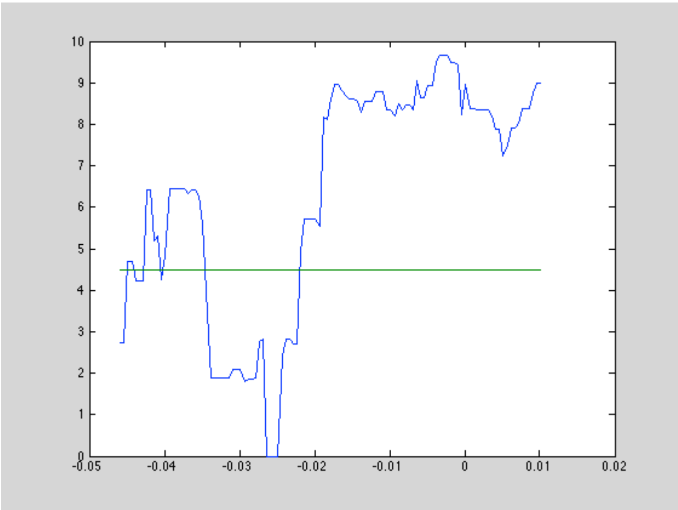
(*)The 90 per cent confidence region for the threshold $\overline{c}$

Table 5: Short-run Asymmetries and asymmetric Adjustment Speeds

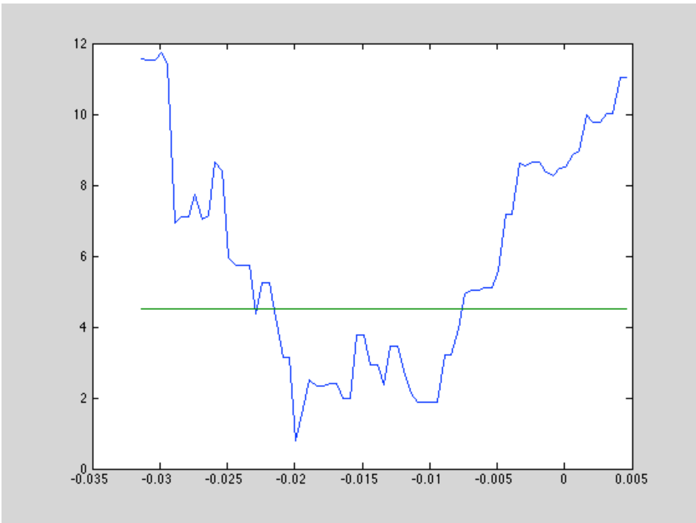
	TAR-ECM	
	Gasoline	Diesel
Test	t-Statistic	t-Statistic
$H_0:\ \gamma_0^{(1)} = \gamma_0^{(2)}$ $H_1:\ \gamma_0^{(1)} \neq \gamma_0^{(2)}$	2.2939**	2.0105**
$H_0:\ \gamma_1^{(1)} = \gamma_1^{(2)}$ $H_1:\ \gamma_1^{(1)} \neq \gamma_1^{(2)}$	1.3678	2.6179***
$H_0:\ \delta^{(1)} = \delta^{(2)}$ $H_1:\ \delta^{(1)} \neq \delta^{(2)}$	2.4304**	1.0544

A single (double, triple) asterisk denotes rejection of the null hypothesis with significance at 10% (5%, 1%) level

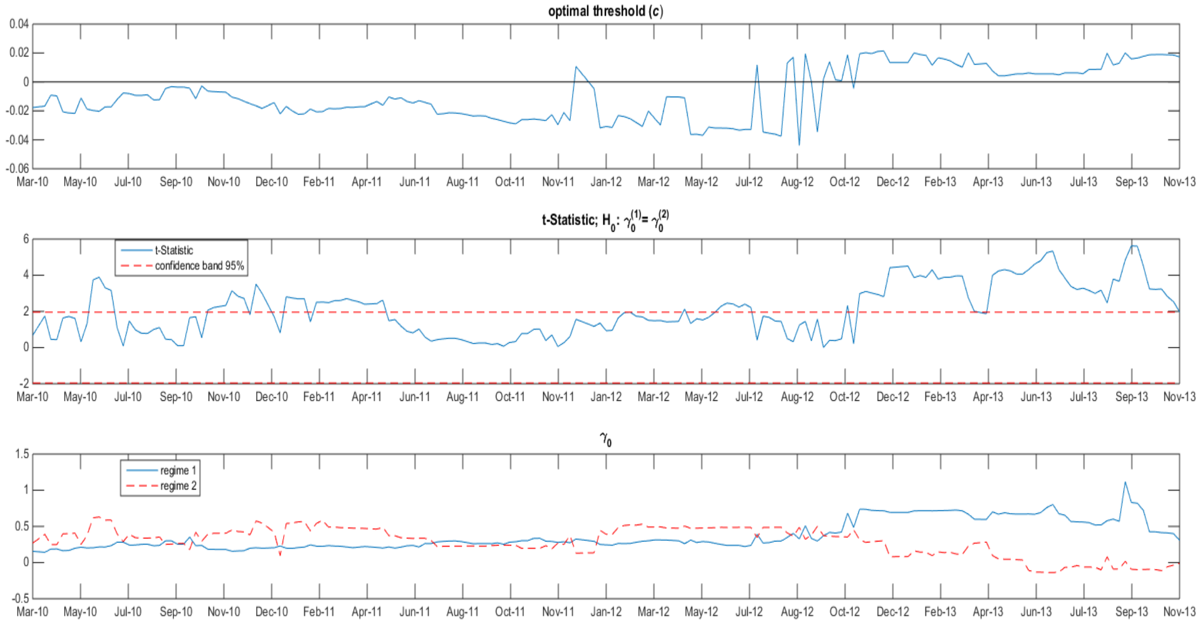
Graph 1: Gasoline. Likelihood ratio test forthethreshold.



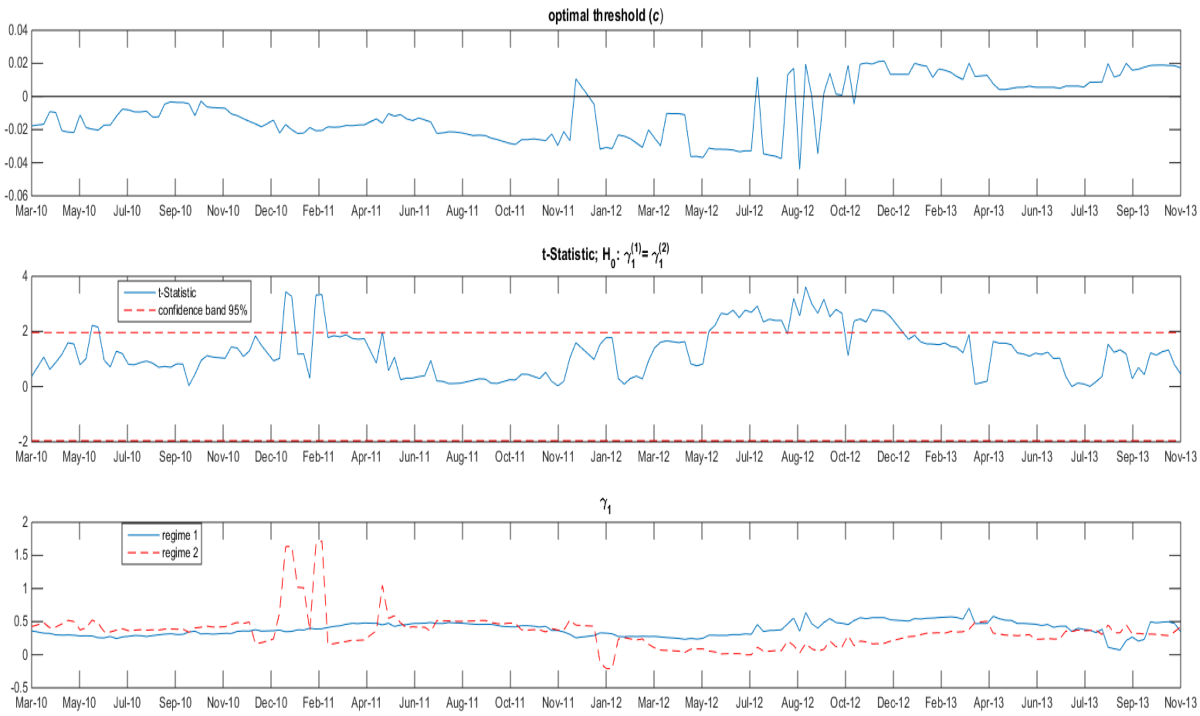
Graph 2: Diesel. Likelihood ratio test forthethreshold.



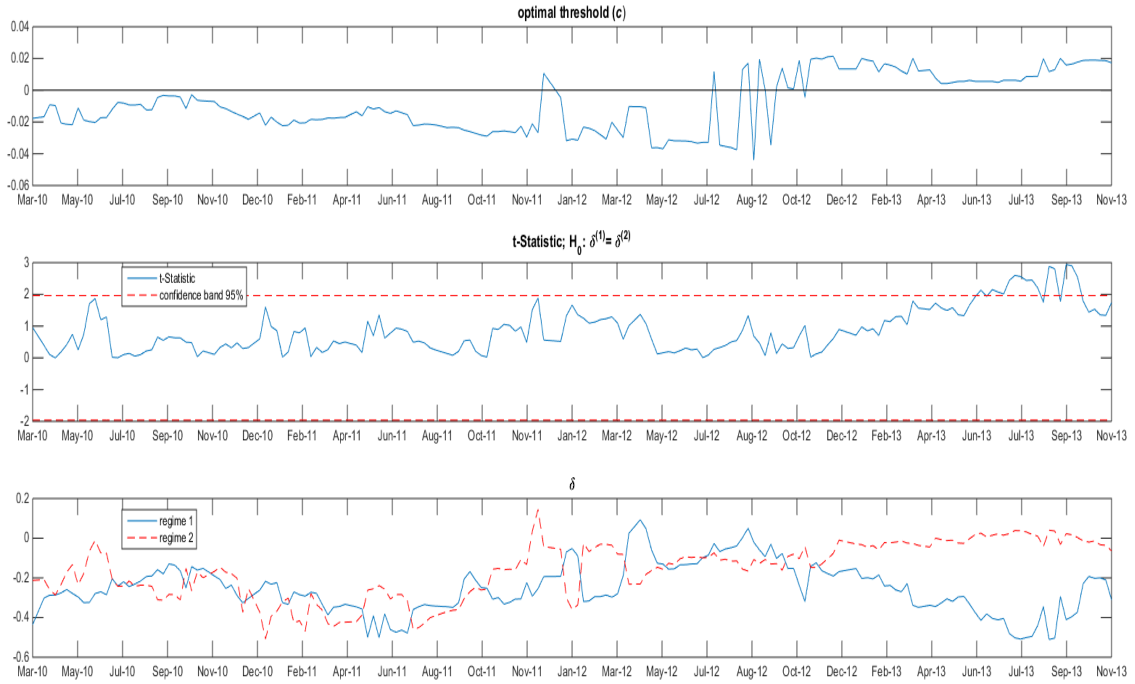
Graph 3.A: Time-varying TAR-ECM model (Rolling Windows analysis) for the gasoline market. Threshold parameter and short-run asymmetries: instantaneous effect



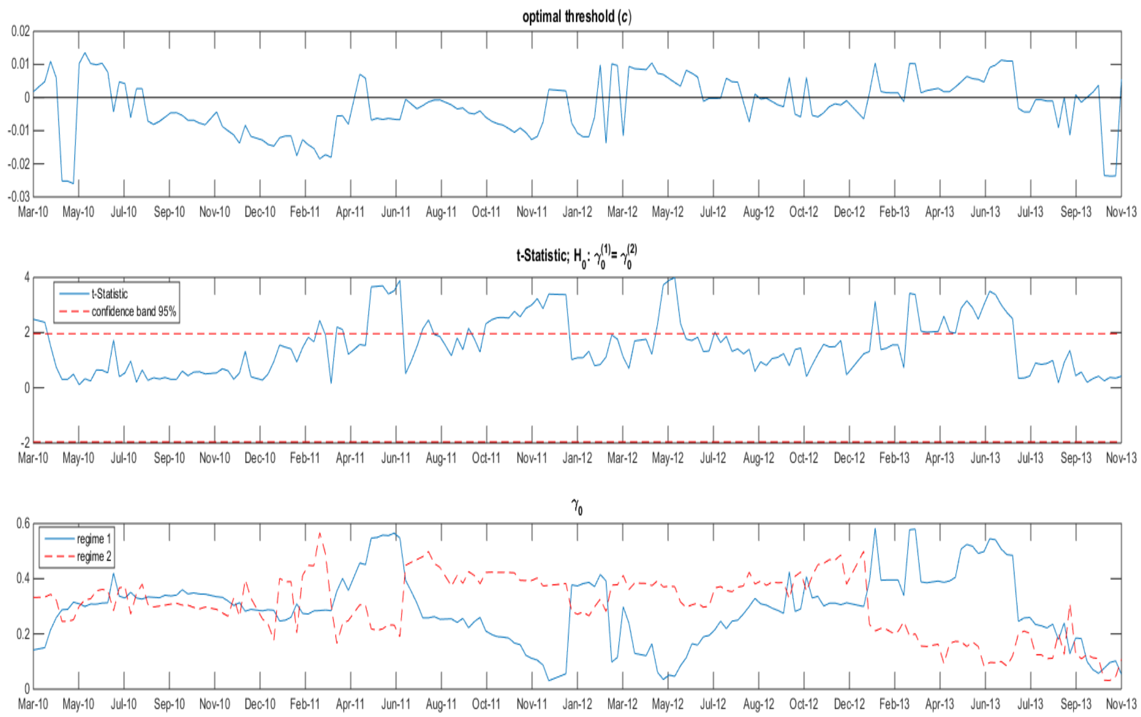
Graph 3.B: Time-varying TAR-ECM model (Rolling Windows analysis) for the gasoline market. Threshold parameter and short-run asymmetries: delayed effect



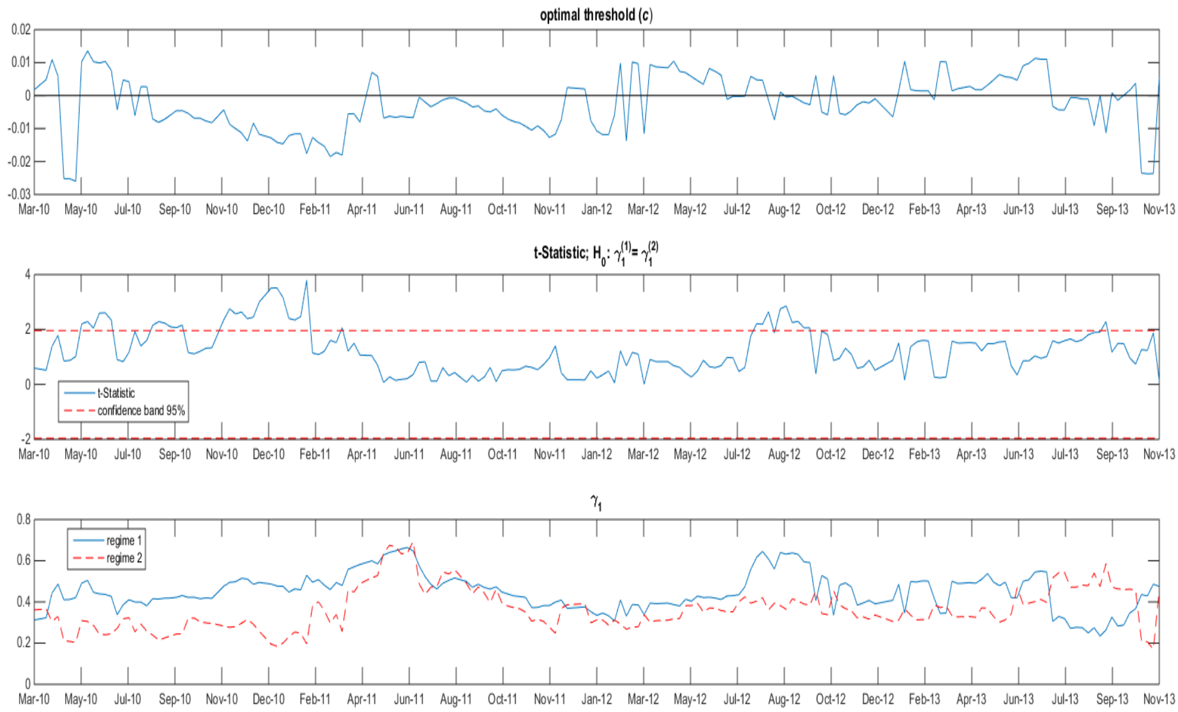
Graph 3.C: Time-varying TAR-ECM model (Rolling Windows analysis) for the gasoline market. Threshold parameter and long-run asymmetries: adjustment speed



Graph 4.A: Time-varying TAR-ECM model (Rolling Windows analysis) for the diesel market. Threshold parameter and short-run asymmetries: instantaneous effect



Graph 4.B: Time-varying TAR-ECM model (Rolling Windows analysis) for the diesel market. Threshold parameter and short-run asymmetries: delayed effect



Graph 4.C: Time-varying TAR-ECM model (Rolling Windows analysis) for the diesel market. Threshold parameter and long-run asymmetries: adjustment speed

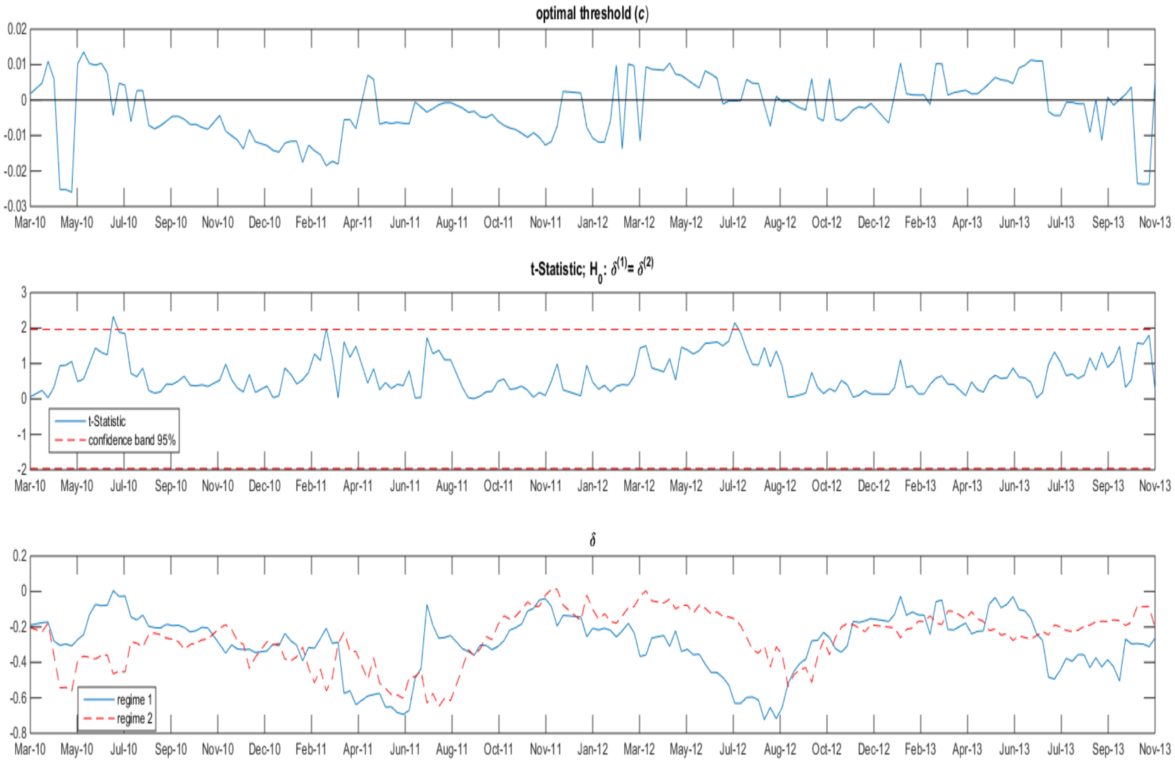


Table 6: Gasoline-crude Oil Markov-switching models

	Parameters	M.1	M.2	M.3	M.4	M.5
Non regime-switching	β	0.0006 (0.0010)	0.0006 (0.0010)	-0.0000 (0.0009)	0.0006 (0.0010)	0.0007 (0.0007)
Regime 1	$\gamma_0^{(1)}$	**0.2159 (0.0323)**	**0.2113 (0.0351)**	**0.3297 (0.0256)**	**0.2173 (0.0311)**	**0.2788 (0.0333)**
	$\gamma_1^{(1)}$	**0.3730 (0.0302)**	**0.3635 (0.0325)**	**0.2657 (0.0275)**	**0.3736 (0.0298)**	**0.3330 (0.0337)**
	$\delta^{(1)}$	**-0.1340 (0.0258)**	**-0.1321 (0.0258)**	**-0.1397 (0.0373)**	**-0.1250 (0.0275)**	**-0.1478 (0.0308)**
	$\sigma^2_{(1)}$	**0.0140 (0.0007)**	**0.0138 (0.0009)**	**0.0175 (0.0013)**	**0.0140 (0.0007)**	**0.0162 (0.0009)**
	p_{11}	**0.9606 (0.0301)**	**0.9563 (0.0377)**	**0.9272 (0.0600)**	**0.9645 (0.0256)**	**0.9386 (0.0473)**
	Expected regime duration (weeks)*	**26**	**23**	**14**	**29**	**16**
Regime 2	$\gamma_0^{(2)}$	**0.6878 (0.1073)**	**0.6747 (0.1309)**	$\gamma_0^{(1)}$	**0.6563 (0.2019)**	**0.2101 (0.0189)**
	$\gamma_1^{(2)}$	0.0625 (0.1135)	0.1346 (0.1790)	$\gamma_1^{(2)} = \gamma_1^{(1)}$	0.0342 (0.1099)	**0.3366 (0.0191)**
	$\delta^{(2)}$	$\delta^{(2)} = \delta^{(1)}$	$\delta^{(2)} = \delta^{(1)}$	**-0.1404 (0.0407)**	**-0.2211 (0.0987)**	**-0.0652 (0.0339)**
	$\sigma^2_{(2)}$	$\sigma^2_{(2)} = \sigma^2_{(1)}$	**0.0169 (0.0044)**	**0.0075 (0.0020)**	$\sigma^2_{(2)} = \sigma^2_{(1)}$	**0.0024 (0.0008)**
	p_{22}	**0.6727 (0.1693)**	**0.6859 (0.1886)**	**0.8059 (0.1504)**	**0.6968 (0.1545)**	**0.4677 (0.1971)**
	Expected regime duration (weeks)*	**4**	**4**	**6**	**4**	**2**
	AIC test BIC test	$-1.25*10^3$ $-1.22*10^3$	$-1.25*10^3$ $-1.22*10^3$	$-1.25*10^3$ $-1.23*10^3$	$-1.25*10^3$ $-1.22*10^3$	$-1.24*10^3$ $-1.22*10^3$

* Expected duration of the regime i: ceiling of $\left(1/\left(1-p_{ii}\right)\right)$, see Appendix.

Table 7: Diesel-crude Oil Markov-switching models

	Parameters	M.1	M.2	M.3	M.4	M.5
Non regime-switching	β	0.0004 (0.0007)	0.0004 (0.0007)	0.0007 (0.0007)	0.0005 (0.0007)	0.0005 (0.0007)
Regime 1	$\gamma_0^{(1)}$	**0.2354 (0.0261)**	**0.2266 (0.0288)**	**0.2862 (0.0231)**	**0.2353 (0.0260)**	**0.2273 (0.0268)**
	$\gamma_1^{(1)}$	**0.3745 (0.0229)**	**0.3762 (0.0238)**	**0.3465 (0.0206)**	**0.3776 (0.0230)**	**0.3791 (0.0235)**
	$\delta^{(1)}$	**-0.1306 (0.0249)**	**-0.1359 (0.0251)**	**-0.1367 (0.0352)**	**-0.1464 (0.0284)**	**-0.1532 (0.0285)**
	$\sigma^2_{(1)}$	**0.0102 (0.0005)**	**0.0098 (0.0008)**	**0.0127 (0.0012)**	**0.0101 (0.0005)**	**0.0097 (0.0007)**
	p_{11}	**0.9454 (0.0345)**	**0.9388 (0.0392)**	**0.9428 (0.0606)**	**0.9465 (0.0326)**	**0.9392 (0.0371)**
	Expected regime duration (weeks)*	**18**	**17**	**18**	**19**	**16**
Regime 2	$\gamma_0^{(2)}$	**0.6275 (0.0758)**	**0.5712 (0.1115)**	$\gamma_0^{(1)}$	**0.6010 (0.0746)**	**0.5543 (0.0908)**
	$\gamma_1^{(2)}$	**0.2190 (0.0699)**	**0.2490 (0.0731)**	$\gamma_1^{(2)} = \gamma_1^{(1)}$	**0.2187 (0.0685)**	**0.2418 (0.0678)**
	$\delta^{(2)}$	$\delta^{(2)} = \delta^{(1)}$	$\delta^{(2)} = \delta^{(1)}$	**-0.1108 (0.0541)**	-0.0381 (0.0777)	-0.0436 (0.0752)
	$\sigma^2_{(2)}$	$\sigma^2_{(2)} = \sigma^2_{(1)}$	**0.0120 (0.0020)**	**0.0065 (0.0017)**	$\sigma^2_{(2)} = \sigma^2_{(1)}$	**0.0117 (0.0017)**
	p_{22}	**0.6868 (0.1530)**	**0.7606 (0.1433)**	**0.8373 (0.0959)**	**0.7259 (0.1363)**	**0.7746 (0.1188)**
	Expected regime duration (weeks)*	**3**	**5**	**7**	**4**	**4**
	AIC test BIC test	$-1.39*10^3$ $-1.37*10^3$	$-1.39*10^3$ $-1.37*10^3$	$-1.38*10^3$ $-1.36*10^3$	$-1.39*10^3$ $-1.36*10^3$	$-1.39*10^3$ $-1.36*10^3$

* Expected duration of the regime i: ceiling of $\left(1/\left(1-p_{ii}\right)\right)$, see Appendix.

Table 8:Short-run Asymmetries and asymmetric Adjustment Speeds

	Switching-Markov	
	Gasoline	Diesel
Test	t-Statistic	t-Statistic
$H_0:\ \gamma_0^{(1)} = \gamma_0^{(2)}$ $H_1:\ \gamma_0^{(1)} \neq \gamma_0^{(2)}$	1.7728*	3.8007***
$H_0:\ \gamma_1^{(1)} = \gamma_1^{(2)}$ $H_1:\ \gamma_1^{(1)} \neq \gamma_1^{(2)}$	0.0914	1.9181*
$H_0:\ \delta^{(1)} = \delta^{(2)}$ $H_1:\ \delta^{(1)} \neq \delta^{(2)}$	1.8228*	5.3754***
	F-Statistic	F-statistic
$H_0:\ \sigma^{(1)} = \sigma^{(2)}$ $H_1:\ \sigma^{(1)} \neq \sigma^{(2)}$	6.7392***	1.2021

A single (double, triple) asterisk denotes rejection of the null hypothesis with significance at 10% (5%, 1%) level

Appendix

In this appendix we briefly summarize the methodology for the estimation of *Markov regime-switching* regression models. A more detailed explanation can be found in Chapter 11 of Hamilton (1994).

Without loss of generality, let the estimated model be (model M.5 in the paper):

$$\nabla x_{jt} = \beta + \gamma_1^{(S_t)} \nabla p_t + \gamma_2^{(S_t)} \nabla p_{t-1} + \delta^{(S_t)} \hat{\varepsilon}_{t-1} + \zeta_t, \quad \zeta_t \underset{iid}{\sim} N\left(0, \sigma_{S_t}^2\right), \; S_t = \{1, 2\},$$

where S_t evolves according to a Markov chain independent from the past observations of ∇x_{jt} and from the present and past observations of ∇p_t and $\hat{\varepsilon}_{t-1}$:

$$\text{Prob}\left\{S_t = j \mid S_{t-1} = i, S_{t-2} = k, \ldots, \nabla p_t, \mathscr{Y}_{t-1}\right\} = \text{Prob}\left\{S_t = j \mid S_{t-1} = i\right\} = p_{ij},.$$

$$\text{where } \mathscr{Y}_{t-1} = \left\{\nabla x_{jt-1}, \nabla x_{jt-2}, \ldots, \nabla p_{t-1}, \nabla p_{t-2}, \ldots, \hat{\varepsilon}_{t-1}, \hat{\varepsilon}_{t-2}, \ldots\right\},$$

Because there are only two possible states of nature, the transition matrix can be defined as:

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}.$$

Let η_t be a 2×1 vector which includes the conditional density functions of ∇x_{jt} for each one of the two different states or regimes:

$$\eta_t = \begin{bmatrix} \dfrac{1}{\sigma_1 \sqrt{2\pi}} \exp\left\{ \dfrac{-(\nabla x_{jt} - \beta - \gamma_1^{(1)} \nabla p_t - \gamma_2^{(1)} \nabla p_{t-1} - \delta^{(1)} \hat{\varepsilon}_{t-1})^2}{2\sigma_1^2} \right\} \\ \\ \dfrac{1}{\sigma_2 \sqrt{2\pi}} \exp\left\{ \dfrac{-(\nabla x_{jt} - \beta - \gamma_1^{(2)} \nabla p_t - \gamma_2^{(2)} \nabla p_{t-1} - \delta^{(2)} \hat{\varepsilon}_{t-1})^2}{2\sigma_2^2} \right\} \end{bmatrix}.$$

We also assume that these conditional densities only depend on the current regime S_t and do not depend on past regimes:

$$f(\nabla x_t \mid \nabla p_t, \mathscr{Y}_{t-1}, S_t = j; \omega) = f(\nabla x_t \mid \nabla p_t, \mathscr{Y}_{t-1}, S_t = j, S_{t-1} = i, S_{t-2} = k, \ldots; \omega)$$

$$\text{for } j, i, k = 1, 2, \text{ where } \omega = \left\{\beta, \gamma_1^{(1)}, \gamma_1^{(2)}, \gamma_2^{(1)}, \gamma_2^{(2)}, \delta^{(1)}, \delta^{(1)}, \sigma_1^2, \sigma_2^2\right\}.$$

Let θ be a vector of parameters including ω as well as the probabilities p_{ij}. Our purpose is then to estimate θ based on the past observations in $\mathscr{Y}_T$.

Given the observed data and knowledge on the population parameter θ, let us assume that $\text{Prob}\left\{S_t = j \mid \mathscr{Y}_t; \theta\right\}$ represents the probability that the unobserved regime for observation t was regime j.

These probabilities are collected in vector $\hat{\xi}_{t|t}$:

$$\hat{\xi}_{t|t} = \begin{bmatrix} \text{Prob}\left\{S_t = 1 \mid \mathcal{Y}_t;\theta\right\} \\ \\ \text{Prob}\left\{S_t = 2 \mid \mathcal{Y}_t;\theta\right\} \end{bmatrix}.$$

The probability that the analyst assigns to the possibility that observation t+1 was generated by regime j, given that the data obtained through date t is:

$$\hat{\xi}_{t+1|t} = \begin{bmatrix} \text{Prob}\left\{S_{t+1} = 1 \mid \mathcal{Y}_t;\theta\right\} \\ \\ \text{Prob}\left\{S_{t+1} = 2 \mid \mathcal{Y}_t;\theta\right\} \end{bmatrix}.$$

The optimal inference and forecast for each date t can be obtained by iterating on these two equations:

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t|t-1} \odot \eta_t}{\mathbf{1}_2'\left(\hat{\xi}_{t|t-1} \odot \eta_t\right)} \qquad \text{(A.1)}$$

$$\hat{\xi}_{t+1|t} = P\hat{\xi}_{t|t} \qquad \text{(A.2)}$$

where $\mathbf{1}_2'$=(1, 1), and the symbol $\odot$ denotes element by element multiplication.

Given a starting value $\hat{\xi}_{1|0}$ and an assumed value for the population parameter vector θ, one can iterate on (A.1) and (A.2) for$t$=1, 2,…,T. The log-likelihood function $\mathcal{L}(\theta)$ for the observed data $\mathcal{Y}_T$, evaluated at the value of θ that was used to perform the iterations, is:

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \log\left[f\left(\nabla x_t \mid \nabla p_t, \mathcal{Y}_{t-1};\theta\right)\right],$$

$$\text{where } f\left(\nabla x_t \mid \nabla p_t, \mathcal{Y}_{t-1};\theta\right) = \mathbf{1}_2'\left(\hat{\xi}_{t|t-1} \odot \eta_t\right).$$

Once the value of the log likelihood implied by the value of θ has been obtained, the value of θ that maximizes the log likelihood can be found numerically.

On the other hand, the estimated probabilities p_{11} y p_{22} contain information about the expected duration of one state or regime. In this case the question is: given that the current regime is j, how much will it last? To find the answer, let us define Das the duration of state 1:

$$D = 1, \text{ if } S_t = 1 \text{ and } S_{t+1} = 2; \text{ then, Prob}(D = 1) = p_{12} = 1 - p_{11}.$$
$$D = 2, \text{ if } S_t = S_{t+1} = 1 \text{ and } S_{t+2} = 2; \text{ then, Prob}(D = 2) = p_{11}p_{12} = p_{11}(1 - p_{11}).$$
$$D = 3, \text{ if } S_t = S_{t+1} = S_{t+2} = 1 \text{ and } S_{t+3} = 2; \text{ then, Prob}(D = 3) = p_{11}^2 p_{12} = p_{11}^2(1 - p_{11}).$$
$$\ldots$$

Then, the expected value of the duration can be estimated as:

$$E(D) = \sum_{i=1}^{\infty} i \cdot \text{Prob}(D = i) = \sum_{i=1}^{\infty} i \cdot p_{11}^{i-1}(1 - p_{11}) = \frac{1 - p_{11}}{p_{11}} \sum_{i=1}^{\infty} i \cdot p_{11}^{i} = \frac{1}{1 - p_{11}}.$$

Analogously, the expected duration for regime 2 is $\dfrac{1}{1 - p_{22}}$.