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Modeling Energy Prices with a Markov-Switching dynamic regression model: 2005-2015

Georgios Galyfianakis[1], Evagelos Drimbetas[2] and Nikolaos Sariannidis[3]

Abstract

In this paper we employ a Markov-switching dynamic regression (MS-DR) model for a period before and after the financial crisis of 2008. Using data from 2005 to 2015, we examine the behavior of five energy prices series (Crude oil WTI, Heating oil, Unleaded gasoline, Diesel and Jet kerosine). The results reveal and confirm the existence of 2 distinct regimes. The first corresponds to a tranquil (calm) regime and the other to a crisis (turbulence) regime. Furthermore, we find robust evidence for the existence of several "recessions" in energy market prices. Given the relevance of the energy prices for the real economy, but also for monetary policy and stock markets, our findings are helpful to financial managers and energy analysts. We prove the undeniable need for more energy policy and regulation in order to help investors and market participants.

JEL classification numbers: G1; C1; Q4
Keywords: Energy Market, Crude Oil, Petroleum products, Markov-Switching Dynamic Regression, Regimes.

1 Introduction

The recent financial crisis of 2008 - considered to be the most serious crisis since the Great Depression – has struck energy markets and global economy and cause a significant decline in economic activity, affecting as well energy market prices. Essentially, energy markets are tightly interconnected with global economic recession.

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[1] Technological Education Institute of Crete, Department of Accounting and Finance, Greece.
Democritus University of Thrace, Department of Economics, Greece.
Email: galifianakis@staff.teicrete.gr
[2] Department of Economics, Democritus University of Thrace, Greece.
[3]Department of Accounting and Finance Technological Education Institute of Western Macedonia, Greece.

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During the last decade, a lot of changes have taken place in the world wide energy market. Globalization of the economy, as well as erratic trend of the energy prices are factors affecting the prices of energy products and lead market participants to be more aware of world financial crisis. Investors reduce risk exposure by using risk management models as geo-political events have likely led to greater economic uncertainty. Additionally, the prices of energy products are classically driven by the balance between supply and demand. Also, other factors such as economic policy, market structure and institutional policies may affect energy prices especially after the 2008 financial crisis. Further, unexpected fluctuations in energy demand, regional conflicts, political and other (weather) conditions may have a significant impact on the behavior of prices but also the modeling of energy markets. Energy commodity markets are unique, complicated, dynamic and global. Nevertheless, they are considered to operate independently, although, events in one may influence trends in another. Nonrenewable energy sources - Petroleum, Natural Gas, Coal, Nuclear power- continue to dominate the global energy consumption representing about 90% of the U.S. energy consumption in 2014. The rest 10% represents renewable energy sources - biomass, hydroelectric, wind, solar, geothermal[4]. There has been a recent revival of interest in energy markets, stirred by high oil prices in the period up to July 2008. At the same time, the global economic crisis that arises reaches a critical point in September 2008. High energy prices, in that period, followed by the growing demand for fossil fuels in developing and emerging economies which require an uninterrupted supply of energy and uninterrupted energy trade which is synonymous to energy security. In the global energy market, petroleum products represent 35% of current global energy consumption of nonrenewable energy sources. Although petroleum products suffer a long run decline in energy market share - while natural gas steadily gains - it is expected to dominates the energy market for the next decades because of the rapidly-growing -non OECD- developing economies. Our concern in this paper can be identified as follows; investigating the behavior of petroleum products during the period 2005 – 2015, confirming the existing literature and underlying changes in economy during those periods which are closely associated with specific geopolitical events and economic recessions.

The necessity of doing this arises from three main practical observations. Firstly, despite the stagnant global economy, developing countries and emerging economies – especially in Asia – push to a growth of global energy consumption in order to generate better living standards and fueling the growing prosperity of their population. In order to do that, emerging countries consume energy commodities that our analysis centers on. Secondly, the tightening of the energy markets and financial crises and the contagion effects arising from economic shocks, leading us, in this paper, to examine energy market, in terms of crude oil, and it's refined products, during the specific period under investigation. Third, because of the energy market conditions are not stable over time market participants give more attention to the behavior of energy prices in order to manipulate better their portfolios according to the regime shifts behavior of energy commodities and the state that occurs over the time.

The main geopolitical discrete events for the period under investigation (2005 – 2015) that we could mention are related with the economic crisis of 2008 which had a great impact in the crashing of energy prices and specifically in oil prices at the second half of

[4] U.S. Energy Information Administration, Monthly Energy Review, March 2015.

that year[5]. Strong turbulence in the prices of energy commodities after the year 2008, confirming as well the observation that after the historic peak of 145$ per barrel, in July of 2008, and the sudden drop at the end of 2008, of $40 per barrel, oil prices became more erratic and unpredicted. Crude oil prices gained traction at the beginning of 2014, reaching $107 per barrel, founding support as crude oil inventories shrank at Cushing, Oklahoma, and Chinese demand was robust due to the stockpiled crude oil for its strategic petroleum reserves (Yang et al., 2010). Crude oil prices began to decline at the second half of the year 2014, because of the raising supply concerns of political instability in Iraq, and the economic concerns arose after the World's Bank cuts in GDP forecast. Additionally, the appreciation of dollar index and the failure of OPEC to cut crude production contributed to a -46% fall in prices of crude at $52 per barrel (*see Figure 1*). In summary, during the period 2005 – 2015 major recessions are associated with specific energy market events[6]. Related to this, earlier studies advocate that crude oil and oil refining products affect the cost in everyday life as well as the global economy (Chen and Ji, 2005). Consequently, it is of great interest to examine the behavior of energy commodity prices, focusing on petroleum commodities as most papers consider and investigate only the crude oil market. We fill this gap by using recent data from five energy commodities. To be more specific, following energy price's spikes and crashes over the last decade we investigate whether the energy market of crude oil, heating oil, unleaded gasoline, diesel and jet kerosene has been driven by states of the economy (the "regimes").

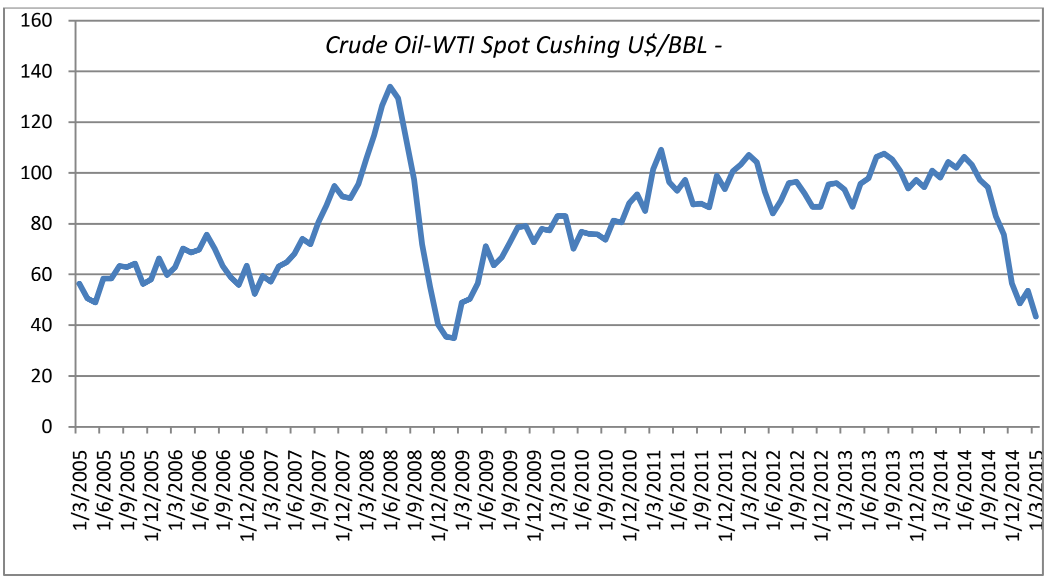

Figure 1: WTI Crude Oil Price, in dollars, from January 1986 to April 2015. (Source: DataStream).

[5] Global economic activity is a key determinant of oil prices. Researchers have concluded that global economic activity is a driver of crude oil prices (see, Wang et al., 2009).

[6] Oil price shocks could affect global economy due to the uncertainty that they create. The respond to an oil price shock could be positive or negative, regarding which side the shock originates (demand-side or supply side. (Filis et al., 2011).

The purpose of this paper is to extend the existing literature (e.g., Hammoudeh and Choi, 2010; Regnier 2006) by examining shifts in returns between two regimes on petroleum commodities and their interrelations using Markov regime-switching (MRS) models. In order to do so, we focus on the MRS which is popular in the energy economics literature (e.g**.**, Janczura and Weron, 2010; Filis et al. 2015). MRS allows for spikes and temporary dependence within regimes; they may admit temporal changes of model dynamics. It is important to employ a MRS that captures temporary dependence within the regimes as this is a characteristic of most energy prices. In contrast with previous studies, we estimate a basic MS model which is more robust for our case[7]. The Markov regime-switching model can detect switches between different states of the returns, measuring on the one hand lengths of duration in each state and the correlations of movements between energy commodity markets in the other. The main objective of this paper is, firstly, to measure the switch in returns between two regimes for the five energy commodities, and, secondly, to measure the duration of each regime for all the commodities under examination.

Using data from oil and petroleum products, we consider a period of calm and a period of turbulences (i.e. we consider two states or regimes), and we find that regime shifts are clearly present. We report robust evidence for the existence of several recessions in energy prices during the last decade. Our findings are helpful to financial managers and energy analysts. We prove the need for more energy policy and regulation to help investors and market participants. This paper is structured as follows: The second section presents an overview of the existing theory and relevant literature. In the third section methodology is displayed. The following -fourth- section describes analytically the data used. Section five exposes the econometric methodology and presents the empirical findings. Finally, the last section poses the main conclusions deduced by this paper.

2 Literature Review

The important role of energy commodity market in the global economy has attracted a great deal of attention among researchers (Regnier, 2006; Sadorsky, 2006). Increasing integration and high volatility of energy commodity markets are both associated with financial crises and uncertainty in the global economy (Sariannidis et al., 2015). Thus, energy commodity market's impact on the international economy is enormous, and may affect most sectors of the economies.

In the last years, many empirical studies were focused on the shifts behavior in energy prices. Oil market has experienced some periods in which prices changed dramatically (Galyfianakis et al., 2015). All these events and changes motivate the use of regime switching models. Aloui and Jammazi (2009) argue that energy prices in general, and oil prices in particular, are likely to have a major role of explaining equity market behavior and the probability of transition across regimes. Further, the energy markets are prone to

[7] Various other RSMs have emerged as a means of identified changing states within economic time series data i.e., a two regime Markov-Switching EGARCH model, introduced by Henry in 2009 (Aloui and Jammazi, 2009).

large price fluctuations and uncertainty (Nomikos et al., 2008). Most research studies mainly focus on the return prices, the forecasting performance of energy prices, or they examine the linkages between these prices and the macroeconomy (e.g. Kilian, 2007). There is substantial empirical evidence to show that shocks in energy market, and specifically in crude oil market, have significant effects on a variety of economic activities. A number of research studies have examined the impact of oil price changes across the world economy or across different market**s (**Kilian 2009). Additionally, Treepongkaruna et al., (2010), using a general Markov switching model examines the relationship between returns of energy market commodities, precious metals, financial and real estate assets, and confirm the existence of two distinct regimes, a "tranquil" and a "crisis" regime.

Furthermore, petroleum products and crude oil itself attract the attentions of many researchers. There is a large volume of literature trying to understand the nature of energy price shocks and their effects on the economy. Large fluctuations in the real oil prices put stress to global economy and seem to affect negatively the economies of oil importing countries in particular. Malik and Ewing (2013) argue that oil prices directly impacts both consumer behavior and financial markets and thus affects the performance of the overall economy. Hammoudeh and Choi (2010) use weekly data for the closing spot prices of WTI oil, Brent oil, gold, silver, cooper and the US S&P 500 index, for the period of 1990 to 2006, and examine shifts in volatility between the two unobserved regimes of the above mentioned data using the Markov regime-switching model. They conclude that there exist high and low volatility regimes for the five commodity prices and S&P index. For WTI crude oil, they report the strongest sensitivity to relative changes from low to high growth regimes. Similarly, Chiou and Lee (2011), using the Markov regime-switching model to examine oil prices from 1992 to 2008, conclude that when there is severe fluctuations in oil prices, unexpected asymmetric changes in oil prices will have a negative impact on the US S&P 500 index. In the same line, Aloui and Jammazi (2009) develop a two regime Markov - switching model to examine the relationship between crude oil shocks and stock markets of UK, France and Japan over a period of January 1989 to December 2007 using data in monthly frequency . Their findings show that rises in crude oil prices has an important role in determining both, stock returns and the probability of transition across regimes.

Fong and See (2002) using a generalized Regime switching model examines the returns on crude oil showing that regime shifts are clearly present in the data. Thus, they allow the conditional volatility to switch between a finite number of regimes and they assume that the timing of regime switch is usually governed by a first order Markov process which determines the probability that volatility will switch to another regime. The conclude that RS models provide the financial historian a very useful frame work in understanding factors affecting energy prices. Hamilton and Susmel (1994) examine weekly stock returns employing a Markov-Switching Model to account for regime changes. They found that high-volatility regime is to some degree associated with economic recessions.

Other findings indicate the role of developing countries in energy market. Chen and Ji (2005) underline the role of expanding demand of mobility in emerging countries claiming that, highways transport is associated with the large crude oil and refined products consumption. However, some other previous analysis focuses on energy commodities and finds evidence of interaction between crude oil and refined products. In related work, Kaufman and Laskowski (2005) conclude that prices of motor gasoline and heating oil rise faster in response to an increase in the price of crude oil.

Recent oil crises forced the oil price risk managers to give more attention to the behavior of energy prices. Global economic and political activity has proven to play a crucial role in the stability of oil prices, driving the market to relatively high levels of volatility (Nomikos et al., 2008). Given the unstable times, investors, traders, portfolio managers are interested in understanding the above mentioned behavior of energy market and particular oil market and petroleum products, as the most widely traded commodities.

It is clear from the existing literature that oil demand shocks caused by global economic activity (e.g. Kilian, 2009; Kilian and Murphy, 2010; Filis et al. (2013). Further, energy price changes lead to speculative bubbles due to financial shocks; this refers to destabilizing which allows speculators to bet on further rising of prices. Further, energy products, and in particular oil, are important input factors of many financial products (Kilian, 2007). In other words, increasing energy prices may lead to monetary policy adjustment or financial losses and bubbles.

To sum up, previous studies on regime-switching models for energy markets find that energy prices have experience some periods in which they change dramatically. All these events and changes motivate the use of regime switching models. The use of a simple MS-DR model indicates that two distinct regimes exist for each of energy assets examined in the existing literature; i.e. a tranquil regime and a crisis regime. These findings have important implications for diversification and asset allocation.

In this paper, using an MS-DR model, we examine the behavior of our data in a two Markov regime model. This model is flexible enough to capture the potential of regime shifts and lead to better forecasting devices than time invariant linear models and traditional robustifying methods. In particular, with a two-state MRS model, we allow for switches between two different processes and states. In this study, we examine the performance of energy prices generated from MRS model.

3 Methodology

Energy prices, and specifically oil prices, have experienced some periods in which their behavior seem to change dramatically. All these periods motivate the use of regime switching models. A number of specifications have been suggested in the literature. Depending on the regimes, a model class has to be selected. Furthermore, regime-switching approaches for energy prices are often employed in the literature due to their jumps (spike regime) and base regime. For instance, a two Markov-regimes is employed in order to distinguish between stable and explosive phases; in other words, regimes of "risky" and "stable" energy market as given by Huang et al. (2011).

The Markov-Switching (MS) autoregressive models were largely used to capture the regime shifts behavior. Starting with the work of Hamilton (1989, 1990), the MS autoregressive time series models describe specific features of the business cycle. Other researchers used this econometric framework in order to model other economic variables like exchange rates, interest rates and stock returns[8].

The MS model can detect switches in returns, measure lengths of duration in each state and help measure the correlations of movements between parameters in each state.

In this basic specification, the Markov Switching model assumes that deviations of output growth from its mean follow a *p*-th order autoregressive process:

The objective of a regime-switching model is to allow for different behavior in different states of nature, while simultaneously estimating when there is transition from one state to another.

A simple regime switching model would be:

Regime 0: $y_t = \mu_0 + \rho y_{t-1} + \varepsilon_t$, ε_t ~N [0, σ^2],

Regime 1: $y_t = \mu_1 + \rho y_{t-1} + \varepsilon_t$, ε_t ~N [0, σ^2]

The numbering of the regime is arbitrary. If we write s_t for the variable denoting the regime, then the mean can be written as a function of s_t :

μ(s_t)= μ_0 , if s_t =0

μ(s_t)= μ_1 , if s_t =1

In a Markov-switching model, the unobserved random variable s_t follows a Markov chain, defined by transition probabilities between the N states:

$$pi/j = P[s_{t+1} = i/s_t = j], i, j = 0,..N-1,$$

So the probability of moving from stage j in one period to stage i in the next, only depends on the previous state. Because the system has to be in one of the N states we have that:

$$\sum_{i=0}^{N-1} pi/j = 1,$$

the full matrix of transition probabilities P is:

$$P = (pi/j),$$

with conditional probabilities in columns summing to one. Suppose that s=2, then

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[8] For other relevant studies see Chiou and Lee (2010);Treepongkaruna et al. (2010)

$$P = \left(\begin{array}{c|cc} & s_t = 0 & s_t = 1 \\ \hline s_{t+1} = 0 & p_{0|0} & p_{0|1} \\ s_{t+1} = 1 & p_{1|0} & p_{1|1} \\ \hline \Sigma & 1 & 1 \end{array} \right)$$

In this paper, we employ the MS method that reduces many empirical problems and is straightforward. We also distinguish between two types of Markov-switching models: the Markov-switching dynamic regression models (MS or MS-DR) and Markov-switching autoregression models (MS-AR or MS- ARMA).

The MS-DR specification follows the dynamic regression model in the specification of the dynamics.

$y_t = \nu(s_t) + \alpha y_{t-1} + x'\beta + \varepsilon_t$, ε_t ~N $[0, \sigma^2]$

The related MS -AR model is written as follows:

$y_t - \mu(s_t) - x_t'\gamma = \rho(y_{t-1} - \mu(s_{t-1}) - x_t''\gamma) + \varepsilon_t$, ε_t ~N $[0, \sigma^2]$

Without regime switching both specifications are identical; one can be written as the other. This is not the case for Markov-switching models. The MS-AR model requires a state vector of dimension $N = S^{(1+P)}$ to obtain the Markov representation for likelihood evaluation of S regimes and autoregressive order p.

4 Data

We use monthly spot prices from major energy markets; crude oil WTI, heating oil, unleaded gasoline, diesel and jet kerosene. The sample totals 121 monthly observations and covers the period March 17, 2005 to March 18, 2015. We further examine the closing spot prices of five strategic commodities, i.e. West Texas Intermediate (WTI) crude oil - traded on the US spot market at Cushing Oklahoma center, heating oil, unleaded gasoline, diesel oil and jet kerosene. The WTI prices are expressed in US dollars per barrel (U$/BBL), the heating oil and jet kerosene are expressed in US dollars per gallon (U$/GAL), and finally diesel and gasoline are expressed in US cents per gallon (UC/GAL).

All the data have been extracted from DataStream Database. Spot prices were chosen since trade in spot prices results in physical delivery, and hence, limit speculative aspects that are present in the corresponding future prices. The prices are extremely spiky due to the nature of energy markets with strong fluctuations (volatile markets); hence, we analyze the logarithms of prices. A visual representation of the variables can be seen in the following Figure 2.

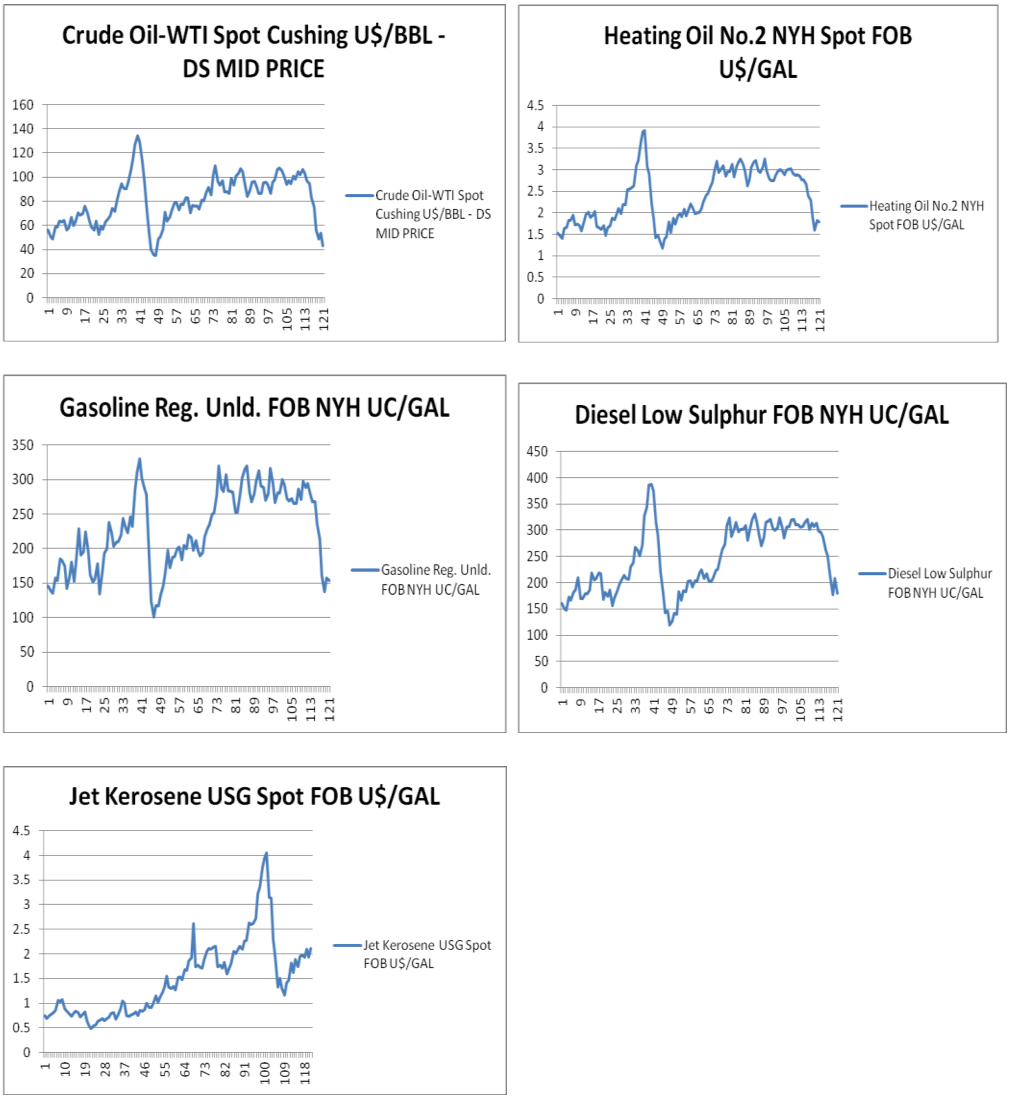

Figure2: Growth rates plots for the variables under investigation. The sample period runs from March, 2005 to March, 2015. (Source: DataStream).

Descriptive statistics are shown in Table 1. They aid our understanding of the nature and distributional characteristics for our data. They all follow the stylized facts of financial econometrics.

Table1: Descriptive Statistics. The sample period runs from March 2005 to March 2015.

Statistics	loil	lhoil	lgasln	ldsl	lker
Observations	121	121	121	121	121
Mean	4,357864	0,825057	5,389960	5,464488	0.267016
Median	4,416428	0,811375	5,411780	5,436556	0,288407
Maximum	4,897765	1,365556	5,797849	5,957546	1,398816
Minimum	3,554205	0,163054	4,610556	4,782479	-0,743809
Std. Dev.	0,270382	0,275346	0,273729	0,2735333	0,506349
Skewness	-0,624183	-0,199193	-0,563464	-0,298208	0,118720
Kurtosis	3,042547	1,911581	2.446160	2,047219	2,034079
Jarque-Bera	7,866147	6,772805	7.949213	6,370163	4,988126
ADF Test	-8,700424*	-5,446526*	-9,639926*	-5,823563*	-11,36871*

Notes:* denotes that we reject the null hypothesis that first difference of Log prices has a unit root.

Jarque Bera (JB) for normality is rejected. We were unable to reject the hypothesis that the level of each series was non stationary. In other words, over the sample period all the data series evidence significant skewness and kurtosis implying the existence of market movements with great frequency.

Moreover, consistent with earlier research, our analysis show that the price series were non stationary in levels (i.e., we were unable to reject the hypothesis that the level of each series contained a unit root). Thus, the use of augmented Dickey - Fuller (ADF) test, allowing for intercept and a time trend, shows that the sample series had been produced by stationary series at first difference.

The above time series data, covering a period before and after the 2008 financial crisis, appear that rather than being a simple random walk, the time series consists of distinct time periods of both upwards and downwards trends.

5 Empirical Findings

In this section, we report the empirical results obtained from the regressions. We first extract the states of energy market by using a regime switching model. A two-state regime switching model is estimated for all the variables under investigation. The following Table 2 exhibits the estimated coefficients of the regime switching models.

Several observations merit attention. Variables μ_0 and μ_1 are constant probabilities in regime 0 (low- calm) or regime1 (high - risky), respectively. The regimes are quite persistent as the probability to stay in the low (high) risk environment is equal to 19.81% (1.53%) for the crude oil (WTI), 17.93% (1.42%) for heating oil, 29.83% (1.35%) for gasoline, 18.49% (2,21%) for diesel and 23.05% (3.89%) for jet kerosene. In other words the probability to stay in regime 0 is higher than the probability of staying in regime 1, suggesting that regime 0 is more persistent than regime 1. These results indicates that regime 0 (low or calm regime) is more stable and markets spend more time in this regime than in regime 1 (high or risky regime) for all commodities, which is more comfortable for risk averse investors. We rich a similar conclusion for all petroleum products series with calm state (regime 0) proved to be more persistence than crisis state (regime 1).

Furthermore, parameter σ represents volatility. Among the five commodity prices, gasoline has the highest variance of returns followed by jet kerosene (σ parameter is significant in all cases).

Transition probabilities are reported and analyzed as well in the following paragraph, demonstrating that there is a strong tendency for all variables to switch from one state to another. We also obtain the average expected durations for all series as given in table 2. Duration for the regime 0 is defined by 1/(1-p) and for the regime 1 by 1/(1-q). Thus, the average length to stay in regime 0 (regime1) is 3.6 (1.02) months for crude oil WTI, 2.78 (1.02) months for heating oil, 2.78 (1.02) for gasoline, 1.67 (1.07) for diesel and 1.65 (1.07) for jet kerosene. According to the empirical results, all the series stay longer in regime 0 than in regime 1.

Table 2: Estimation of Markov-switching model

Parameter	Oil (WTI)	Heating Oil	Gasoline	Diesel	Kerosene
μ_0	0.198119	-0.179318	-0.298330	-0.184988	-0.230540
	(5.12)*	(-4.89)*	(-4.61)*	(-7.67)*	(-5.88)*
μ_1	0.0153493	0.0142594	0.0135700	0.0221031	0.0389759
	(1.74)*	(1.85)*	(1.34)*	(3.18)*	(3.72)*
σ	0.0851003	0.0739563	0.0958346	0.0659156	0.0885139
	(13.7)*	(13.2)*	(12.6)*	(12.8)*	(11.9)*
$Ps=0$	0.727792	0.641152	0.407325	0.402046	0.394416
	(3.90)*	(2.98)*	(1.64)*	(2.32)*	(1.87)*
$Ps=1$	0.0269841	0.0257417	0.0255807	0.0694452	0.0727321
	(1.42)*	(1.23)*	(1.21)*	(2.29)*	(1.99)*
$D_t=0$	3.673661	2.786695	1.687265	1.672369	1.651299
$D_t=1$	1.027732	1.026422	1.026252	1.074628	1.078437

Notes: The sample period ranges from March 2005 to March 2015. t-values are reported in the parenthesis. *indicates statistical significance at the 10% level.

Further, we specify the mechanism that describes how to move from one regime to another. This is achievable with the *Markov transition matrix* which contains probabilities of jumping from one regime to another (Huisman and Mahieu, 2003).

The probability of moving from state j in one period (regime 1) to state i in the next period (regime 0) only depends on the previous state. We thus obtain, as presented in the following Table 3, the matrix of transition probabilities, with conditional probabilities in columns summing to one for all the parameters under investigation.

Table 3: Transition probabilities

	Oil WTI		**Heating Oil**		**Gasoline**		**Diesel**		**Jet Kerosine**	
	Reg. 0,t	Reg. 1,t	Reg. 0,t	Reg. 1,t	Reg. 0,t	Reg.1,t	Reg. 0,t	Reg.1,t	Reg. 0,t	Reg.1,t
Reg.0	0.72779	**0.02698**	0.64115	**0.02574**	0.40732	**0.02558**	0.40205	**0.06945**	0.39442	**0.07273**
Reg.1	**0.27221**	0.97302	**0.35885**	0.97426	**0.59268**	0.97442	**0.59795**	0.93055	**0.60558**	0.92727

Notes: The system has to be in one of N states and we have that $\sum_{i=0}^{N-1} p_{i/j} = 1$

The results show that for crude oil WTI, there is a 2.5% probability to move from regime 1 to regime 0 but is much easier to get out of regime 0 with a probability of 27% each month. Similarly, the results obtained for heating oil and gasoline exhibit a 2.5% probability to move from regime 0 to regime 1, while there is a and 27% and 35% probability respectively, to get out from regime 0. Analogically, gasoline, diesel and jet kerosine provide us with similar results with the other commodities by moving from one regime to another but much higher probability (60%) of getting out of regime 0.

To further assist with the economic interpretation of the different regimes, the Smoothed Regime Probabilities depicted in *Figures 3-7* for all the parameters under investigation. The smooth probability enables the researcher to look back and to determine, when a particular regime has emerged, or, in other words, if and what specific time the regime switches occur. Our results indicate that our model corresponds to two regimes; a calm regime (regime 0) and a crisis regime (regime 1) for all of our energy commodities with the exception of gasoline which plots some more recessions (or crisis regimes). We note that for all our data series, episodes of the crisis regime (regime 1) occur in two distinct periods. The first begins at about the 40th month of our data and coincides the sub-prime mortgage crisis, at the second half of 2008, which caused a global economic crisis and a sharp decline in energy commodities prices. The second distinct period, beginning almost at the 120th month of our data, coincides the recent global economic slowing, beginning in the second half of 2014 because of the Middle East conflicts, and lasting till nowadays with the same negative results in petroleum commodities prices.

Lastly, in order to assess the quality of regime switching in our model, we report the Regime Classification Measure (RCM). RCM was proposed by Ang and Bekaert (2002) and it is a sample estimate of the variance of the probability series. It is defined as the probability of being in a certain regime at time *t*. The idea behind RCM was that perfect classification of regime would infer a value of 0 or 1 for the probability series and be a Bernoulli random variance. A value of 0 means perfect regime classification and a value of 100 means that we have no information about the regimes. The estimation results for the regime classification based on smooth probabilities are given in *Tables 4 and 5.*

According to our estimates in regime 0 (calm or tranquil) crude oil and heating oil present an average duration of almost 3.6 months, with gasoline diesel and Jet kerosine exhibit similar results with an average duration of 1.6 months in regime 0. Impressively, in regime 1 (crisis or turbulence regime) all commodities present significantly higher average duration, so regime 0 implies better information about regimes.

All findings support our hypothesis that Financial crisis of 2008 had a great impact in the crashing of energy prices and specifically in oil prices. Our results, for the period from 2005 to 2015, confirm the existence of two distinct regimes and indicate as well the existence of two distinct main recession episodes in regime 1, which are illustrated; i.e. the first, at the second half of 2008, and the other one, at the second half of 2014, reflecting to our discretion the great and global recession of 2008, and the recent global economic slowing beginning at 2014.

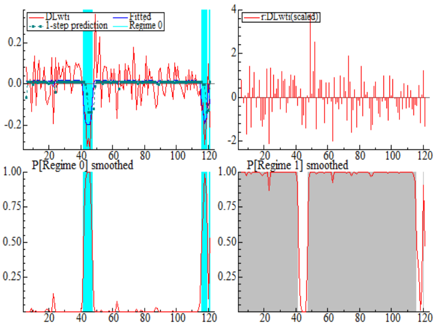

Figure3: Regime smoothed probabilities for oil WTI.

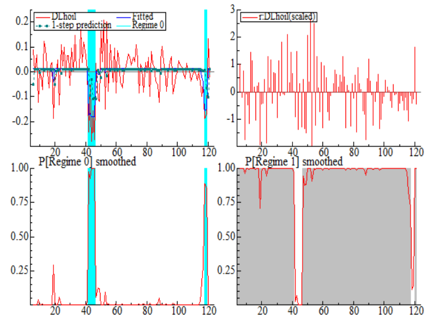

Figure4: Regime smoothed probabilities for heating oil.

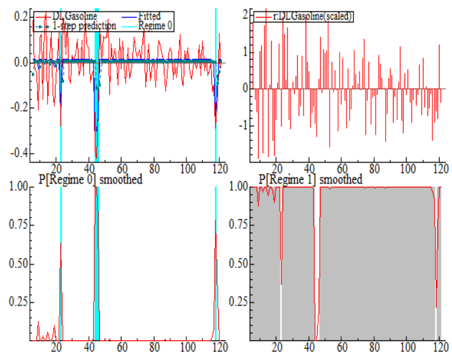

Figure5: Regime smoothed probabilities for gasoline

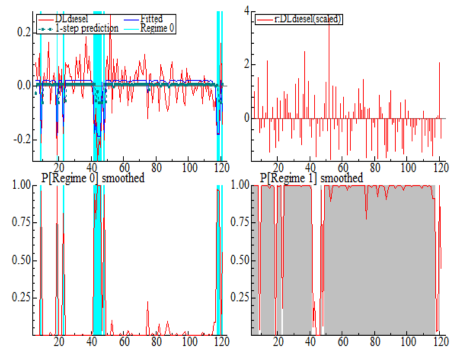

Figure 6: Regime smoothed probabilities for diesel

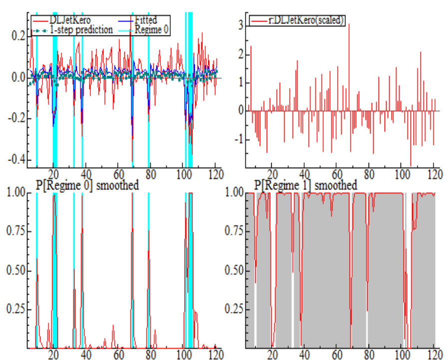

Figure 7: Regime smoothed probabilities for Jet kerosene

Table 4: Regime classification based on smoothed probabilities for regime 0

RCM	*Crude oil (WTI)*	*Heating oil*	*Gasoline*	*Diesel*	*Jet kerozine*
	3.66	3.50	1.66	1.71	1.50

Table 5: Regime classification based on smoothed probabilities for regime1

RCM	Crude oil (WTI)	Heating oil	Gasoline	Diesel	Jet kerozine
	35	30	27.75	14.85	11.12

Global economy face a new economic slowdown indicating that a new great recession may emerges. Furthermore, our findings verifies the existence of strong turbulence in the prices of energy commodities after the year 2008, confirming as well the observation that after the historic peak of 140$ per barrel, in July of 2008, and the sudden drop at the end of 2008, of $40 per barrel, oil prices became erratic, highly volatile and unpredicted.

6 Conclusions

Energy markets have been analysed by empirical economists for decades. Short- and long-run financial decisions are based on information provided by the behaviour of energy prices with oil being among the main drivers of global economies.

This paper's contribution to the energy prices literature is twofold. It, firstly, aims at explaining the behaviour of five energy prices series using a MRS model and, secondly, it supplies several practical implications for traders, portfolio managers and policymakers.

Interestingly, most of the previous studies on energy commodities concentrate only on crude oil and give scant attention on other refined petroleum products. In this study, we investigate five energy commodities during a period that the watershed of regimes occurs around the start of the subprime crisis in 2007-2008, after which the risky regime dominates the evolution of energy market. To the best of our knowledge, this is maybe the first empirical work which considers recent data from crude oil, heating oil, unleaded gasoline diesel and jet kerosene and discusses their behaviour before and after the 2007-2008 financial crisis covering a period from March 2005 to March 2015.

More importantly, our results confirm the existing literature of two regimes in energy market. We specificallyconfirm the existence of two regimes of high and low returns and indicate the existence of two main recessions which are illustrated; i.e. the first, at the second half of 2008, and the other one, at the second half of 2014, reflecting to our discretion, the great and global recession of 2008 and the recent global economic slowing beginning at 2014, indicating the existence of a new great recession. Our analysis indicates that two regimes exist for each of the commodities examined. We confirm the existence of a "tranquil" regime and a "crisis" regime, or in other words, periods of calm and turbulence. The first is characterized by lower return profile. By contrast, the crisis regime is characterized by higher return. The duration of regime 0 is found to be at least twice longer than that of a regime 1. Additionally, smoothed probabilities of all energy commodities display that downswings are abrupt and shorter compared to upswings which are more gradual and highly persistent. These are very important implications for investors and for portfolio diversification and price allocation even if regime switches cannot be perfectly predicted, especially during periods of turbulences. Investors in energy market must demand higher compensations when the markets switch from one regime to another. In practice, investors can use information obtained from energy market to trade or try to obtain extra information in other commodity markets. In other words, they could be enabled for the understanding of the impact of different levels of uncertainty in different regimes, on energy commodity markets.

Lastly, our findings have important implications for the energy market participants regarding the contagion effects that could arise during financial or geopolitical crisis. All findings support our hypothesis that Financial crisis of 2007-2008 had a great impact in the crashing of energy prices and specifically in oil prices, verifying the existence of strong turbulence in the prices of energy commodities after the year 2008 and confirming as well the observation that after the historic peak of 140$ per barrel, in July of 2008, and the sudden drop at the end of 2008, of $40 per barrel, oil prices became erratic, highly volatile and finally, unpredicted for the distant future.

The assumption that energy products are more erratic than prices for non-energy products has been used to explain macroeconomic decisions, formulating monetary policy, and impose microeconomic implications. Thus, the understanding of risks associated with oil and energy prices can allow better decisions and evaluate real investments using modern asset pricing techniques. Overall, the results indicate that, using a simple MRS model, financial analysts of energy markets may be able to obtain superior gains in terms of regime switching modeling (i.e. when it allows different states of the economy). An interesting direction for future research is to explore energy market using a Markov-regime switching GARCH approach.

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