FREQUENCY AND TIME FREQUENCY DOMAIN METHODS IN THE OIL MARKET ANALYSIS

MANUEL MONGE

DEPARTMENT OF ECONOMICS

SCHOOL OF ECONOMICS AND BUSINESS

UNIVERSITY OF NAVARRA

Ph.D., 2017

FREQUENCY AND TIME FREQUENCY DOMAIN METHODS IN THE OIL MARKET ANALYSIS

UNIVERSITY OF NAVARRA

SCHOOL OF ECONOMICS AND BUSINESS

DEPARTMENT OF ECONOMICS

A dissertation submitted by Manuel Monge for the degree of
Doctor of Philosophy

Supervised by:

Luis Alberiko Gil-Alaña
Fernando Pérez de Gracia

Dedicado a
María, mi mujer, por ser luz e inspiración.

Agradecimientos

Se dice que una tesis doctoral, al igual que una aventura, se empieza con inquietud y se termina con melancolía.

En el final de mi aventura como doctorando en la Universidad de Navarra, en primer lugar, quiero expresar en estas líneas mi más sincero agradecimiento a mi director de tesis y un muy buen amigo, el profesor Luis Alberiko Gil-Alaña por su apoyo incondicional, su confianza y sus buenos consejos antes y durante el programa de doctorado. Luis es una persona brillante, con alta capacidad de trabajo y con un profundo conocimiento en métodos estadísticos y econométricos, que han sido mi motivación día a día. Por ello quiero agradecer la oportunidad que me ha dado de poder trabajar junto a él durante todo este tiempo. Me ha enseñado a que todo planteamiento tiene una solución valida. Junto a él he reafirmado la creencia de que algo solo es imposible hasta que alguien lo duda y acaba probando lo contrario.

Al profesor Fernando Pérez de Gracia le quiero agradecer la confianza depositada en mí. Fernando fue quien me puso en el camino del análisis del mercado del petróleo. Me siento muy agradecido por enseñarme a expresar mis ideas de una forma concisa, a ser metodológico y fijarme en los pequeños detalles. Le estoy muy agradecido por sus buenos consejos y sugerencias.

Dar las gracias también al profesor Ignacio Rodríguez Carreño por contagiarme su entusiasmo por las wavelets.

Agradecer de una manera especial al profesor Jesús Fernández-Villaverde por darme la oportunidad de formarme e investigar junto a él durante un semestre lectivo en la University of Pennsylvania, donde pude alcanzar un gran nivel investigador.

También me gustaría dar las gracias de una manera muy especial a mi mujer, María, pilar fundamental para mí durante el recorrido de mi doctorado.

Es bien sabido que los pasos que uno recorre te llevan hasta donde estás hoy. No puedo terminar este apartado sin agradecer a mi familia, en especial a mis padres Zoila y Tomás, por todo lo que han hecho por mí.

Finalmente agradecer a la Asociación de Amigos de la Universidad de Navarra el soporte económico, por el cual esta tesis ha sido posible realizar.

Introduction

One of the most important commodities of the world is the crude oil, whether in terms of its price, its impact on the economy, its role in international relations and in the environment.

This dissertation attempts to better understand oil market behaviour using novel methodologies based on frequency and time-frequency domain.

To carry out this research I examine the statistical properties of the series from an univariate viewpoint, estimating and testing the order of integration of the time series. I have employed methodologies based on the concepts of long run dependence and long memory using fractional integration techniques. Fractional Integration is a technique that assumes that the number of differences required to render a series I(0) stationary may be a fractional value rather than an integer one. In this context, the fractional differencing parameter d becomes the crucial parameter to indicate the degree of dependence or persistence in the data.

Also I have employed wavelet analysis to perform the estimation of the spectral characteristics of a time series as a function of time, revealing how the different periodic components of the time series change over time. In this context, I use the continuous wavelet transform that maps the original time series, which is a function of just one variable (time) into a function of two variables (time and frequency); mainly wavelet coherence, that measures the degree of local correlation between two-time series in the time-frequency domain and the wavelet coherence phase differences.

In the thesis' first paper, *Crude Oil Price Behaviour Before and After Military Conflicts and Geopolitical Events*[1], We provide an analysis of the statistical properties of the real oil prices as well as its log-transformation, along with the absolute and squared returns values. Then I give a solution to the following question: Does the crude oil price behave in the same way before and after a military conflict or geopolitical problem in the producer countries? To answer this question I analyse the real oil prices of West Texas Intermediate (WTI) before and after the different military conflicts and political events that occurred after World War II using techniques based on unit roots

[1] Monge, M., Gil-Alana, L.A., Perez de Gracia, F. 2017. Crude Oil Price Behaviour Before and After Military Conflicts and Geopolitical Events. Energy, 120, 79-91

and fractional integration. I find evidence of persistence and breaks in the oil prices series and stationary long memory in the absolute returns. However, we do not observe significant differences before and after the conflict and geopolitical events.

In the second and the third paper, *Fractional Integration and Cointegraton in Merger and Acquisitions in the U.S. Petroleum Industry*[2] and *Are Mergers and Acquisitions in the Petroleum Industry affected by Oil Prices?*[3], I contribute to the literature on crude oil price behavior and examine how this affects mergers and acquisitions in the petroleum industry in the U.S. We analyze the relationship of these two series by studying its dynamic in the time and time-frequency domain, respectively, using data from January 1980 to June 2012. In the second paper, we employ methodologies based on fractional integration and cointegration. The results indicate that an increase in the crude oil price produces a significant increase in the MA data between 2 and 3 months after the initial shock. The third paper, employs wavelet tools, observing a shift to higher frequencies of the wavelet coherency during the mid-1990s and late 2000s. The results also indicate that during the mid-1990s and late-2000s an increase in mergers and acquisitions took place that was led by the increase in WTI crude oil prices, which is in line with the results reported in the second paper.

The paper *U.S. Shale Oil Production and WTI Prices Behaviour*[4], analyzes the relationship of total United States crude oil production (including shale oil production) and WTI crude oil prices by studying its performance in the time-frequency domain applying wavelet tools for its resolution. The results indicates a shift to higher frequencies of the wavelet coherency for the time period 2003-2009 and lower frequencies for the period 2009-2014. The results also indicate that during the period 2003-2009 the U.S. oil production and WTI oil prices time series are in phase; they move together, with total United States oil production leading. During the period 2009-2014 oil production and WTI oil prices time series are out of phase (negatively correlated), suggesting that oil production increases precede a decrease in WTI oil prices. In the second part of the paper and to give greater credibility to the results obtained through the wavelet transform, we analyze the behavior of WTI crude oil before and after the shale oil boom in the United States employing methodologies based on long run dependence. The results indicate that mean reversion takes place only for the data corresponding to the first subsample, ending at 2003. For the second subsample, as well as for the whole sample, lack of mean reversion is detected with orders of integration equal to or higher than 1 in all cases.

[2]Monge, M., Gil-Alana, L.A. 2016. Fractional integration and cointegration in merger and acquisitions in the US petroleum industry. Applied Economics Letters, 23, 701-704.

[3]Monge, M., Gil-Alana, L.A., Perez de Gracia, F. and Rodriguez Carreño, I. 2017. Are Mergers and Acquisitions in the Petroleum Industry in U.S. affected by oil prices?. Energy Sources, Part B: Economics, Planning and Policy, 12, 420-427.

[4]Monge, M., Gil-Alana, L.A., Perez de Gracia, F. (Forthcoming). U.S. Shale Oil Production and WTI Prices Behaviour. Energy.

Contents

Chapter 1

Crude oil price behaviour before and after military conflicts and geopolitical events

Crude oil price behaviour depends on all the events that have the potential to disrupt the flow of oil. We understand that these causes could be geopolitical issues and/or military conflicts in/with the producer countries and a problem relating to demand and supply. In the paper we first investigate the statistical properties of the real oil prices as well as its log-transformation, along with the absolute and squared returns values. Then, we also address the following issue: Does the crude oil price behave in the same way before and after a military conflict or geopolitical problem in the producer countries? To answer this question we analyse the real oil prices of West Texas Intermediate (WTI) before and after the different military conflicts and political events that occurred after World War II. For this purpose we use techniques based on unit roots and fractional integration. The empirical results provide evidence of persistence and breaks in the oil prices series and stationary long memory in the absolute returns. However, we do not observe significant differences before and after the conflict and geopolitical events.

1.1 Introduction

According to U.S. Energy Information Administration (EIA), much of the world's crude oil is located in regions that have been prone historically to political upheaval or have had their oil production disrupted due to political events. Since the Second World War there have been several military conflicts around the world that have been associated with significant changes in the price of oil. According to Hamilton (2013) and Kilian (2014), the seven most important conflicts have been the Suez Crisis of 1956-1957, the oil embargo implemented by Arab members of OPEC, the

Iranian revolution in 1978 [1], the Iran-Iraq War initiated in 1980, the first Persian Gulf War in 1990-1991, the Second Persian Gulf War and strikes in Venezuela, and the Libyan Revolution in 2011.

Each conflict analysed in this chapter, has the peculiarity of having occurred in an oil producing country. This has clearly negatively affected the production of this commodity in the daily flow of oil. During the last decade, many researchers have questioned the long-held beliefs about the causes and consequences of oil price behaviour and the oil price shocks. According to Kilian (2014), traditionally, the real oil price was to be determined primarily by political events in the Middle East that were outside of the confines of macroeconomic models and could simply be taken as given when conducting policy analysis. Nowadays, there is no consensus on whether oil price changes are due to fundamental shifts in supply and demand or speculation (Vansteenkiste, 2011). For example, the prominent study by Kaufmann and Ullman (2009) using Granger causality between spot and forward oil prices found that the rise in crude oil prices through March 2008 was driven in part by market fundamentals which support the arguments for the importance of demand growth in developing economies[2]. Alternatively, Hamilton (2009) studies the causes and consequences of the oil shock of 2007-08 obtaining that speculation played some role in the price increase in the summer of 2008[3].

Kilian (2014) argues that in the past, it was thought that the oil price shocks caused recessions for reasons unrelated to the state of the economy, but we are now aware that they were merely symptoms of a booming world economy. This was evident after 2005. Economists for many years have tended to confound the recessionary effects of oil price shocks with other causes of those earlier recessions (e.g. those in the 70s and 80s). Unexpected oil price increases sometimes may be associated with strong recessionary effects, but also, many of them can coexist with strong domestic economic growth at other times. Alluding to the issue of military conflicts, Hamilton (1983, 2013) argued that oil price increases are responsible for almost every post-war recession, except 1960.

This paper also relates with the literature that analyses asymmetric responses of macroeconomic variable to oil price shocks (Mork, 1989; Hamilton, 1996, 2003; Cunado and Perez de Gracia, 2005; Cologni and Manera, 2009; Naccache, 2010). Previous papers found that oil price increases tend to generate recessions while oil prices decreases do not stimulate real economic activity. In order to

[1] The Iran Revolution and the Iran and Iraq War have been considered as the same conflict. Hamilton (2013) considers the two events as two separate shocks, while others as a single prolonged episode, with the real price of oil doubling between 1978 and 1981.

[2] For example, Fattouh (2011) considers some forward oil markets are dominated by physical traders rather than financial players suggesting that the dichotomy between spot- and futures markets as a tool to identify the role of financial speculation versus the role of fundamentals is not well founded.

[3] For a recent survey on the determinants of oil price increases and the possible role of speculation see Fattouh et al. (2013).

test the asymmetric dynamics of oil prices Mork (1989) and Hamilton (1996, 2003) propose alternative oil price specifications such as "oil price increases" and "net oil price increases" respectively. In this chapter we examine the time series properties of real oil prices (i.e., log of oil prices and squared and absolute returns) before and after six military conflicts and political events that occurred after World War II. The contributions of the paper are twofold. First, to our knowledge this is the first paper that instead of using long span oil price data (see, for example, Pindyck, 1999), proposes to study time series properties before and after over six military conflicts and political events using monthly data. As we mentioned before, the six selected military conflicts have been previously identified by Hamilton (2013) and Kilian (2014). Second, in this chapter we use some recently developed methods based on the concepts of long run dependence and long memory using fractional integration techniques (Gil-Alana and Hualde, 2009), including structural breaks (Gil-Alana, 2008) and non-linearities (Cuestas and Gil-Alana, 2016). These techniques are relevant because depending on the order of integration of the series we can determine if the effect of the shocks is going to be transitory or permanent, and this is crucial when implementing policy measures.

The results obtained can be summarized as follows: performing standard unit root methods (ADF, PP and ERS) on the original and log-transformed oil prices series the results indicate nonstationarity I(1) while stationarity I(0) for the first differences. However, extending this approach to the fractional case, the order of integration of the WTI series was found to be fractional and significantly below 1 meaning that the series is mean reverting with the shocks disappearing by themselves in the long run. Moreover, allowing for structural breaks, still in the context of fractional integration, two significant breaks were detected, one at October 1973 and the other one at October 1980. The results on the volatility (measured in terms of the absolute and squared returns) indicate evidence of stationarity and long memory in case of the absolute returns. We also observe several outliers, corresponding to different episodes of violence, and removing these outliers, the same results were obtained in terms of the estimates of d. Finally, in the second part of the empirical work, we focus on the subsamples according to the different conflicts, examining if there is a different degree of integration before and after the breaks. Our results indicate that there is no any systematic pattern before and after the conflicts.

The rest of the paper is structured as follows. Section 2 reviews the behaviour of crude oil prices from the point of view of flow supply shocks. Section 3 focuses on the behaviour of the crude oil prices from a demand shocks viewpoint. Section 4 reviews the literature on modelling oil prices. Section 5 presents the methodology applied in the paper. In Section 6 we discuss the empirical results, and Section 7 concludes.

1.2 Crude oil price behaviour from a flow supply shocks viewpoint

Hamilton (2013) and Kilian (2014) identified different military conflicts and political events that could directly affect the oil prices due to flow supply disruption. Such political events were the 1973 Yom Kippur War followed by the Arab oil embargo in 1973/74, the Iranian Revolution of 1978/79, the Iran-Iraq War of 1980-1988, the Persian Gulf War of 1990/91, the Venezuelan crisis of 2002 and the Iraq War of 2003, and the Libyan uprising of 2011.

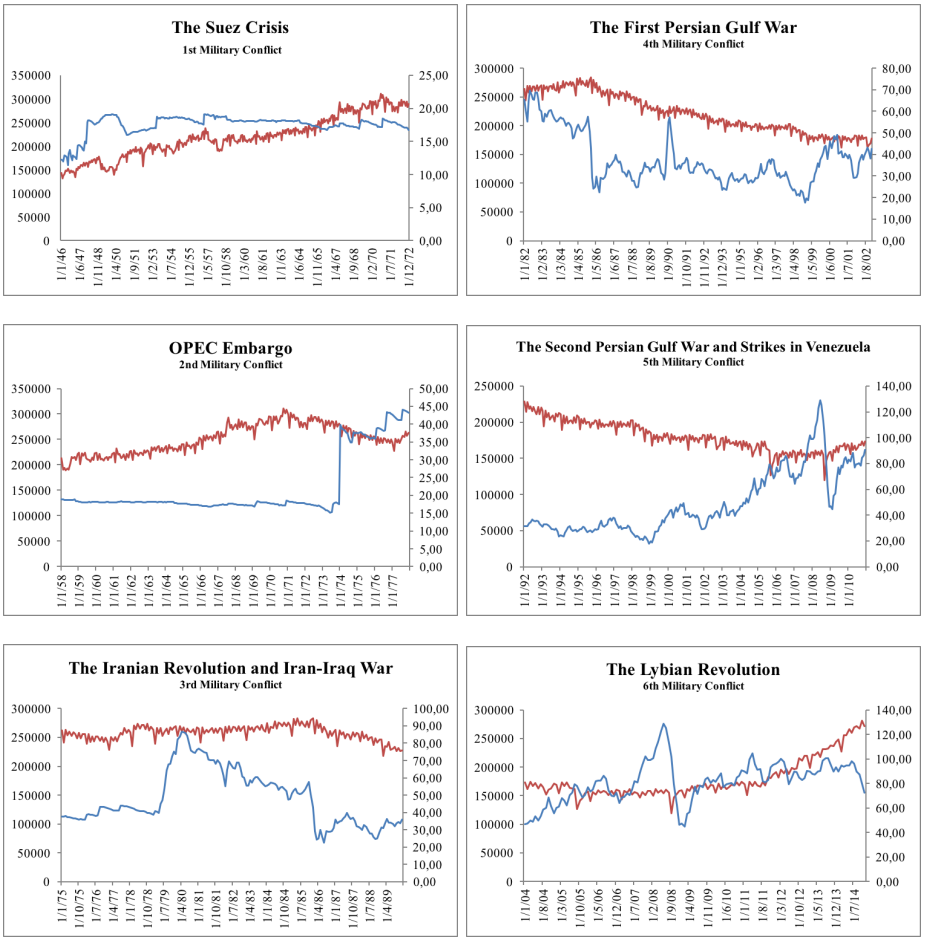

Figure 1: Real crude oil price and U.S. crude oil production in each military conflict and geopolitical event.

Figure 1 shows the comparison between the real crude oil price and the U.S. crude oil production. It is possible to distinguish between the different military conflicts and geopolitical events and the behaviour of crude oil production.

Hamilton (2003) suggested that all major fluctuations in the price of oil could be attributed to disruptions of the flow of oil production caused by political events in the Middle East. Kilian (2014) identifies three problems relating to this explanation. The data frequently does not fit. Second, more formal regression analysis confirms that quantitative measures of exogenous oil supply shocks associated with political events in the Middle East invariably have little predictive power for the percent change in the real price oil (Kilian 2008a, b). Third, numerous subsequent empirical studies have shown that most major oil price increases since late 1973 have had an important endogenous component associated with the global business cycle. Hamilton (2003) and Kilian (2008a) proposed measures of exogenous oil supply shocks, however, they only explain at most 25% of the observed oil price increase in 1973-1974. In accordance with Kilian (2014), the answer to the question of what explains the remaining oil price increase, is that at least, 75% of that oil price increase must be attributed to shifts in the demand for oil. Barsky and Kilian (2002) proved that there was a global demand boom in the early 1970s in all industrial commodity markets across the board, reflecting that, for the first time in post-war history, there was a simultaneous peak in the business cycle in the U.S., in Europe and in Japan.

1.3 Crude oil price behaviour from a flow demand shocks viewpoint

Referring to the definition of Kilian (2014), flow demand is the demand for oil to be consumed immediately in the process of producing refined products such as gasoline, diesel, heating oil, kerosene, or jet fuel. Kilian (2014) argues that the flow demand shocks associated with the global business cycle were a primary determinant not only of the 1973-1974 oil price increase, but of most of the major oil price increases. Thus, when the global economy increases, flow demand increases. At the end of 2014 crude petroleum represented, according to U.S. EIA, 44% of fossil fuel consumption, clearly thus, an important component of the modern economy.

Barsky and Kilian (2002) arrived at the conclusion that the role of flow demand for the real price of oil remained unappreciated for a long time. They also demonstrated co-movement fluctuations related with oil and other commodity prices in the 1970s and early 1980s that appear associated with fluctuations in the global business cycle.

Kilian (2009a) proposed a Structural Vector AutoRegressive (SVAR) model of the global market for

crude oil since 1973 that enables a breakdown of that evolution of the real price of oil into distinct components associated with demand and supply shocks. He showed that most large and persistent fluctuations in the real price of oil since the 1970s were associated with the cumulative effects of oil demand rather than oil supply shocks. Kilian and Murphy (2012) found an alternative, identifying assumptions based on the signs of responses to shocks like those identified in Kilian's (2009) paper. Baumeister and Peersman (2013) in addition allow for time-varying parameters in a similar VAR model. Kilian and Murphy (2013) and Kilian and Lee (2014), refine earlier structural oil market models by allowing for an explicit role for speculation in oil markets, again confirming the substance of the earlier results. These studies have provided evidence that oil demand shocks collectively explain most major oil price fluctuations since 1973 with a central role-played by flow demand shocks.

1.4 Economic literature on modelling oil prices

Pindyck (1978, 1980) is a first attempt to model oil price behaviour. More recently, the literature has turned into studying the integration order of energy prices. The importance of the latter is that, if oil prices contain unit roots, then shocks will have permanent effects; yet, if they are stationary, they would be mean-reverting. There are some papers, including those by Berck and Roberts (1996); Ferreira et al. (2005) and Pindyck (1999) that conclude that oil prices follow a nonstationary path, but these do not take into account the existence of structural breaks, which strongly diminishes the power of the tests.

The first step in this research is to examine the stationarity of oil prices. This is important because if the variables are nonstationary, the results obtained from standard regression analysis are clearly invalid and, therefore, producing spurious results. Empirically, a number of studies have examined the stationarity of oil prices using conventional unit root tests, such as the Augmented-Dickey Fuller (ADF, Dickey and Fuller, 1979) tests. The majority of the studies using this method find that oil prices are nonstationary. (See, for example, Amano and Norden, 1998; Bekiros and Diks, 2008; Bentzen, 2007; Bhar et al., 2008; Chaudhuri and Daniel, 1998; Jahan-Parvar and Mohammadi, 2011; Jawadi and Bellalah, 2011; Lardic and Mignon, 2008; Pindyck, 1999; Zhang et al., 2008, and Zhou, 1995). In these studies, the authors are unable to reject the unit root null for different oil prices. On the other hand, Moshiri and Foroutan (2006) find, also using the ADF tests and daily observations from April 1983 to January 2003, that crude oil future prices are stationary. A problem with the above studies is that they employ conventional unit root tests that lack power,

especially in short samples. Postali and Picchetti (2006) argue that a sample size of more than 100 years of annual data would be required to reject the unit root null when the autoregressive parameter is close to one. Using conventional tests and annual data on international oil prices from 1861 to 1999, these authors are able to reject the unit root null for full samples, but not for sub-samples. In the same way, many authors argue that most unit root tests lack power in the presence of structural breaks (Perron, 1989; Zivot and Andrews, 1992). Postali and Picchetti (2006) apply unit root tests with structural breaks and they were able to reject the unit root null with two endogenous breaks, concluding that their inability to reject the unit root null for the sub-periods was due to disregarding structural breaks. Lee et al. (2006) obtained similar results by employing a Lagrange Multiplier (LM) test allowing up to two endogenously determined structural breaks, showing that the unit root hypothesis can be rejected for the price of oil. On the contrary, Tsen (2011), using Zivot and Andrews (1992) unit root tests, was unable to reject the unit root null for the real oil price. Others use panel data and are unable to reject the unit root null. Thus, Chen and Chen (2007), using monthly data from 1972 to 2005, find that the real oil prices of Brent, Dubai, the World, and WTI are nonstationary with no evidence of structural breaks.

In a recent study, Li and Thompson (2010) study the trend in the monthly real price of oil between 1990 and 2008 using a generalized autoregressive conditional heteroskedasticity model. Their results support a deterministic trend in the price of oil implying that oil shocks are transitory. Another paper by Bildirici and Ömer Ersin (2014) consider fractional integration of oil prices by focusing on non-linearity and asymmetry. They find that the impacts of shocks possess significant persistence and non-linearity characteristics in oil prices.

Alvarez-Ramirez et al. (2002) used multifractal analysis to find that the crude oil market is a persistent process with long-run memory effects. Alvarez-Ramirez et al. (2008) analysed the autocorrelations of international crude oil prices: over long horizons, the crude oil market is consistent with the efficient market hypothesis, and the market exhibits a time-varying short-term inefficient behaviour that becomes efficient in the long term. Also, in the context of long memory, Elder and Serletis (2008) analyse long-range dependence behaviour in energy futures prices in a fractional integration dynamic model, finding evidence of anti-persistence. Fattouh (2010) analyses crude oil price differentials using a two-regime Threshold Auto-Regressive (TAR) model, and finds that the prices of different varieties of crude oil move closely together. Dvir and Rogoff (2010) examine changes in persistence and volatility of crude oil prices across three periods from 1861 to 2009 and documented striking similarities between the periods of 1861-1878 and 1973-2009. Erten and Ocampo (2013) use an asymmetric band-pass filter to study the super-cycles (periods lasting from 20 to 70 years) in the price of WTI crude oil. By filtering out the long-term trend, they argue that

the super-cycles in the price of crude oil were rather modest in the early twentieth century, but became more pronounced after the 1970s. Zellou and Cuddington (2012) apply similar band-pass filter methods to the same crude oil price data as used in the paper by Mu and Ye (2015), and found, similar cyclical patterns, namely a short cycle of 6 years and a long cycle of 29 years.

Finally, Serletis and Gogas (1999) tested for deterministic chaos in seven Mont Belview, Texas hydrocarbon markets and found evidence consistent with a chaotic non-linear generation process in all five natural gas liquid markets (but not in the crude oil and natural gas markets). Chaos represents a radical change of perspective in the explanation of fluctuations observed in economic and financial time series. In fact, if chaos can be shown to exist, the implication would be that (non-linearity-based) prediction is possible, at least in the short run and provided the actual generating mechanism is clearly understood[4].

1.5 Methodology

1.5.1 Unit roots methods

There exist many different ways of testing for unit-roots. The most common ones are those of Fuller (1976) and Dickey and Fuller (1979), the ADF tests. They are asymptotically optimal when the data are stationary. However, in the unit root case there are many other tests available that have greater power. Phillips (1987) and Phillips and Perron (1988) consider tests that employ a non-parametric estimate of the spectral density of ut at the zero frequency, for example, a weighted autocovariance estimate. The ERS test (Elliot et al., 1996) has been found to outperform other commonly used unit root tests, when the series contains an unknown mean or a time trend. This test is based on GLS detrending that is nearly asymptotically efficient in terms of local power when no additional trend break is present.

1.5.2 Fractional integration

We will also employ long memory methods, using techniques based on fractional integration, which means that the number of differences required to render a series I(0) stationary may be a fractional value rather than an integer. A given time series x_t, t = 1,2... is said to follow an integrated of order d process (and denoted as $x_t \approx I(d)$) if

[4]See Barnett et al. (2006) regarding the issue of where and when the ideas of chaos could profitably be applied to real systems.

$$(1-L)^d x_t = u_t, \qquad t = 1, 2, ..., \tag{1.1}$$

where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is I(0), defined for our purposes as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Thus, u_t may display some type of time dependence of the weak form, i.e., the type of an Autoregressive Moving Average (ARMA) form such that, for example, if u_t is ARMA (p, q), x_t is said to be ARFIMA (p, d, q).

Based on the specification in (1.1) different features can be observed depending on the value of d. Thus, if $d = 0$ in (1.1), $x_t = u_t$ and the process is said to be short memory or I(0). In this case, if u_t is ARMA, the autocorrelations decay exponentially fast. On the other hand, if $d > 0$ the process is said to be long memory, so-named due to the high degree of association between observations which are far distant in time. In this context, if $d < 0.5$ the process is still covariance stationary and the autocorrelations decay hyperbolically fast. As long as d is smaller than 1, the process is mean reverting with shocks disappearing in the long run, contrary to what happens with $d \geq 1$ where shocks are expected to be permanent, i.e. lasting forever.

We estimate the fractional differencing parameter d by means of both parametric and semiparametric techniques. In the parametric approach, we use the Whittle function in the frequency domain (Dahlhaus, 1989), while in the semiparametric case, we use a Gaussian semiparametric method that also uses the Whittle function on a band of frequencies that degenerates to zero (Robinson, 1995a)[5].

Note that the issue of fractional integration is very much related to the Hurst exponent, widely employed in the long memory literature. A process is long memory if there exists a real number $H \in (0.5, 1)$ and a finite positive constant C such that the autocorrelation function $\rho(k)$ at lag k has the following rate of decays:

$$\rho(k) \sim Ck^{2H-2} \;\; as \;\; k \longrightarrow \infty. \tag{1.2}$$

The parameter which is referred to as the Hurst exponent (Hurst, 1951), is a numerical estimate that represents the degree of long memory properties in a series. The value of can be interpreted

[5]Other parametric approaches (Sowell, 1992) or even semiparametric ones (Robinson, 1995b, Phillips and Shimotsu, 2004; Abadir et al., 2007) produced essentially the same type of results as those reported in the paper.

as follows:

i) For $0.5 < H < 1$, the process is said to be long memory (long-range dependence or persistent). This indicates that larger values tend to be followed by larger values, smaller values tend to followed by smaller values.

ii) For $0 < H < 0.5$, the process is said to be anti-persistent. This means that larger values will be followed smaller values and vice versa.

iii) For $H = 0.5$, the process is said to be short memory or weak dependence (including, ARMA). As explained in Baillie (1996), Tsay (2002), Mills and Markellos (2008) and others, there is a linear relationship between the two parameters, d and H, given by $d = H - 0.5$.

Finally, due to the long span of the data (back to the early 70s) the possibility of structural breaks is also taken into account. This is a relevant issue in the context of fractional integration and long memory processes in general, since it has been argued by many authors (Cheung, 1993; Diebold and Inoue, 2001; and more recently, Ben Nasr et al., 2014 and others) that fractional integration may be an artificial artifact generated by the presence of breaks that have not been taken into account in the models. Related to this final issue a procedure developed by Cuestas and Gil-Alana (2016) for testing fractional integration in the context of non-linear deterministic terms will also be implemented in the manuscript.

1.6 Empirical results

1.6.1 Data

In this chapter we used WTI crude oil over the period 1946:01–2014:11. The data were obtained from the Federal Reserve Bank of St. Louis[6]. The database was in nominal prices, and we have deflated to real prices. We have used the Producer Price Index for All Commodities from the Federal Reserve Bank of St. Louis[7]. The base year to obtain the new crude oil prices has been 2011. The data analyzed in the article correspond to the (logged) real monthly crude oil price in US dollars per barrel.

[6]Spot Oil Price: West Texas Intermediate, retrieved from FRED, Federal Reserve Bank of St. Louis. `https://research.stlouisfed.org/fred2/series/OILPRICE/`, September 8, 2015.

[7]US Bureau of Labor Statistics, Producer Price Index for All Commodities, retrieved from FRED, Federal Reserve Bank of St. Louis `https://research.stlouisfed.org/fred2/series/PPIACO/`, September 9, 2015.

1.6.2 Empirical results

We start the analysis by performing the three standard unit root tests outlined in Section 5 (ADF, PP and ERS) to the original series of oil prices as well as its log-transformation, together with their corresponding first differences. Table 1 displays the results, which clearly suggest that the original real oil prices and its logarithm transformation are nonstationary I(1). Furthermore, the firsts differences are stationary I(0). Focusing on the volatility (measured in terms of the absolute and squared returns) the results indicate evidence of I(0) stationarity[8]. Finally, based on the similarity of the results with the original and log-transformed data, in what follows we focus on the log-transformed data and its first differences (i.e., the returns).

	ADF			PP			ERS	
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(ii)	(iii)
	Real oil price							
Level	-0.880	-2.369	-3.655*	-0.332	-1.752	-2.930	5.889	3.558*
First difference	-20.92*	-20.917*	-20.904*	-19.894*	-19.90*	-19.88*	0.117*	0.335*
Logged real oil prices								
Level	0.455	-1.957	-3.208	0.676	-1.688	-2.868	16.142	4.557*
First difference	-23.678*	-23.686*	-23.672*	-23.242*	-23.27*	-23.253*	0.079*	0.265*
$\lvert R_t \rvert$								
Level	-4.408*	-7.016*	-8.6234*	-23.661*	-26.27*	-25.293*	0.629*	0.963*
First difference	-21.74*	-21.734*	-21.721*	-119.85*	-119.7*	119.679*	0.428*	1.567*
R_t^2								
Level	-26.773*	-27.400*	-27.528*	-27.391*	-27.54*	-27.612*	0.061*	0.220*
First difference	-16.812*	-16.802*	-16.792*	-262.50*	-262.3*	-262.11*	5.720	21.273

Table 1: Unit roots tests.
*(i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. F.D. stands for the first difference. The sample period runs from 01/02/1946 to 01/11/2014. *denotes a statistic that is significant at the 5% level of significance.*

Figure 2 displays the logged real oil prices series. We observe that the values have increased across the sample period with a jump around the first oil price crisis in 1973 and several others later on. In spite of the evidence of unit roots presented above and based on the low power of the unit root methods under fractional alternatives[9], we also estimated the fractional differencing parameter d in the following model,

[8]The returns were measured in terms of the first differences of the log prices series. Both measures (squared returns and absolute returns) have been widely used in empirical works for a proxy to the volatility. Thus, for example, absolute returns have been employed among others by Ding et al. (1993), Granger and Ding (1996), Bollerslev and Wright (2000), Gil-Alana (2005), Cavalcante and Assaf (2004), Sibbertsen (2004) and Cotter (2005), whereas squared returns were used in Lobato and Savin (1998), Gil-Alana (2003), Cavalcante and Assaf (2004) and Cotter (2005).

[9]See Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).

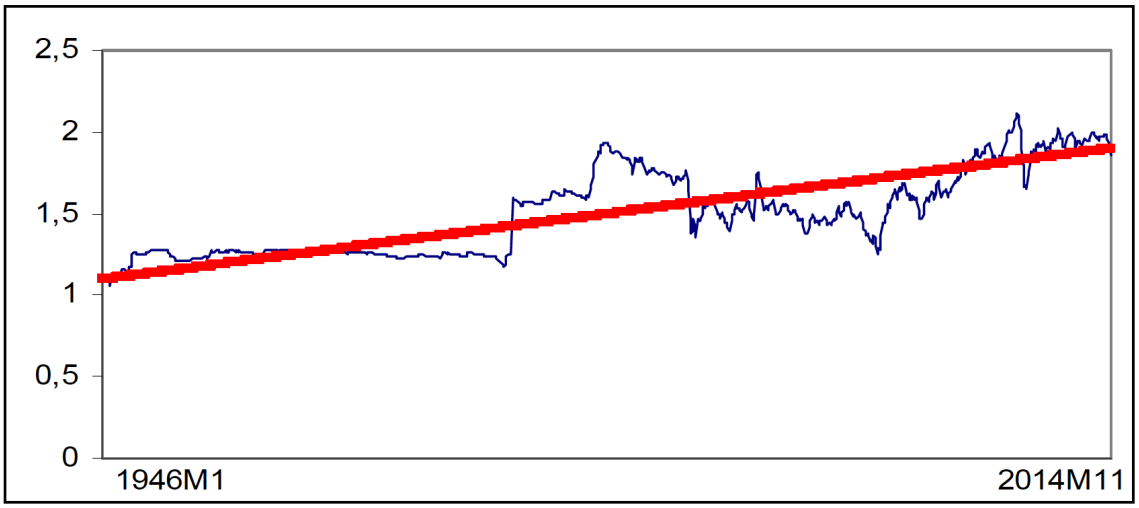

Figure 2: Real oil prices and estimated time trend.

$$y_t = \alpha + \beta t + x_t; \qquad (1-L)^d x_t = u_t \tag{1.3}$$

where y_t is the observed (univariate) time series; α and β are the coefficients corresponding to the intercept and the linear trend respectively, and x_t is assumed to be an I(d) process. Thus, u_t is I(0) and given the parametric nature of the method employed (and based on the Whittle function in the frequency domain, Dahlhaus, 1989), its functional form must be fully specified. In Table 2 we display the estimated values of d under the assumption that u_t is a white noise process, an AR(1) process and, also autocorrelated using the exponential spectral model of Bloomfield (1973). The latter is a non-parametric approach that produces autocorrelations with a slow exponential decay as in the AR models [10].

	No regressors	An intercept	A linear time trend
White noise	1.00 (0.95, 1.05)	1.11 (1.04, 1.18)	1.11 (1.04, 1.18)
AR(1)	xxx	0.79 (0.67, 0.93)	**0.78 (0.63, 0.93)**
Bloomfield (1)	0.93 (0.87, 1.02)	0.90 (0.82, 1.00)	0.90 (0.82, 1.00)

Table 2: Estimates of d for the real log-prices series using a Whittle estimate.
In bold the selected specification. xxx means that convergence was not achieved.

We observe in this table that if no deterministic terms are included the I(1) hypothesis cannot be rejected. However, including an intercept and/or a linear time trend, the results substantially

[10] See Gil-Alana (2004).

differ depending on the specification of the error term: thus, under white noise, the I(1) hypothesis is rejected in favour of a higher degree of integration (d > 1); however, if ut is autocorrelated, the I(1) hypothesis is rejected in favour of mean reversion (d < 1).

Focusing on the most appropriate specification for this series (logged real oil prices), it seems that it corresponds to the case of a model with an intercept and a linear time trend and AR(1) disturbances[11]. The estimated deterministic terms are 1.091 and 0.000973 respectively for the intercept and the linear trend (t-values, equal to 38.98 and 3.77 respectively) and the estimated d is equal to 0.78. Figure 2 also displays the estimated trend for this series. It is worth noting that as the estimated value of d is significantly below 1 the series will be mean reverting, i.e., shocks will be transitory and will tend to disappear by themselves in the long run though it will take some time to recover its original trend[12].

Next we examine if some structural breaks might be present in the data and if they might have distorted the estimation of d. For this purpose, we use the approach suggested in Gil-Alana (2008) that divide the sample in different subsamples with different deterministic trends and different differencing parameters for each subsample. Using this approach we consider the following model,

$$y_t = \beta_i^T z_t + x_t; \quad (1-L)^{d_i} x_t = u_t; \quad t = 1, ..., T_b^i; \quad i = 1, ...nb \tag{1.4}$$

where nb is the number of breaks, y_t is the observed time series, the β_i's are the coefficients corresponding to the deterministic terms; the d_i's are the orders of integration for each sub-sample, and the T_b^i's correspond to the times of the unknown breaks. Two breaks are detected using this method, one at October 1973, and the other one at October 1990, which correspond to the first oil price crisis (OPEC embargo) and the first Persian Gulf War respectively. An intercept is required in each of the three subsamples, and the estimated coefficients for the differencing parameters are reported in Table 3.

[11] This was determined by means of diagnostic tests on the residuals. In particular, we conducted tests of no serial correlation (Durbin, 1970; Godfrey, 1978a, b), homoscedasticity (Koenker, 1981) and functional form (Ramsey, 1989).

[12] Based on this specification we can easily obtain the impulse responses though we have not reported since this is not the goal of the present work.

	No regressors	An intercept	A linear time trend
1st subsample	0.99 (0.93, 1.07)	**0.94 (0.88, 1.02)**	0.94 (0.88, 1.02)
2nd subsample	1.00 (0.92, 1.10)	**1.22 (1.09, 1.41)**	1.22 (1.09, 1.41)
3rd subsample	0.93 (0.86, 1.03)	**1.16 (1.05, 1.29)**	1.16 (1.05, 1.29)

Table 3: Estimates of d for the real log-prices series using using Gil-Alana (2008)
In bold the selected specification.

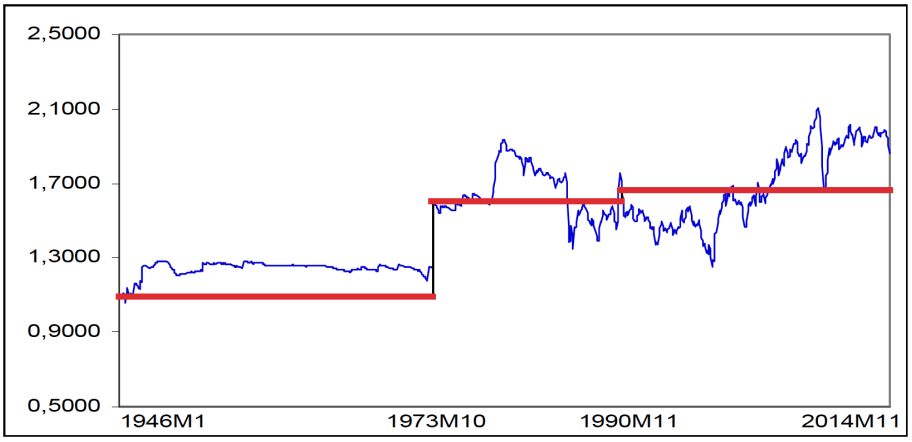

Figure 3: Real oil prices and estimated time trend.

Focusing on the case of the intercept, the estimate of the constant was found to be 1.0892 for the first subsample; 1.6015 for the second subsample, and 1.6568 for the finite subsample. Figure 3 displays the estimated (segmented) trend and we observe a clear mean shift around the first oil prices crisis in 1973 and another one, of a much smaller magnitude, at the time of the first Gulf war.

Which one of the two figures (2 and 3) better represent the data is an open question. Note however, that authors such Lobato and Savin (1998), Diebold and Inoue (2001), Gourieux and Jasiak (2001), Granger and Ding (1996), Granger and Hyung (2004), Shimotsu (2006), Ohanissian, Russell and Tsay (2008), Perron and Qu (2010) and Qu (2011) among many others have argued that these two issues (fractional integration and mean shifts) are very much related. In fact, the results presented in Table 2 and based on a linear trend supported the hypothesis of mean reversion in the logged real oil prices, however, if structural breaks are allowed for, we observe in Table 3 that this hypothesis is decisively rejected and even the unit root null is now rejected in favour of higher orders of integration in the second and third subsamples. Noting then that the existence of conflicts may have produced alterations in the behaviour of the oil prices, the possibility of non-linear deterministic trends is also taken into account. Here we use the approach suggested by Cuestas and Gil-Alana (2016) that focuses on the estimation of d in the context of non-linear

deterministic trends by means of using Chebyshev polynomials in time. The model examined is the following:

$$y_t = \sum_{i=0}^{m} \theta_i P_{iT}(t) + x_t, \quad (1-L)^d x_t = u_t; \quad t = 1, 2, ... \tag{1.5}$$

with m indicating the order of the Chebyshev polynomials, $P_{i,T}(t)$ in (1.5), defined as:

$$P_{0,T}(t) = 1; \quad P_{i,T}(t) = \sqrt{2} cos(i\pi(t-0.5)/T); \quad t = 1, 2, ..., T; \quad i = 1, 2, ..., \tag{1.6}$$

(see Hamming (1973) and Smyth (1998) for a detailed description of these polynomials). Bierens (1997) uses them in the context of unit root testing. According to Bierens (1997) and Tomasevic and Stanivuk (2009), it is possible to approximate highly non-linear trends with rather low degree polynomials. If m = 0 the model in (1.5) contains an intercept, if m = 1 it also includes a linear trend, and if m > 1 it becomes non-linear - the higher m is the less linear the approximated deterministic component becomes. The results, for different values of m, are displayed in Table 4[13].

i) White noise errors			
	m = 1	m = 2	m= 3
Estimated d	1.11 (1.04, 1.18)	1.11 (1.04, 1.18)	1.10 (1.04, 1.13)
θ - Estimated coeff.	θ_0 = 1.369 (1.95) θ_1 = -0.199 (-0.40)	θ_0 = 1.372 (1.79) θ_1 = -0.199 (-0.40) θ_2 = -0.002 (-0.01)	θ_0 = 1.475 (1.44) θ_1 = -0.242 (-0.38) θ_2 = 0.154 (0.54) θ_3 = 0.258 (1.44)
ii) AR (1) errors			
Estimated d	1.11 (1.07, 1.15)	1.11 (1.07, 1.15)	1.11 (1.05, 1.14)
θ - Estimated coeff.	θ_0 = 1.367 (1.95) θ_1 = -0.199 (-0.42)	θ_0 = 1.373 (1.78) θ_1 = -0.197 (-0.37) θ_2 = -0.002 (-0.01)	θ_0 = 1.471 (1.42) θ_1 = -0.242 (-0.39) θ_2 = 0.153 (0.54) θ_3 = 0.257 (1.42)

Table 4: Estimates based on a non-linear I(d) model.
In parenthesis for the estimated values of d the 95% confidence intervals; for the θ-coefficients, their corresponding t-values.

The estimated values of d for the two cases of white noise and AR(1) disturbances are displayed in Table 4. We see that they are very similar for the three cases presented (i.e., m = 1 (linear) and 2 and 3 (non-linear) cases, with a value of d equal to 1.10, and the unit root null being slightly

[13]The choice of m is based on the t-values of the estimated coefficients. (See Cuestas and Gil-Alana, 2016).

rejected in favour of d > 1. However, focusing on the deterministic terms, we observe that none of those corresponding to the non-linear cases are found to be statistically significant, finding thus no support to this hypothesis. Due to this, the rest of the analysis will focus on the analysis of the conflicts investigating if they may have had an influence on the behaviour of oil prices.

Nevertheless, prior to this, we take a look at the volatility issue, and for this purpose, we also examine the squared and the absolute returns from a fractional viewpoint.

Starting with the squared returns, (displayed in Figure 4a) we observe several outliers, clearly corresponding to different episodes of violence. The largest one clearly corresponds to the OPEC embargo in 1973 but we also observe some others at different conflict periods. The estimates of the differencing parameters are presented in Table 5a. We observe that the estimated values of d are slightly positive though the I(0) hypothesis cannot be rejected.

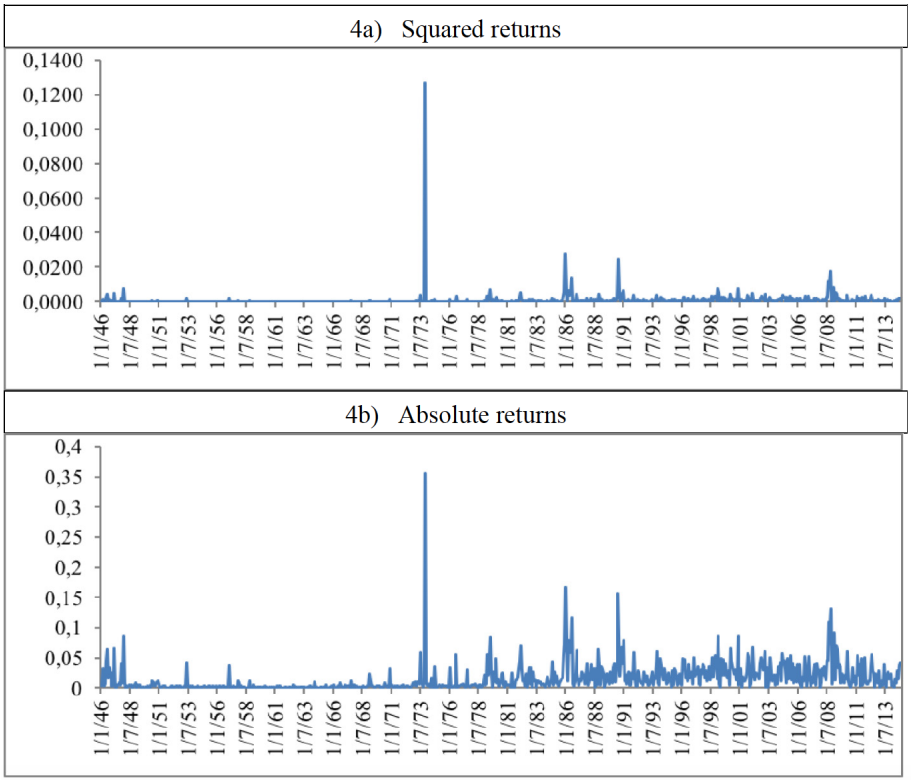

Figure 4: Squared and absolute returns of the real oil prices.

However, if we focus on the absolute returns (Figure 4b and Table 5b) the plots also display outliers corresponding to the conflict periods, and the estimates of the differencing parameters are all significantly positive ranging from 0.19 (white noise with a linear trend) to 0.28 (Bloomfield with an intercept). Removing these outliers, the same results are obtained in terms of the estimates of d.

5a) Estimates of d for the squared returns			
	No regressors	An intercept	A linear time trend
White noise	0.04 (0.00, 0.09)	0.04 (0.00, 0.09)	0.03 (-0.02, 0.09)
AR(1)	0.04 (-0.02, 0.12)	0.05 (-0.02, 0.13)	0.02 (-0.07, 0.11)
Bloomfield (1)	0.05 (-0.02, 0.13)	0.05 (-0.03, 0.12)	0.02 (-0.06, 0.12)
5b) Estimates of d for the absolute returns			
	No regressors	An intercept	A linear time trend
White noise	0.22 (0.19, 0.26)	0.23 (0.20, 0.27)	0.19 (0.15, 0.24)
AR(1)	0.25 (0.21, 0.31)	0.27 (0.23, 0.32)	0.21 (0.14, 0.29)
Bloomfield (1)	0.26 (0.21, 0.32)	0.28 (0.23, 0.34)	0.22 (0.14, 0.30)

Table 5: Estimates of d for the squared and the absolute returns.
The values in parenthesis refer to the 95% confidence intervals for the values of d.

1.6.3 Real oil price – military conflicts subsamples

The second part of this empirical work focuses on the subsamples according to the conflicts presented in Section 2. There are six conflicts and the first thing we do is to examine if there is a different degree of integration before and after the breaks. For this purpose, we first take the same number of observations (60) before and after the conflicts and estimate d in the levels of the log-prices, the squared and the absolute returns.

6a) Log prices				
Conflict	White noise		Autocorrelation (Bloomfield)	
	Before	After	Before	After
1st conflict	0.94 (0.80, 1.17)	0.98 (0.85, 1.18)	0.84 (0.65, 1.23)	1.02 (0.69, 1.36)
2nd conflict	1.05 (0.84, 1.35)	1.29 (1.16, 1.48)	0.70 (0.53, 1.15)	1.30 (0.86, 1.70)
3rd conflict	1.29 (1.16, 1.48)	1.11 (0.88, 1.49)	1.31 (0.86, 1.70)	0.57 (0.38, 0.90)
4th conflict	1.18 (0.97, 1.49)	1.05 (0.85, 1.38)	0.64 (0.29, 1.12)	0.64 (0.39, 0.98)
5th conflict	1.06 (0.91, 1.29)	1.45 (1.25, 1.67)	0.95 (0.67, 1.35)	1.51 (0.54, 1.97)
6th conflict	1.38 (1.18, 1.62)	1.17 (0.47, 1.71)	1.33 (0.63, 1.74)	-0.31 (-0.95, 0.93)
6b) Squared and absolute returns				
Conflict	Squared returns		Absolute returns	
	Before	After	Before	After
1st conflict	-0.06 (-0.22, 0.17)	-0.03 (-0.16, 0.17)	-0.06 (-0.22, 0.17)	-0.02 (-0.14, 0.17)
2nd conflict	-0.03 (-0.24, 0.24)	0.18 (0.03, 0.39)	0.05 (-0.16, 0.35)	0.25 (0.12, 0.44)
3rd conflict	0.18 (0.03, 0.39)	0.27 (0.13, 0.49)	0.25 (0.12, 0.44)	0.41 (0.26, 0.63)
4th conflict	0.26 (0.11, 0.49)	0.06 (-0.12, 0.33)	0.33 (0.17, 0.58)	0.01 (-0.16, 0.29)
5th conflict	0.10 (-0.05, 0.33)	0.95 (0.71, 1.17)	0.04 (-0.10, 0.26)	0.42 (0.18, 0.69)
6th conflict	0.39 (0.23, 0.64)	0.21 (-0.11, 0.81)	0.31 (0.17, 0.52)	0.18 (-0.12, 0.63)

Table 6: Estimates of d for the subsamples in the log-prices and absolute and squared returns.
The values in parenthesis refer to the 95% confidence intervals for the values of d.

The results are presented in Table 6. Starting with the case of the log prices (Table 6a), the first thing we observe is that the results are very similar for the two cases of uncorrelated and autocorrelated (Bloomfield) errors. However, we do not observe any systematic pattern in the sense, for example, that higher or lower estimates of d are observed before or after the conflicts. In fact, for the first, second and fifth conflicts, higher estimates of d are obtained after the breaks and the contrary happens in the other conflicts. Focusing on the absolute and squared returns (in Table 6b) we observe an increase in the estimates of d corresponding to the 1st, 2nd, 3rd and 5th conflicts, while the estimated values of d are lower after the break in the 4th and 6th conflicts.

Apparently, in the above results, we cannot find any systematic pattern before and after the conflicts, and noting that in the sub-periods we could have incorporated subsequent conflicts due to the proximity of one to another, in what follows, we consider different sizes for each subsample, avoiding the interpolation with other conflicts. The results respectively for the cases of log-prices, squared returns and absolute returns are presented respectively in Tables 7a, b and c. Again here we do not observe any systematic pattern. Thus, we find cases where the estimated values of d are higher before the conflict while in others just the contrary happens.

7a) Log prices				
Conflict	White noise		Autocorrelation (Bloomfield)	
	Before	After	Before	After
1st conflict	0.89 (0.79, 1.02)	0.99 (0.86, 1.15)	0.93 (0.76, 1.14)	0.71 (0.48, 1.00)
2nd conflict	0.99 (0.86, 1.15)	0.85 (0.67, 1.22)	0.70 (0.48, 1.00)	0.60 (0.32, 1.01)
3rd conflict	0.85 (0.67, 1.22)	1.11 (0.93, 1.37)	0.60 (0.35, 0.99)	0.64 (0.48, 0.93)
4th conflict	1.11 (0.93, 1.38)	1.07 (0.94, 1.23)	0.64 (0.49, 0.93)	0.91 (0.70, 1.17)
5th conflict	1.07 (0.94, 1.23)	1.24 (1.07, 1.46)	0.91 (0.70, 1.16)	1.12 (0.48, 1.87)
6th conflict	1.24 (1.07, 1.44)	1.13 (0.39, 1.64)	1.12 (0.44, 1.81)	0.37 (0.08, 1.04)
7b) Squared returns				
Conflict	White noise		Autocorrelation (Bloomfield)	
	Before	After	Before	After
1st conflict	0.08 (0.00, 0.19)	0.01 (-0.07, 0.13)	0.12 (0.00, 0.23)	-0.03 (-0.15, 0.13)
2nd conflict	0.01 (-0.07, 0.19)	-0.20 (-0.41, 0.15)	-0.03 (-0.14, 0.13)	-0.46 (-0.86, 0.07)
3rd conflict	-0.20 (-0.41, 0.19)	0.26 (0.14, 0.44)	-0.43 (-0.88, 0.10)	0.14 (-0.08, 0.41)
4th conflict	0.26 (0.14, 0.19)	0.09 (0.00, 0.21)	0.14 (-0.08, 0.41)	0.02 (-0.09, 0.18)
5th conflict	0.09 (0.00, 0.19)	0.34 (0.21, 0.52)	0.02 (-0.09, 0.18)	0.33 (0.06, 0.71)
6th conflict	0.34 (0.21, 0.19)	0.15 (-0.22, 0.71)	0.33 (0.07, 0.72)	0.51 (-0.84, 0.72)
7c) Absolute returns				
Conflict	White noise		Autocorrelation (Bloomfield)	
	Before	After	Before	After
1st conflict	0.20 (0.12, 0.31)	0.06 (-0.01, 0.18)	0.25 (0.12, 0.43)	0.04 (-0.06, 0.20)
2nd conflict	0.06 (-0.01, 0.17)	-0.33 (-0.54, 0.02)	0.04 (-0.06, 0.21)	-0.52 (-0.86, -0.09)
3rd conflict	-0.33 (-0.52, 0.02)	0.35 (0.23, 0.54)	-0.51 (-0.81, -0.11)	0.22 (0.00, 0.53)
4th conflict	0.35 (0.23, 0.53)	0.07 (-0.01, 0.19)	0.22 (0.00, 0.52)	0.02 (-0.08, 0.16)
5th conflict	0.07 (-0.01, 0.19)	0.23 (0.12, 0.40)	0.02 (-0.09, 0.16)	0.33 (0.06, 0.67)
6th conflict	0.24 (0.13, 0.40)	0.12 (-0.22, 0.59)	0.34 (0.06, 0.74)	-0.52 (-0.83, 0.84)

Table 7: Estimates of d for each of the subsamples in the log-prices series.
The values in parenthesis refer to the 95% confidence intervals for the values of d.

Next we use a different strategy, and estimate d for subsequent samples increasing in size. Thus, the first subsample includes only the first conflict, the second one the first two, and so on till the one including the last subsample with all the conflicts. The results, again for the three cases of no regressors, an intercept, and an intercept with a linear time trend and the two types of errors (white noise and Bloomfield) are presented in Table 8.

i) White noise disturbances			
Size	No regressors	An intercept	A linear time trend
01/01/1946 – 01/12/1957	0.97 (0.87, 1.10)	**0.89 (0.80, 1.01)**	0.90 (0.82, 1.01)
01/01/1946 – 01/12/1974	1.00 (0.93, 1.07)	**0.96 (0.89, 1.03)**	0.96 (0.89, 1.03)
01/01/1946 – 01/12/1981	0.97 (0.92, 1.03)	**1.01 (0.96, 1.09)**	1.01 (0.96, 1.09)
01/01/1946 – 01/12/1991	1.00 (0.94, 1.07)	**1.09 (1.01, 1.18)**	1.09 (1.01, 1.18)
01/01/1946 – 01/12/2003	1.03 (0.98, 1.09)	**1.10 (1.02, 1.19)**	1.10 (1.02, 1.17)
01/01/1946 – 01/12/2011	1.04 (0.98, 1.10)	**1.11 (1.04, 1.18)**	1.11 (1.04, 1.18)
ii) Autocorrelated (Bloomfield) disturbances			
Size	No regressors	An intercept	A linear time trend
01/01/1946 – 01/12/1957	0.96 (0.78, 1.19)	**0.93 (0.77, 1.14)**	0.94 (0.80, 1.12)
01/01/1946 – 01/12/1974	1.01 (0.92, 1.14)	**0.97 (0.87, 1.11)**	0.97 (0.88, 1.11)
01/01/1946 – 01/12/1981	0.97 (0.90, 1.10)	**1.02 (0.93, 1.17)**	1.02 (0.93, 1.17)
01/01/1946 – 01/12/1991	0.93 (0.86, 1.04)	**0.89 (0.81, 0.99)**	0.89 (0.81, 1.00)
01/01/1946 – 01/12/2003	0.98 (0.91, 1.09)	**0.87 (0.80, 0.99)**	0.87 (0.80, 0.99)
01/01/1946 – 01/12/2011	0.99 (0.92, 1.07)	**0.90 (0.82, 1.00)**	0.90 (0.82, 1.00)

Table 8: Estimates of d for subsamples increasing in size.
In bold the selected models according to the deterministic terms.

Focusing here on the cases with an intercept (which is the most realistic model according to the t-values of the deterministic terms, unreported values) the most remarkable issue is the fact that the values of d increase as we increase the sample size, incorporating a new conflict. This happens especially for the uncorrelated case. Including autocorrelated errors, the evidence is not so strong, observing a reduction in the estimates of d with the inclusion of the fourth conflict in the sample. Finally, we separate the full sample into two subsamples, corresponding to pre and post-data for each of the conflicts. The results again for log-prices, squared and absolute returns are displayed across Table 9.

i) 1st conflict (The Suez crisis)		
	First subsample [- 12/1955]	Second subsample [1/1958 -]
White noise	0.89 (0.79, 1.02)	1.12 (1.06, 1.20)
AR (1) errors	0.92 (0.76, 1.11)	0.77 (0.65, 0.94)
Bloomfield errors	0.93 (0.76, 1.14)	0.89 (0.80, 1.01)
ii) 2nd conflict (The OPEC embargo)		
	First subsample [- 12/1972]	Second subsample [1/1975 -]
White noise	0.92 (0.86, 0.99)	1.18 (1.08, 1.29)
AR (1) errors	0.96 (0.87, 1.06)	0.70 (0.58, 0.85)
Bloomfield errors	0.96 (0.86, 1.09)	0.86 (0.76, 1.01)
iii) 3rd conflict (The Iranian revolution and Iran-Iraq war)		
	First subsample [- 12/1977]	Second subsample [1/1982 -]
White noise	0.95 (0.90, 1.03)	1.17 (1.07, 1.29)
AR (1) errors	0.96 (0.88, 1.07)	0.68 (0.57, 0.84)
Bloomfield errors	0.96 (0.57, 0.84)	0.83 (0.73, 0.99)
iv) 4th conflict (The first Persian Gulf)		
	First subsample [- 12/1989]	Second subsample [1/1992 -]
White noise	1.05 (0.99, 1.12)	1.14 (1.04, 1.27)
AR (1) errors	0.95 (0.84, 1.07)	0.56 (0.08, 1.10)
Bloomfield errors	0.97 (0.87, 1.08)	0.92 (0.75, 1.16)
v) 5st conflict (The second Persian Gulf war)		
	First subsample [- 12/2002]	Second subsample [1/2004 -]
White noise	1.08 (1.01, 1.16)	1.22 (1.06, 1.41)
AR (1) errors	0.84 (0.69, 0.97)	0.90 (0.51, 1.20)
Bloomfield errors	0.89 (0.82, 0.99)	0.92 (0.54, 1.44)
vi) 6st conflict (The Libian revolution)		
	First subsample [- 12/2010]	Second subsample [1/2012 -]
White noise	1.11 (1.04, 1.19)	1.13 (0.39, 1.62)
AR (1) errors	0.79 (0.70, 0.96)	
Bloomfield errors	0.91 (0.82, 1.00)	

Table 9a: Estimates of d for subsamples increasing in size

i) 1st conflict (The Suez crisis)		
	First subsample [- 12/1955]	Second subsample [1/1958 -]
White noise	0.08 (0.00, 0.19)	0.04 (-0.01, 0.09)
AR (1) errors	0.13 (0.00, 0.33)	0.03 (-0.05, 0.12)
Bloomfield errors	0.13 (0.00, 0.12)	0.03 (-0.04, 0.12)
ii) 2nd conflict (The OPEC embargo)		
	First subsample [- 12/1972]	Second subsample [1/1975 -]
White noise	0.11 (0.06, 0.17)	0.25 (0.19, 0.33)
AR (1) errors	0.18 (0.10, 0.28)	0.18 (0.04, 0.29)
Bloomfield errors	0.17 (0.10, 0.28)	0.19 (0.07, 0.30)
iii) 3rd conflict (The Iranian revolution and Iran-Iraq war)		
	First subsample [- 12/1977]	Second subsample [1/1982 -]
White noise	-0.01 (-0.06, 0.07)	0.25 (0.18, 0.34)
AR (1) errors	-0.01 (-0.11, 0.11)	0.14 (-0.06, 0.30)
Bloomfield errors	-0.02 (-0.10, 0.12)	0.14 (0.03, 0.29)
iv) 4th conflict (The first Persian Gulf)		
	First subsample [- 12/1989]	Second subsample [1/1992 -]
White noise	0.02 (-0.03, 0.08)	0.27 (0.20, 0.37)
AR (1) errors	0.02 (-0.06, 0.12)	0.26 (0.09, 0.43)
Bloomfield errors	0.02 (-0.06, 0.13)	0.26 (0.13, 0.43)
v) 5st conflict (The second Persian Gulf war)		
	First subsample [- 12/2002]	Second subsample [1/2004 -]
White noise	0.03 (-0.01, 0.08)	0.33 (0.23, 0.47)
AR (1) errors	0.03 (-0.04, 0.11)	0.35 (0.06, 0.64)
Bloomfield errors	0.03 (-0.04, 0.13)	0.36 (0.13, 0.68)
vi) 6st conflict (The Libian revolution)		
	First subsample [- 12/2010]	Second subsample [1/2012 -]
White noise	0.04 (0.00, 0.09)	0.13 (-0.21, 0.68)
AR (1) errors	0.04 (-0.03, 0.13)	-0.51 (-0.77, 0.39)
Bloomfield errors	0.05 (-0.03, 0.12)	-0.54 (-0.81, 0.37)

Table 9b: Estimates of in the sq. returns for two subsamples depending on the conflict.

i) 1st conflict (The Suez crisis)		
	First subsample [- 12/1955]	Second subsample [1/1958 -]
White noise	0.20 (0.12, 0.31)	0.23 (0.19, 0.27)
AR (1) errors	0.25 (0.11, 0.44)	0.26 (0.21, 0.32)
Bloomfield errors	0.25 (0.11, 0.44)	0.27 (0.21, 0.33)
ii) 2nd conflict (The OPEC embargo)		
	First subsample [- 12/1972]	Second subsample [1/1975 -]
White noise	0.21 (0.16, 0.28)	0.27 (0.21, 0.33)
AR (1) errors	0.28 (0.20, 0.38)	0.25 (0.16, 0.35)
Bloomfield errors	0.28 (0.20, 0.39)	0.24 (0.17, 0.35)
iii) 3rd conflict (The Iranian revolution and Iran-Iraq war)		
	First subsample [- 12/1977]	Second subsample [1/1982 -]
White noise	0.07 (0.03, 0.14)	0.25 (0.18, 0.33)
AR (1) errors	0.12 (0.05, 0.21)	0.21 (0.06, 0.35)
Bloomfield errors	0.13 (0.04, 0.22)	0.20 (0.10, 0.36)
iv) 4th conflict (The first Persian Gulf)		
	First subsample [- 12/1989]	Second subsample [1/1992 -]
White noise	0.21 (0.17, 0.26)	0.18 (0.11, 0.26)
AR (1) errors	0.25 (0.19, 0.32)	0.20 (0.10, 0.32)
Bloomfield errors	0.25 (0.19, 0.33)	0.21 (0.09, 0.36)
v) 5st conflict (The second Persian Gulf war)		
	First subsample [- 12/2002]	Second subsample [1/2004 -]
White noise	0.23 (0.19, 0.27)	0.23 (0.13, 0.35)
AR (1) errors	0.26 (0.21, 0.32)	0.30 (0.10, 0.54)
Bloomfield errors	0.27 (0.21, 0.33)	0.31 (0.12, 0.64)
vi) 6st conflict (The Libian revolution)		
	First subsample [- 12/2010]	Second subsample [1/2012 -]
White noise	0.24 (0.20, 0.28)	0.12 (-0.21, 0.59)
AR (1) errors	0.28 (0.23, 0.33)	-0.47 (-0.87, 0.40)
Bloomfield errors	0.28 (0.23, 0.34)	-0.42 (-0.84, 0.43)

Table 9c: Estimates of in the abs. returns for two subsamples depending on the conflict.

We start by explaining the results in Table 9a which refers to the log prices series. We observe that the same pattern is observed in relation to the first four conflicts; however, the results differ depending on the inclusion or not of autocorrelation. Thus, if ut is white noise, in the four cases we observe an increase in the value of d after the break due to the conflict. However, under AR(1) or Bloomfield-type disturbances, the contrary happens and we observe a substantial reduction in the estimation of d after the breaks. For the 5th and 6th conflicts this is not the case. For the fifth conflict, the estimate of d increases for the three specifications of the error term and for the sixth conflict we do not have enough observations to estimate d properly after the break.

Focusing now on the squared and absolute returns (Tables 9b and c), the first thing that we note is that, as earlier mentioned, lower estimated values of d are obtained in the case of the absolute returns. The most notorious feature is observed in the squared returns, and in all except in the case of the first conflict, we observe a significant increase in the estimated value of d after the conflicts. However, this evidence is not so clear in case of the absolute returns.

1.7 Discussion and conclusions

A time series with a unit root means that the effect of a shock lasts forever. A nonstationary but persistent time series displays long memory behaviour. If an oil price series is highly persistent, even a small shock will influence the future realization of this series for a very long time on account of lags in the effect of monetary policy on the economy.

In this article our objective and focus has been first to analyse the statistical properties of real oil prices by using unit roots and fractional integration methods, and then to understand the behaviour of oil prices before and after military conflicts and geopolitical events, located in these producing countries. The results from Kilian (2008a, b) indicate that quantitative measures of exogenous oil supply shocks associated with political events in the Middle East have very little predictive power for the percentage change in the real price of oil. In a subsequent paper (Kilian, 2014), he shows that, at least, 75% of the oil price increase must be attributed to shifts in the demand for oil.

We started by performing several standard unit root methods, ADF, PP and ERS. The results suggest that the real oil prices and its logarithm transformations are nonstationary I(1), while the first differences are stationary I(0). These results are in line with other related studies such as Amano and Norden (1998), Pindyck (1999) and Lardic and Mignon (2008) among others, which all found evidence of I(1) behaviour in the oil prices series.

We also estimated the differencing parameter d in terms of a fractional model. In the first case, we

analyze the real oil price of the WTI's series and its time trend. It is worth noting that since the estimated value of d is significantly below 1 the series seems to be mean reverting, meaning that shocks will be transitory and will disappear by themselves in the long run, though it will take some time to recover its original trend. For example, Elder and Serletis (2008) using wavelets to estimate the fractional integration parameter obtained that energy prices display long memory. They also found that the variance of energy prices is dominated by high frequency (low wavelet scale) components. Using, however, the approach suggested in Gil-Alana (2008) that divides the sample into different subsamples with different deterministic trends and different differencing parameters for each subsample, we detect two significant breaks, one at October 1973 and the other one at October 1990. The break date of 1973 is also detected by Postali and Picchetti (2006). They concluded that the first oil shock is a trend-break, independently of the chosen sample. Focusing on the volatility (measured in terms of the absolute and squared returns) the results indicate evidence of stationarity (and long memory in case of the absolute returns). We also observe several outliers, corresponding to different episodes of violence. Removing these outliers, the same results were obtained in terms of the estimates of d.

In the second part of our empirical work, we focus on the subsamples according to the different conflicts. There are six conflicts and the first thing we do is to examine if there is a different degree of integration before and after the breaks. First, we take the same number of observations (60) before and after the conflicts and we estimate d in the levels of the log-prices, the squared and the absolute returns. We cannot find any systematic pattern before and after the conflicts, and noting that in the sub-periods we could have incorporated subsequent conflicts due to the proximity of one to another, we also considered different sizes for each subsample, avoiding the interpolation with other conflicts. Once more, the results did not show up any significant difference before and after the conflicts.

Finally, we estimate d for subsequent sub-samples increasing in size incorporating one conflict each time. We observe here a significant monotonic increase in the estimated values of d with the conflicts, implying a continuous increase in the degree of persistence of the series. However, this evidence is not so clear in the case of the absolute returns.

The results presented in this chapter may help to a better understanding of the dynamic behaviour of oil prices and its volatility across different military conflicts and geopolitical events. In addition, they can be relevant for commodities analysts and financial-macroeconomic forecasters.

1.8 References

Abadir, K.M., Distaso, W., Giraitis, L. 2007. Nonstationarity-extended local Whittle estimation. Journal of Econometrics, 141, 1353-1384.

Alvarez-Ramirez, J., Alvarez, J., Rodriguez, E. 2008. Short-term predictability of crude oil markets: A detrended fluctuation analysis approach. Energy Economics, 30, 2645-2656.

Alvarez-Ramirez, J., Cisneros, M., Ibarra-Valdez, C., Soriano, A. 2002. Multifractal Hurst analysis of crude oil prices. Physica, 313, 651-670.

Amano, R.T. 1996. Oil prices and rise and fall of the US real exchange rate. Journal of International Money and Finance, 17, 299-316.

Baillie, R.T. 1996. Long memory processes and fractional integration in econometrics. Journal of Econometrics, 73, 5-59.

Barnett, W.A., Serletis, A., Serletis, D. 2006. Nonlinear and complex dynamics in real systems. International Journal of Nonlinear Sciences and Numerical Simulation, 7, 191-196.

Barsky, R. B., Kilian, L. 2002. Do we really know that oil caused the great stagflation? A monetary alternative. In: Bernanke, B., Rogoff, K., (eds), NBER Macroeconomics Annual, 2001, 137-183.

Baumeister, C., Peersman, G. 2013. The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. Journal of Applied Econometrics, 28, 1087-1109.

Bekiros, S., Diks, C. 2008. The relationship between crude oil spot and futures: Cointegration, linear and nonlinear causality. Energy Economics, 30, 2673-2685.

Bentzen, J. 2007. Does OPEC influence crude oil prices? Testing for co-movements and causality between regional crude oil prices. Applied Economics, 39, 1375-1385.

Ben Nasr, A., Ajmi, A.N., Gupta, R. 2014. Modeling the volatility of the Dow Jones islamic market world index using a fractionally integrated time varying GARCH (FITVGARCH) model. Applied Financial Economics, 24, 993-1004.

Berck, P., Roberts, M. 1996. Natural resource prices: will they ever turn up? Journal of Environmental Economics and Management, 31, 65-78.

Bhar, R., Hammoudeh, S., Thompson, M. 2008. Component structure for nonstationary time series: Application to benchmark oil prices. International Review of Financial Analysis, 17, 971-983.

Bierens, H. J. 1997. Testing the unit root with drift hypothesis against nonlinear trend stationarity with an application to the US price level and interest rate. Journal of Econometrics, 81, 29-64.

Bildirici, M., Ömer Ersin, Ö. 2014. Nonlinearity, volatility and fractional integration in daily oil prices: Smooth transition autoregressive ST-FI(AP)GARCH models. Journal for Economic Forecasting, 3, 108-135.

Bollerslev, T., Wright, J.H. 2000. High frequency data, frequency domain inference and volatility forecasting. Review of Economics and Statistics, 83, 596-602.

Cavalcante, J., Assaf, A. 2004. Long range dependence in the returns and volatility of the Brazilian stock market. European Review of Economics and Finance, 3, 5-22.

Chaudhuri, K., Daniel, C. 1998. Long-run equilibrium real exchange rates and oil prices. Economics Letter, 58, 231-238.

Chen, S.S., Chen, H.C. 2007. Oil prices and real exchange rates. Energy Economics, 29, 390-404.

Cheung, Y.W. 1993. Tests for fractional integration. A Monte Carlo investigation. Journal of Time Series Analysis, 14, 331-345.

Cologni A., Manera M. 2009. The asymmetric effects of oil shocks on output growth: A Markov-Switching analysis for the G-7 countries. Economic Modelling, 26, 1-29.

Cotter, J. 2005. Uncovering long memory in high frequency UK futures. European Journal of Finance, 11, 325-337.

Cuestas, J.C., Gil-Alana, L.A. 2016. A non-linear approach with long range dependence based on Chebyshev polynomials. Studies in Nonlinear Dynamics and Econometrics, 23, 445-468.

Cunado, J., Perez de Gracia, F. 2005. Oil prices, economic activity and inflation: Evidence for some Asian economies. The Quarterly Review of Economics and Finance, 45, 65-83.

Dahlhaus, R. 1989. Efficient parameter estimation for self-similar process. Annals of Statistics, 17, 1749-1766.

Dickey, D., Fuller, W. 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74, 427-31.

Diebold, F. X., Inoue, A. 2001. Long memory and regime switching. Journal of Econometrics, 105, 131-159.

Diebold, F.X., Rudebusch, G. D. 1991. On the power of Dickey-Fuller test against fractional alternatives. Economics Letters, 35, 155-160.

Ding, Z., Granger, C. W. J., Engle, R. F. 1993. A long memory property of stock markets and a new model. Journal of Empirical Finance, 1, 83-106.

Durbin, J. 1970. Testing for serial correlation in least squares regression when some of the regressors are lagged dependent variables. Econometrica, 38, 410-421.

Dvir, E, Rogoff, K. 2010. Three epochs of oil. Mimeo, Harvard University.

Elder, J., Serletis, A. 2008. Long memory in energy futures prices. Review of Financial Economics, 17, 146-155.

Elliot, G., Rothenberg, T. J., Stock, J. H. 1996. Efficient tests for an autoregressive unit root. Econometrica, 64, 813-836.

Erten, B., Ocampo, J.A. 2013. Super cycles of commodity prices since the Mid-Nineteenth Century. World Development, 44, 14-30.

Fattouh, B. 2010. Energy subsidies in the Middle East: Issues and implications. Presentation to the conference: Increasing the momentum of fossil-fuel subsidy Reform, Geneva.

Fattouh, B. 2011. An anatomy of the crude oil price system. WPM 40, Oxford Institute for Energy Studies.

Fattouh, B., Kilian, L., Mahadeva, L. 2013. The role of speculation in oil markets: What have we learned so far? Energy Journal, 34, 7-33.

Ferreira, P., Soares, I., Araújo, M. 2005. Liberalisation, consumption heterogeneity and the dynamics of energy prices. Energy Policy, 33, 2244-2255.

Fuller, W.A. 1976. Introduction to Statistical Time Series. Willey, New York.

Gil-Alana, L.A. 2003. Fractional integration in the volatility of asset returns. European Review of Economics and Finance, 2, 41-52.

Gil-Alana, L. A. 2004. The use of the Bloomfield (1973) model as an approximation to ARMA processes in the context of fractional integration. Mathematical and Computer Modelling, 39, 429-436.

Gil-Alana, L.A. 2005. Long memory in daily absolute and squared returns in the Spanish stock market. Advances in Investment Analysis and Portfolio Management, 1, 198-217.

Gil-Alana, L.A. 2008. Fractional integration and structural breaks at unknown periods of time. Journal of Time Series Analysis, 29, 163-185.

Gil-Alana, L.A., Hualde, J. 2009. Fractional integration and cointegration. An overview with an empirical application. The Palgrave Handbook of Applied Econometrics, Volume 2. Edited by Terence C. Mills and Kerry Patterson, MacMillan Publishers, 434-472.

Godfrey, L. G. 1978a. Testing against general autoregressive and moving average models when the regressors include lagged dependent variables. Econometrica, 43, 1293-1301.

Godfrey, L. G. 1978b. Testing for higher order serial correlation in regression equations when the regressors include lagged dependent variables. Econometrica, 43, 1303-1310.

Gourieroux, C., Jasiak, J. 2001. Memory and infrequent breaks. Economics Letters, 70, 29-41.

Granger, C.W.J., Ding, Z. 1996. Varieties of long memory models. Journal of Econometrics, 73, 61-77.

Granger, C.W.J., Hyung, N. 2004. Occasional structural breaks and long memory with an application to the SP 500 absolute stock returns. Journal of Empirical Finance, 11, 399-421.

Hamilton, J. D. 1983. Oil and the macroeconomy since World War II. Journal of Political Economy, 91, 228-248.

Hamilton, J. D. 1996. This is what happened to the oil price-macroeconomy relationship. Journal of Monetary Economics, 38, 215-220.

Hamilton, J. D. 2003. What is an oil shock? Journal of Econometrics, 113, 363-398.

Hamilton, J. D. 2009. Causes and consequences of the oil shock of 2007-08. Brookings Papers on Economic Activity, 40, 215-283.

Hamilton J. D. 2013. Historical oil shocks. Routledge Handbook of Major Events in Economic History, 239-265.

Hamming, R. W. 1973. Numerical methods for scientists and engineers, Dover.

Hassler, U., Wolters, J. 1994. On the power of unit root tests against fractional alternatives. Economics Letters 45, 1-5.

Hurst, H. E. 1951. Long-term storage capacity of reservoirs. Transactions of the American Society of Civil Engineering, 116, 770-779.

Jahan-Parvar, M., Mohammadi, H. 2011. Oil prices and real exchange rates in oil-exporting countries: a bound testing approach. Journal of Developing Areas, 25, 309-318.

Jawadi, F., Bellalah, M. 2011. Nonlinear mean reversion in oil and stock markets. Review of Accounting and Finance, 10, 316-326.

Kaufmann, R. K. 2011. The role of market fundamentals and speculation in recent price changes for crude oil. Energy Policy, 39, 105-115.

Kaufmann, R. K., Ullman, B. 2009. Oil prices, speculation, and fundamentals: Interpreting causal relations among spot and futures prices. Energy Economics, 31, 550-558.

Kilian L. 2008a. Exogenous oil supply shocks: how big are they and how much do they matter for the U.S. economy? Review of Economics and Statistics, 90, 216-240.

Kilian L. 2008b. The economic effects of energy price shocks. Journal of Economic Literature, 46, 871-909.

Kilian L. 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review, 99, 1053-1069.

Kilian L. 2014. Oil price shocks: causes and consequences. Annual Review of Resource Economics, 133-154.

Kilian, L., Lee, T.K. 2014. Quantifying the speculative component in the real price of oil: The role of global oil inventories. Journal of International Money and Finance, 42, 71-87.

Kilian, L., Murphy, D.P. 2012. Why agnostic sign restrictions are not enough: understanding the dynamics of oil market VAR models. Journal of the European Economic Association, 10, 1166-1188.

Koenker, R. 1981. A note of studentizing a test for heteroscedasticity. Journal of Econometrics, 17, 107-112.

Lardic, S., Mignon, V. 2008. Oil prices and economic activity: an asymmetric cointegration approach. Energy Economics, 30, 847-855.

Lee, J., List, J.A., Strazicich, M.C. 2006. Non-renewable resource prices: deterministic or stochastic trends. Journal of Environmental Economics and Management, 51, 354-370.

Lee, D., Schmidt, P. 1996. On the power of the KPSS test of stationarity against fractionally integrated alternatives. Journal of Econometrics, 73, 285-302.

Li, J., Thompson, H., 2010. A note on the oil price trend and GARCH shocks. The Energy Journal, 31, 185-196.

Lobato, I.N., Savin, N.E. 1998. Real and spurious long memory properties of stock-market data. Journal of Business and Economic Statistics, 16, 261-268.

Mills, T.C., Markellos, R.N. 2008. The Economic Modelling of Financial Time Series. 3 Ed. Cambridge University Press, New York.

Mork, K.A. 1989. Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results. Journal of Political Economy, 91, 740-744.

Moshiri, S., Foroutan, F. 2006. Forecasting nonlinear crude oil futures prices. Energy Journal, 27, 81-95.

Mu, X., Ye, H. 2015. Small trends and big cycles in crude oil prices. Energy Journal, 36, 49-72.

Naccache T. 2010. Slow oil shocks and the "weakening of the oil price-macroeconomy relationship". Energy Policy, 38, 2340-2345.

Ohanissian, A., Russell, J.R., Tsay, R.S. 2008. True or spurious long memory? A new test, Journal of Business and Economic Statistics, 26, 161-175.

Perron, P. 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica, 57, 1361-1401.

Perron, P., Qu, Z. 2010. Long memory and level shifts in the volatility of stock market return indices. Journal of Business and Economic Statistics, 28, 275-290.

Phillips, P. 1987. Time series regression with a unit root. Econometrica, 55, 277-301.

Phillips, P., Perron, P. 1988. Testing for a unit root in time series regression. Biometrika, 75, 335-346.

Phillips, P.C.B., Shimotsu, K. 2004. Local Whittle estimation in nonstationary and unit root cases. Annals of Statistics 32, 656-692.

Pindyck, R.S. 1978. The optimal exploration and production of nonrenewable resources. Journal of Political Economy, 86, 841-861.

Pindyck, R.S. 1980. Uncertainty and exhaustible resource markets. Journal of Political Economy, 80, 1203-1225.

Pindyck, R.S. 1999. The long-run evolution of energy prices. Energy Journal, 20, 1-27.

Postali, F., Picchetti, P. 2006. Geometric Brownian motion and structural breaks in oil prices: a quantitative analysis. Energy Economics, 28, 506-522.

Qu, Z. 2011. A test against spurious long memory. Journal of Business and Economic Statistics, 29, 423-438.

Ramsey, J.B. 1969. Tests for specification errors in classical linear least squares regression analysis. Journal of the Royal Statistical Society, Series B 31, 350-371.

Robinson, P.M. 1995a. Gaussian semi-parametric estimation of long range dependence. Annals of Statistics, 23, 1630-1661.

Robinson, P.M. 1995b. Log-periodogram regression of time series with long range dependence. Annals of Statistics, 23, 1048-1072.

Serletis, A., Gogas, P. 1999. The North American natural liquid gas markets are chaotic. The Energy Journal, 20, 83-103.

Shimotsu, K. 2006. Simple (but effective) tests of long memory versus structural breaks. Working paper, Queen's University.

Sibbertsen, P. 2004. Long memory in volatilities of German stock returns. Empirical Economics, 29, 477-488.

Smyth, G.K. 1998. Polynomial Aproximation. John Wiley & Sons, Ltd, Chichester, 1998.

Sowell, F.B. 1992b. Maximum likelihood estimation of stationary univariate fractionally integrated time series models. Journal of Econometrics, 53, 165-188.

Tomasevic, N.M., Stanivuk, T. 2009. Regression analysis and approximation by means of Chebyshev polynomial. Informatologia, 42, 166-172.

Tsay, R.S. 2002. Analysis of Financial Time Series. John Willey & Sons, Inc. New York.

Tsen, W. 2011. The real exchange rate determination: An empirical investigation. International Review of Economics and Finance, 20, 800-811.

Vansteenkiste, I. 2011. What is driving oil futures prices? Fundamentals versus speculation. ECB, Working Paper Series No 1371.

Zellou, A., Cuddington, J.T. 2012. Is there evidence of super cycles in oil prices? SPE Economics and Management, 4, 171-181.

Zhang, Y.J., Fan, H.T., Wei, Y.M. 2008. Spillover effect of US dollar exchange rate on oil prices. Journal of Policy Modeling, 30, 973-991.

Zhou, S. 1995. The response of real exchange rates to various economic shocks. Southern Economic Journal, 61, 936-954.

Zivot, E., Andrews, D. 1992. Further evidence on the great crash, the oil-price shock, and the unit root hypothesis. Journal of Business and Economic Statistics, 10, 251-270.

Chapter 2

Fractional integration and cointegration in merger and acquisitions in the U.S. petroleum industry

This paper employs methodologies based on fractional integration and cointegration to analyse the time series properties of Merger and Acquisitions (M&A) activity and crude oil prices in the United States from 1980 to 2012. Our results indicate that an increase in the crude oil price produces a significant increase in the M&A data between 2 and 3 months after the initial shock.

2.1 Introduction

There are different sources and sets of Mergers and Acquisitions (M&A) data, and they all confirm the existence of several peaks of activity during more than a century of history. According to Resende (1996), the empirical studies on mergers can be broadly divided into two categories: reduced form regressions and time series analysis. Focusing on the second category, it aims to describe the stochastic process generating the data in order to shed light on the apparently erratic behaviour of mergers.

Recent empirical macroeconomic literature has paid considerable attention to the distinction between the polar cases of transitory shocks (associated with trend stationary processes) and permanent shocks (related to difference stationary processes); however, as emphasized by Diebold and Nerlove (1989), rather than seek sharp testing of unit roots, one should be concerned with the assessment of the degree of persistence observed in the series. The present paper analyses the mergers and acquisitions in the petroleum industry and the WTI crude oil prices in the United

States between 1980 and 2012 using monthly data with the aim of investigating and measuring the degree of persistence of the series. The data were obtained from Thomson Reuters SDC Platinum M&A database[1] and US Department of Energy[2], respectively.

The present study makes the following two-fold contribution. Firstly, it applies univariate tests based on long memory in order to establish the order of integration of the individual series, extending the analysis from the I(1)/I(0) cases to the more general case of fractional integration. Secondly, it examines bivariate relationships between the variables using some of the most recent fractional cointegration techniques, which also allows for slow adjustment to equilibrium. Based on the lack of evidence of cointegrating relationships, we finally examine a regression model where lagged oil prices are used as an explanatory variable in the analysis of M&A data still in the context of fractional integration. Our results suggest that an increase in oil prices produces a significant increase in M&A two or three months after the initial shock. The implications of the findings are also discussed. The paper is organized as follows. In Section 2, we discuss the empirical results. Finally, Section 3 concludes.

2.2 Empirical results

The data examined in this work correspond to the mergers and acquisitions in the petroleum industry and the WTI crude oil prices in the United States between 1980 and 2012 using monthly data. The US mergers and acquisitions data are daily, obtained from the Thomson Reuters SDC Platinum M&A database. We considered the number of mergers and acquisitions from each day between January 1980 and June 2012 to obtain the monthly data. The West Texas Intermediate (WTI) crude oil price series is monthly, and obtained from the US Department of Energy. The database was in nominal prices and we deflated to real prices, using 2011 as the base year.

[1] We considered aggregated data of the daily number of Merger and Acquisition (M&A) data from 1980 to 2012.
[2] The database was in nominal prices, and we deflated to real prices, using 2011 as the base year.

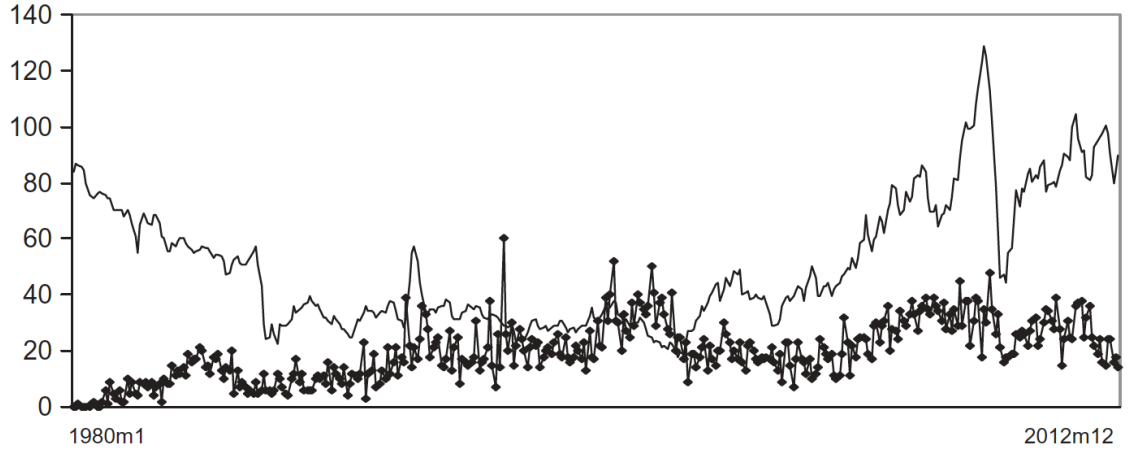

Figure 2: Time-series plots: M&A and oil prices.
Note: The strong line refers to the M&A data. The thin line is crude oil prices.

We first conducted standard unit root tests (ADF, Dickey and Fuller, 1979; ERS, Elliot et al. 1996; PP, Phillips and Perron, 188 and KPSS, Kwiatkowski et al., 1992) on the two series and the results were very ambiguous depending on the methodology used and the assumptions made on the error term[3].

Table 1 displays the estimates of d and their associated 95% confidence bands in a model of form:

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, ... \tag{2.1}$$

where y_t is the observed time series (in our case, M&A and oil prices), x_t is $I(d)$ and therefore u_t is supposed to be $I(0)$, adopting the forms of white noise, AR(1) and Bloomfield-type autocorrelated disturbances. We estimate the fractional differencing parameter d for the three standard cases examined in the literature, i.e., the case of no deterministic terms (i.e., $\beta_0 = \beta_1 = 0$ a priori in the undifferenced equation (2.1)), including only a constant (β_0 unknown, and $\beta_1 = 0$ a priori), and finally the case of a constant with a linear time trend (β_0 and β_1 unknown). Together with the estimates, we also present the 95% confidence band of the non-rejection values of d, using a Whittle estimate in the frequency domain.

Table 1 displays the estimates of d using a parametric approach (Dahlhaus, 1989). Starting with the results for the M&A data, the first thing we observe is that the results are very similar for the three cases of the deterministic components and also across the different types of disturbances. We see that the estimated value of d is very close to 0.5, that is, it is in the boundary line between stationary and nonstationary processes. However, for the real oil prices, a different picture emerges, and very different results are obtained depending on our specification for the error term. Thus, if

[3]These results are available from the authors upon request.

u_t is white noise, d is significantly higher than 1. On the other hand, if u_t is AR(1), the estimated value of d is statistically lower than 1, while if we impose the non-parametric approach of Bloomfield (1973), the unit root null (i.e., $d = 1$) cannot be rejected.

i) Merger and Acquisitions			
u_t	No regressors	An intercept	A linear time trend
White noise	0.38 (0.33, 0.44)	0.42 (0.38, 0.47)	0.39 (0.34, 0.45)
AR (1)	0.48 (0.41, 0.57)	0.51 (0.40, 0.58)	0.50 (0.43, 0.58)
Bloomfield – type	0.52 (0.43, 0.63)	0.54 (0.48, 0.65)	0.53 (0.44, 0.65)
ii) Oil prices			
u_t	No regressors	An intercept	A linear time trend
White noise	1.12 (1.02, 1.24)	1.25 (1.14, 1.38)	1.25 (1.14, 1.38)
AR (1)	0.21 (0.14, 0.28)	0.68 (0.58, 0.79)	0.67 (0.57, 0.79)
Bloomfield – type	0.88 (0.77, 1.04)	0.89 (0.77, 1.07)	0.89 (0.77, 1.07)

Table 1: Estimates of d and 95% confidence intervals.
Note: The values in parenthesis refer to the 95% band of the estimates of d.

	M & A	Oil prices	Lower I(1)	Upper I(1)
17	0.757	0.752	0.800	1.199
18	0.816	0.766	0.806	1.193
19	0.789	0.721	0.811	1.188
20	0.728	0.711	0.816	1.183
21	0.773	0.729	0.820	1.179
22	0.726	0.729	0.824	1.175
23	0.761	0.723	0.828	1.171

Table 2: Estimates of d based on a local Whittle semiparametric approach.
Note: m is the bandwidth number. The lower and upper bands refer to the 95% level.

Due in part to this disparity in the results for the oil prices depending on the specification for the error term, we also conducted a semiparametric method, also based on a Whittle estimate of d (Robinson, 1995). The results are now displayed in Table 2. We observe here that the estimated values of d are in the range (0.721, 0.816) depending on the bandwidth number, and the unit root null is now rejected in all cases in favour of mean reversion ($d < 1$).

Next we focus on a potential cointegrating relationship between the two variables, and the first thing we do is to test the homogeneity condition, i.e., that the two individual series display the same degree of integration. Here we employed an adaptation of the Robinson and Yajima (2002) statistic to the Whittle estimation results in Table 2, and the result strongly support the hypothesis

of equal orders of integration in the two series. In the second step, we perform the Hausman test for no cointegration of Marinucci and Robinson (2001) comparing the estimate of $\hat{d}_x$ with the more efficient bivariate one of Robinson (1995b), which uses the information that $d_x = d_y = d^*$. The results here support the null of no cointegration between the two series since the order of integration of the residuals is also in the range (0.7, 0.8), i.e., the same as in the two individual series.

i) White noise disturbances			
k	d (95% confidence band)	β_0 (t-value)	β_1 (t-value)
0	0.42 (0.38, 0.46)	9.884 (2.29)	0.034 (0.73)
1	0.42 (0.38, 0.46)	9.233 (2.39)	0.046 (0.98)
2	**0.42 (0.38, 0.46)**	**6.521 (1.58)**	**0.091 (1.94)**
3	**0.42 (0.38, 0.46)**	**6.514 (1.58)**	**0.091 (1.93)**
4	0.42 (0.38, 0.46)	10.125 (2.44)	0.036 (0.77)
5	0.42 (0.38, 0.46)	9.301 (2.24)	0.051 (1.08)
6	0.42 (0.38, 0.46)	13.089 (3.14)	-0.005 (-0.11)
7	0.42 (0.38, 0.47)	15.804 (3.80)	-0.044 (-0.93)
8	0.42 (0.38, 0.47)	16.038 (3.85)	-0.045 (-0.95)
9	0.42 (0.38, 0.46)	15.271 (3.78)	-0.028 (-0.60)
10	0.42 (0.38, 0.46)	16.875 (4.04)	-0.056 (-1.16)
11	0.42 (0.38, 0.47)	17.531 (4.20)	-0.060 (-1.24)
12	0.41 (0.37, 0.46)	15.768 (3.90)	-0.020 (-0.43)
ii) Autocorrelated (Bloomfield) disturbances			
k	d (95% confidence band)	β_0 (t-value)	β_1 (t-value)
1	0.54 (0.47, 0.64)	4.193 (0.72)	0.037 (0.65)
0	0.54 (0.47, 0.64)	3.681 (0.19)	0.045 (0.80)
2	**0.56 (0.48, 0.66)**	**-2.350 (-0.38)**	**0.120 (2.06)**
3	**0.56 (0.48, 0.66)**	**-2.847 (-0.46)**	**0.124 (2.11)**
4	0.54 (0.47, 0.64)	4.907 (0.84)	0.031 (-0.55)
5	0.54 (0.47, 0.64)	2.155 (0.37)	0.072 (-1.26)
6	0.54 (0.48, 0.65)	8.420 (1.44)	-0.012 (-0.21)
7	0.55 (0.47, 0.65)	12.376 (2.06)	-0.066 (-1.14)
8	0.55 (0.47, 0.65)	12.176 (2.02)	-0.059 (-1.01)
9	0.54 (0.47, 0.64)	9.691 (1.65)	-0.024 (-0.42)
10	0.55 (0.47, 0.64)	12.933 (2.14)	-0.070 (-1.18)
11	0.55 (0.47, 0.64)	14.420 (2.38)	-0.078 (-1.32)
12	0.55 (0.46, 0.64)	10.832 (1.79)	-0.014 (-0.23)

Table 3: Estimates of d and regression coefficients in the model given by (2).
Note: Bold values indicate the significant coefficients at the 5% level.

As a final step, we check if crude oil prices might have had any influence in the number of M&A, and based on the fractional nature of the series examined, we consider the following model,

$$y_t = \beta_0 + \beta_1 z_{t-k} + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, ... \tag{2.2}$$

where y_t is now the M&A data, and z_t is the crude oil prices, with $k = 0$ (immediate effect) and assuming also a lagged effect ($k = 1, ..., 12$) of a maximum of one year of duration[4]. The results in terms of the β_1-coefficient and the differencing parameter d are displayed in Table 3, for the two cases of uncorrelated and autocorrelated (Bloomfield) errors. The most interesting feature observed here is that the estimated value of d is around 0.42 for the white noise case, and it is slightly higher, about 0.55, with Bloomfield disturbances, and in the two cases, we only observe two values of k where the β_1-coefficient is statistically significant. These values are 2 and 3, implying that an increase in the crude oil price produces an increase in the M&A data between 2 and 3 months after the initial shock.

2.3 Concluding remarks

In this chapter we have examined the relationship between M&A and crude oil prices by means of using fractionally integrated techniques. First we show that the two individual series display a high degree of persistence though the series seem to be mean reverting with shocks disappearing in the very long run. Testing the hypothesis of (fractional) cointegration, we see that this is rejected and thus, we consider, as a potential specification, a regression model in which lagged oil prices appear as an explanatory variable in the analysis of M&A data. Our results indicate that an increase in the crude oil price produces an increase in the M&A data between 2 and 3 months after the initial shock.

[4]Note that more dynamics are obtained throughout the autocorrelated structure from the I(0) error term.

2.4 References

Bloomfield, P. 1973. An exponential model for the spectrum of a scalar time series. Biometrika, 60, 217-226.

Dahlhaus, R. 1989. Efficient parameter estimation for self-similar process. Annals of Statistics, 17, 1749-1766.

Dickey, D., Fuller, W. 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74, 427-31.

Diebold, F.X., Nerlove, M. 1989. Unit roots in economic time series: a selected survey. Advances in Econometrics, 8, 3-69.

Elliot, G., Rothenberg, T.J., Stock, J.H. 1996. Efficient tests for an autoregressive unit root. Econometrica, 64, 813-836.

Kwiatkowski, D., Phillips, P.C., Schmidt, P., Shin, Y. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. Journal of econometrics, 54, 159-178.

Marinucci, D., Robinson, P. M. 2001. Semiparametric fractional cointegration analysis. Journal of Econometrics, 105, 225-247.

Phillips, P., Perron, P. 1988. Testing for a unit root in time series regression. Biometrika, 75, 335-346.

Resende, M. 1996. Mergers and acquisitions in the UK: a disaggregated analysis. Applied Economics Letters, 3, 637-640.

Robinson, P.M. 1995. Gaussian semi-parametric estimation of long range dependence. Annals of Statistics, 23, 1630-1661.

Robinson, P.M., Yajima, Y. 2002. Determination of cointegrating rank in fractional systems. Journal of Econometrics, 106, 217-241.

Chapter 3

Are mergers and acquisitions in the petroleum industry affected by oil prices?

In this chapter, we contribute to the literature on crude oil price behavior and examine how this affects mergers and acquisitions in the petroleum industry in the U.S. We analyze the relationship of these two series by studying its dynamic in the time-frequency domain. The novelty of our approach lies in the application of wavelet tools for its resolution. We use monthly data covering the period January 1980 to June 2012. We have observed a shift to higher frequencies of the wavelet coherency during the mid-1990s and late 2000s. The results also indicate that during the mid-1990s and late-2000s an increase in mergers and acquisitions took place that was led by the increase in WTI crude oil prices.

3.1 Introduction

Energy commodities are very important in economic research because affect different markets and different participants. According to Hamilton (1983, 1985); Gisser and Goodwin (1986); Aguiar-Conraria and Wen (2007) and Kilian (2008), in the U.S. there is empirical evidence that until the mid-1980s, oil prices were determinant in economic activity from the point of view of the behaviour of the crude oil.

The researches related with the merger waves in the U.S. of the mid 1980s are described by Nelson (1959), Golbe and White (1988, 1993), and Mitchell and Mulherin (1996). The merger waves of the mid 1990s are described by Andrade et al. (2001) and Harford (2005). Ravenscraft (1987), Shleifer and Vishny (1990) and Holmstrom and Kaplan (2001) have been able to research the causes that trigger the merger waves from the previous researches cited.

Empirical literature suggests that the mergers and acquisitions (M&A) occur in waves. Golbe and White (1993) have tried to identify waves applying sine curve's methodology to historic merger data. Clark et al., (1988), Chowdhury (1993), Barkoulas et al. (2001) and Monge and Gil-Alana (2016) have modelled the wave behaviour using autoregressive processes. And there are others researches like Town (1992), and Resende (1999) have modelled the merger series by using switching models.

In the cited papers, the analysis has been carried out exclusively in the time-domain and hasn't into consideration the frequency-domain. It is common to utilize Fourier analysis to analyse the different relations at different frequencies, omitting the time information, being difficult to identify structural changes with this type of analysis. Our empirical paper tries to explain the merger waves, using wavelet methodology. This methodology is a time-frequency technique that it is able to analyze the evolution of the different frequency components of the time series across time. Applying the wavelet transform it is possible to detect the evolution in time the low frequency. This low frequency is related with the trend or long run component in the time series. Also, applying the wavelet transform we can detect the evolution in time the high frequency components that are related with the seasonality or short run component and the rapid changes in the time series[1].

In our empirical analysis, we use wavelet methodology to analyse the relationship between oil price and mergers and acquisitions in the petroleum industry. Following Aguiar-Conraria and Soares (2011a,b), two tools are used: the wavelet coherency and wavelet phase-difference. The wavelet coherence is a localized correlation coefficient in the time-frequency space. The information on the delay between the oscillations of two time-series is the phase-difference. These concepts have been cited by Aguiar Conraria and we are according with them.

This paper contributes in the field of the waves in M&A in companies belonging to the petroleum industry using wavelet analysis. We study the relation between WTI crude oil prices and M&A in the petroleum industry in the U.S. for the time period 1980-2012, as Aguiar Conraria and Soares (2011) and Naccache (2011) had done previously in their research, analyzing the relationship between oil price and the economy. The analysis is performed in the time-frequency domain, using wavelet analysis. According with Aguiar Conraria and Soares (2011), we use this methodology for three reasons. First, stationarity is not require in the wavelet analysis (in our case, oil prices are non stationary). On the other hand, we can study how relations evolve between time and frequencies with wavelet analysis. And the last reason is related with energy markets and the research by Kyrtsos et al. (2009). He arrives to the conclusion that several energy markets display consistent

[1] Hogan and Lakey (2005) worked about the comparison between time-frequency and time-scale (wavelets) methods.

non-linear dependencies.

We study the relationship in the time-frequency space between WTI oil prices and mergers and acquisitions in petroleum industry. We use monthly data on M&A in the petroleum industry of the U.S. and WTI crude oil prices to estimate the coherence between these variables. This analysis will allow us to characterize how the relationship evolves. In 1995 to 1997 there is high coherency in the 1-2 year band. Also, in 1995 to 2001 there is high coherency in the 3-6 year band and in 2005 to 2009 there is high coherency in the 1.3-2.5 year band.

The paper is organized as follows: In Section 2 we provide a brief introduction to the mathematics of wavelets and explain how to derive the metric that we use to compare the oil prices and mergers and acquisitions in the petroleum industry. We describe the data and present the main results in Section 3, while Section 4 concludes.

3.2 Methodology

3.2.1 Wavelet analysis

The wavelet transform offers localized frequency decomposition, providing information about frequency components. Wavelets have significant advantages over basic Fourier analysis when the series under study is stationary –see Gençay et al., (2002), Percival and Walden (2000) and Ramsay (2002). In our research we use continuous wavelet analysis tools, mainly wavelet coherence, measuring the degree of local correlation between two-time series in the time-frequency domain, and the wavelet coherence phase differences.

The continuous wavelet transform

The continuous wavelet transform of a time series $x(t)$, with respect to the wavelet ψ, is a function $WT_x(a,\tau)$ defined as:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x_t \psi^*_{a,\tau}(t)\, dt \tag{3.1}$$

where $WT_x(a,\tau)$ are the wavelet coefficients of $x(t)$ at a certain scale a and a shift τ, where,

$$\psi^*_{a,\tau} = \frac{1}{\sqrt{a}}\, \psi^* \left(\frac{t-\tau}{a} \right) \tag{3.2}$$

is the complex conjugate of the wavelet function ψ. The parameter a is a scaling factor that controls the stretching factor of the wavelet and τ is a location parameter in time. Then, $WT_x(a,\tau)$, is going to be a matrix of time series. The scaling factor a is a positive real number that simply means stretching it (if $a > 1$), or compressing it (if $a < 1$). If a is positive, we assume that we are using an analytic or progressive wavelet, i.e., its Fourier transform is defined on the positive frequency axis, $\Psi(\omega) = 0$ when $\omega < 0$.

The lower the value of the scaling factor, the higher frequency components are reflected in the continuous wavelet transform, thus we are dealing with the short-run components of the signal. As the scaling factor increases, we deal with lower frequency components of the time series, we focus on the long-run components. Then, the continuous wavelet transform is a multidimensional transform; from one time series we obtain a matrix of time series that show different frequency components (depending on the scaling factor) of the original one.

If the wavelet function ψ is complex, then the wavelet transform $WT_x(a,\tau)$ will also be complex, with amplitude,$|WT_x(a,\tau)|$, and phase, $\phi_x(a,\tau)$. The real part of the wavelet transform, $\Re\{WT_x\}$, and its imaginary part, $\Im\{WT_x\}$ define the phase or phase-angle of the wavelet transform:

$$\phi_x = Arctan\left(\frac{\Im m\{WT_x\}}{\Re e\{WT_x\}}\right) \tag{3.3}$$

The phase of a given time-series x_t is measured in radians, ranging from $-\pi/2$ to $+\pi/2$. Then, the phase is also a matrix containing the angle of each frequency component of the original time series. The phase will be used to extract conclusions of the synchronism between two time series, applying the wavelet coherency and the phase difference between time series (Aguiar-Conraria and Soares, 2011a, 2011b and 2014).

The wavelet or mother wavelet used to analyze the time series must satisfy certain technical conditions to provide effective time-frequency location properties (Daubechies, 1992). First, it has to be a function of finite energy, $\int_{-\infty}^{+\infty} \psi(t)\, dt = 0$. There are many different wavelet families, but the election of a certain wavelet will depend on the application itself.

Related to time localization properties, we can normalize the wavelet function so that $\int_{-\infty}^{+\infty} |\psi(t)|^2\, dt = 1$. $|\psi(t)|^2$ defines a probability density function, and therefore we can obtain the mean, μ_ψ, and the standard deviation, σ_ψ, of this distribution. They are called the center and the radius of the wavelet, respectively. If we consider the Fourier transform of the mother wavelet, $\Psi(\omega)$, in a similar way we can calculate its mean and standard deviation, μ_Ψ and σ_Ψ.

These quantities define the Heisenberg box in the time-frequency plane: $[\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi] \times [\mu_\Psi - \sigma_\Psi, \mu_\Psi + \sigma_\Psi]$. We say that Ψ is localized around the point (μ_ψ, μ_Ψ) of the time-frequency

plane with an uncertainty given by $\sigma_\psi \sigma_\Psi$. In our context, the Heisenberg's uncertainty principle establishes that $\sigma_\psi \sigma_\Psi \geq 1/2$.

The Morlet wavelet,

$$\psi(t) = \pi^{1/4} e^{i\omega_0 t} e^{-t^2/2} \tag{3.4}$$

is a complex valued wavelet, so we will be able to measure the synchronism between two time series. This wavelet has optimal time-frequency concentration, in the sense that $\sigma_\psi \sigma_\Psi = 1/2$. Therefore, using this wavelet, we have the optimum trade off between time and frequency resolution. On the other hand, the Morlet can be considered as a wavelet (with finite energy, defined as before) when the frequency parameter $\omega_0 = 6$. For this value of the Morlet wavelet, the wavelet scale, a, satisfies the inverse relation $f \approx 1/a$, as the rest of the most used mother wavelets.

Wavelet and cross wavelet power spectrum, and wavelet coherency

The wavelet power spectrum (WPS) or the scalogram of a time series $x(t)$, as it is called, is the squared amplitude of the wavelet transform, that is: $WPS_x(a,\tau) = |WT_x(a,\tau)|^2$. The wavelet power spectrum let us know the distribution of the energy (spectral density) of a time-series across the two-dimensional time-frequency representation.

While the wavelet power spectrum shows the variance of a time-series in the time-frequency plane, the cross wavelet power spectrum (CWPS) of two time-series and shows the covariance between these time-series in the time-frequency plane:

$$CWPS_{xy}(a,\tau) = |WT_x(a,\tau) WT_y(a,\tau)^*| \tag{3.5}$$

where the * represents the complex conjugate, as before.

Therefore, the complex wavelet coherency between two time-series $x(t)$ and $y(t)$ is defined as the ratio of the cross-spectrum and the product of the power spectrum of both series:

$$WCO_{xy} = \frac{SO(WT_x(a,\tau) WT_y(a,\tau)^*)}{\sqrt{SO(|WT_x(a,\tau)|^2) SO(|WT_y(a,\tau)|^2)}} \tag{3.6}$$

where SO is a smoothing operator in both time and scale. Without the smoothing operator, the wavelet coherency would be always one at all times and scales (see Aguiar-Conraria et al. (2008) for details).

As the WCO_{xy} is a matrix of complex time series, we can split it again into amplitude and phase, $WCO_{xy} = |WCO_{xy}|\, e^{i\phi_{xy}}$. The amplitude matrix is the wavelet coherency, WC_{xy} and the angle ϕ_{xy} is called the phase difference between both time series:

$$\phi_{xy} = Arctan\left(\frac{\Im m\{WCO_{xy}\}}{\Re e\{WCO_{xy}\}}\right) \tag{3.7}$$

ϕ_{xy} is the phase difference between time series $x(t)$ and $y(t)$, and tells us about the synchronism between those time series. ϕ_{xy} ranges from $-\pi$ to π.

On the one hand, if $\phi_{xy} = 0$ then both time series move in phase. This will mean that both time series increases or decreases their values at the same time. If $\phi_{xy}\epsilon(-\frac{\pi}{2}, 0)$, they move in phase but time series $x(t)$ is leading; if $\phi_{xy}\epsilon(0, \frac{\pi}{2})$, time series $y(t)$ is leading. Therefore, in these cases we can find that one time series anticipates the increase or decrease of the other one. On the other hand, a phase difference of π or $-\pi$ indicates an anti-phase relation, when one time series increases, the other one is decreasing in time. Finally, if $\phi_{xy}\epsilon(-\frac{\pi}{2}, -\pi)$, both time series are out of phase but $x(t)$ is leading; if $\phi_{xy}\epsilon(\frac{\pi}{2}, \pi)$, $y(t)$ is leading. In this case this means that one time series has a time delay with respect to the other one.

Significance tests, Monte Carlo simulations

To check the statistical significance of the wavelet coherency, WC_{xy}, we rely on Monte Carlo simulations (Schreiber and Schmitz,1996). We model each time series as an ARMA(p,q) process where $p = q = 1$, with no pre-conditions. Then we assess the statistical significance of the amplitude, not of the phase. The phase difference is not tested as there is no agreement in the scientific community about how to define the procedure. We should only take into account the phase difference when the amplitude of the wavelet coherency is statistically significant.

3.3 Empirical results

The data examined in this work correspond to the M&A in the petroleum industry and WTI crude oil prices[2] in the United States between January 1980 to June 2012 using monthly data.

We considered the daily number of M&A data to form the aggregate monthly series from 1980 to 2012. The database was obtained from Thomson Reuters SDC Platinum M&A database.

WTI crude oil prices were in nominal prices, and we deflated to real prices, using Producer Price Index for All Commodities and using 2011 as the base year.

Figure 1 shows the comparison between the real crude oil price and the Mergers and Acquisitions in the Petroleum Industry in the U.S.

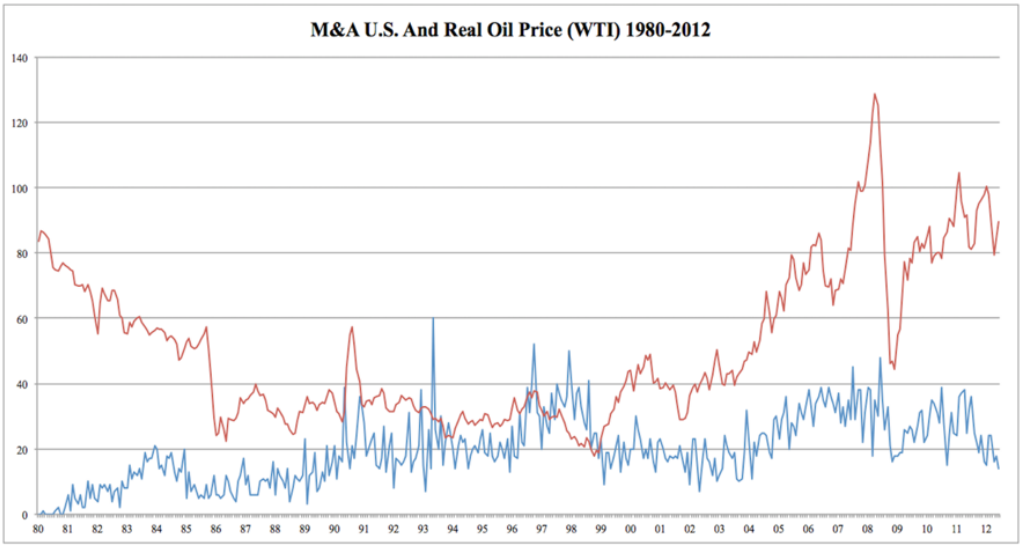

Figure 1: Mergers and Acquisitions in the Petroleum Sector in the US and the WTI Oil Price.

We first estimate the wavelet coherency between the monthly number of mergers and acquisitions in the petroleum industry in U.S. and WTI crude oil prices. We rely on Monte Carlo simulation to test if the similitude of the wavelet coherency is statistically significant. We compute the complex wavelet coherence matrices between a surrogate for WTI crude oil prices and a surrogate for the mergers and acquisitions time series. We do 1000 simulations modelling both time series as an ARMA (p, q) process, with no pre-conditions on p and q, with $p = q = 1$.

We estimate the wavelet coherency for frequencies corresponding to periods between 1.5 and 8 years, which are the ones related to the business cycles (references).

[2]The database was obtained from Dow Jones Company, Spot Oil Price: West Texas Intermediate (DISCONTINUED SERIES)© [OILPRICE], retrieved from FRED, Federal Reserve Bank of St. Louis. `https://research.stlouisfed.org/fred2/series/OILPRICE/`, September 8, 2015.

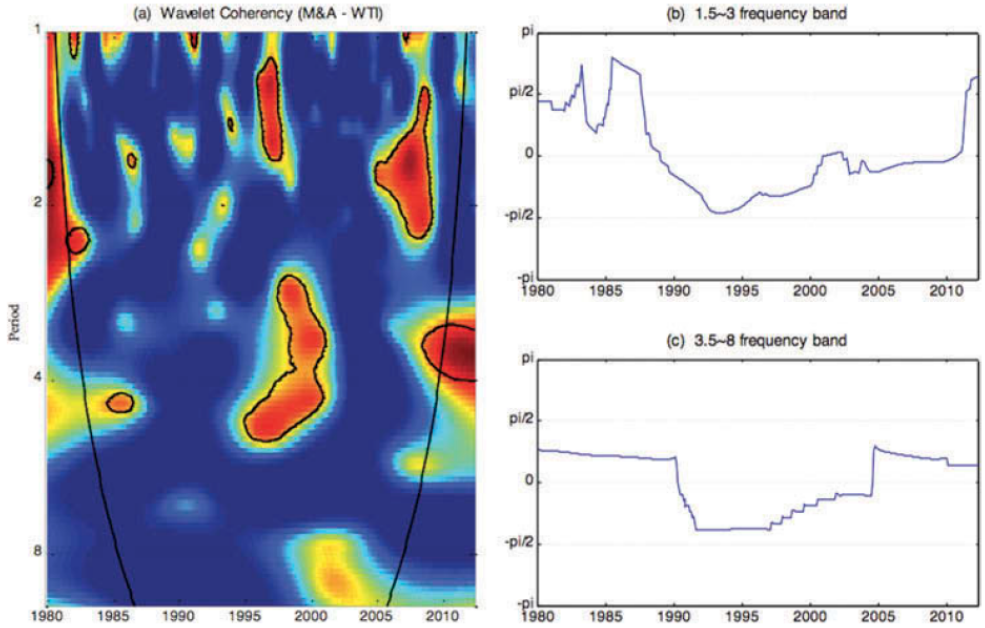

Figure 2: Wavelet coherency and phase-difference between M&A in the petroleum industry in the U.S. and WTI

Note: On the left: Wavelet coherency between M&A in petroleum industry in the U.S. and WTI. On the right: Phase-difference between M&A in the petroleum industry in the U.S. and WTI at $1.5 \backsim 3$ *year (top) and* $3.5 \backsim 8$ *year (bottom) frequency bands.*

In Figure 2 we display the empirical results. On the left panel (a) we have the wavelet coherency between M&A and WTI crude oil prices[3]. On the right, we have the phase-differences: on the top (b) we have the phase-difference in the 1.5-3 year frequency band; at the bottom (c), we have the phase-difference in the 3.5-8 year frequency band. The regions surrounded by the black contour are the high coherency regions with significant values at 5%.

Analysing the wavelet coherency between M&A and WTI crude oil prices, we appreciate that the regions with higher coherency are between the mid-1990s and late-2000s corresponding to the wavelet scales of periods from 1 to 6 year bands. We focus our phase difference analysis on two frequency bands: 1.5-3 and 3.5-8 years. To analyse the wavelet coherency graph, we have to focus in the regions of high coherency of the chart. In those regions we can observe the phase difference of the frequency band to extract some conclusions.

In the 1.5-3 year band, we identify a region of high coherency between the late 1995s and the late 1997s, in frequency bands between 1.1 and 1.7 years with a corresponding phase difference in this band between $-\pi/2$ and 0. This result suggests that WTI oil prices and the Mergers and acquisition time series are in phase, they move together, with WTI oil prices leading. Therefore,

[3]Coherency ranges from blue (low coherency) to red (high coherency). The cone of influence is shown with a thick line, which is the region subject to border distortions.

we can affirm that an increase in mergers and acquisitions is led by the increase in WTI crude oil prices, according to Monge and Gil-Alana (2016).

We can find also a region of high coherency between 1995 to 2001 in the 3.5-8 year band, specifically between the 2.6 and 5 year frequency bands. Again, the phase difference of that period stays between $-\pi/2$ and 0, suggesting the synchronism of both time series, with WTI oil prices leading. Finally, we can find another region of high coherency between 2005 and 2009 in the 1.3-2.5 year band, also presenting phase differences closer to 0. The closer the phase difference values are to 0, the higher the move in phase of both time series.

From this wavelet coherency figure, we can observe a change across time in the common frequency bands between M&A and WTI; there has been a shift to higher frequencies in the 2005 and 2009, suggesting that the influence in this period of time is a short-term relationship, reaching a maximum at the 1.7 year frequency band. This means that the oil shocks influence the M&A faster that in the preceding years. On the other hand, the relationship of both time series in the 1995 to 2001 period had a long term component, i.e., a lower frequency band approximately between 2.6 years and 5 years, suggesting a longer term impact of the oil prices over M&A than in the 2005-2009 period.

With regard to the obtained results, we observe a shift to higher frequencies of the wavelet coherency during mid-1990. According to research from Petitt and Ferris (2013), in the 1990s some companies made mergers and acquisitions to gain access to the knowledge of the acquired assets. Also, some companies viewed this action as an opportunity to consolidate industries characterized by excess market participants and avoid the low profitability. One of the industries affected by this trend include the oil and gas industry (consider the mergers of British Petroleum (BP) and Amoco, and of Exxon and Mobil). Also, with regard to our results we observe a shift to higher frequencies of the wavelet coherency during the mid-2000s. Considering the research from Petitt and Ferris, we conclude that in the 2000s, the low-interest environment joined with the credit availability, produced an increase in LBOs. Also, the Petroleum Industry had increasingly more profits due to an incessant growth of oil prices.

3.4 Conclusions

Unlike most previous studies on waves in mergers and acquisitions, which rely on identifying waves fitting a sine curve to historic data, or modelling by autoregressive processes or by means of parameter-switching models, we rely on time-frequency domain methods. To be more precise, we

used wavelet analysis to study the relationship between mergers and acquisitions in the petroleum industry in the U.S. and oil prices. The regions of high coherency were located at different frequency bands in different time periods. We have observed a shift to higher frequencies of the wavelet coherency during the second half of the 2000s, meaning a short-term influence between oil prices and mergers and acquisitions. The phase differences have consistently been between 0 and $-\pi/2$, suggesting that an increase in mergers and acquisitions is led by the increase in WTI crude oil prices, which is in line with the results reported in Monge and Gil-Alana (2016). Finally, our results also indicate a potential change in the pattern of the relation between the two variables around 1995, where the earlier high coherency region appears. Thus, in future papers we will examine the presence of structural breaks in the relationship around that year.

3.5 References

Aguiar-Conraria, and L., Wen, Y. 2007. Understanding the large negative impact of oil shocks. Journal of Money, Credit and Banking, 39, 925-944.

Aguiar-Conraria, L., Azevedo, N., and Soares, M. J. 2008. Using wavelets to decompose the time-frequency effects of monetary policy. Physica A: Statistical Mechanics and its Applications, 387, 2863-2878.

Aguiar-Conraria, L., and Soares, M.J. 2011a. Oil and the macroeconomy: using wavelets to analyze old issues. Empirical Economics, 40, 645-655.

Aguiar-Conraria, L., and Soares, M.J. 2011b. Business cycle synchronization and the Euro: a wavelet analysis. Journal of Macroeconomics, 33, 477-489.

Aguiar-Conraria, L., and Soares, M.J. 2014. The continuous wavelet transform: moving beyond uni- and bivariate analysis. Journal of Economic Survey, 28, 344-375.

Andrade, G., Mitchell, M.L., and Stafford, E. 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives, 15, 103-120.

Barkoulas, J.T., Baum, C.F., and Chakraborty, A. 2001. Waves and persistence in merger and acquisition activity. Economics Letters, 70, 237-243.

Chowdhury, A.R. 1993. Univariate time-series behaviour of merger activity and its various components in the United States. Applied Financial Economics, 3, 61-66.

Clark, J., Chakrabarti, A. and Chiang, T. 1988. Trend and Stochastic Movements in U.S. Merger Activity. Quarterly Review of Economics and Business, 28, 5-18.

Daubechies, I. 1992. Ten lectures on wavelets. Society for Industrial and Applied Mathematics, Philadelphia.

Gençay, R., Selçuk, F., and Whitcher, B. 2002. An introduction to wavelets and other filtering methods in finance and economics. Academic Press.

Gisser, M., and Goodwin, T.H. 1986. Crude oil and the macroeconomy: Tests of some popular notions: Note. Journal of Money, Credit and Banking, 18, 95-103.

Golbe, D.L., and White, L.J. 1988. A time-series analysis of mergers and acquisitions in the US economy. In Corporate takeovers: Causes and consequences. University of Chicago Press, 265-310.

Golbe, D.L., and White, L.J. 1993. Catch a wave: The time series behavior of mergers. The Review of Economics and Statistics, 75, 493-499.

Hamilton, J.D. 1983. Oil and the macroeconomy since World War II. The Journal of Political Economy, 228-248.

Hamilton, J.D. 1985. Historical causes of postwar oil shocks and recessions. Energy Journal, 6, 97-116.

Harford, J. 2005. What drives merger waves?. Journal of Financial Economics, 77, 529-560.

Hogan J., and Lakey, J. 2005. Time-frequency and time-scale methods: adaptive decompositions, uncertainty principles, and sampling. Birkhäuser, Boston

Holmstrom, B., and Kaplan, S.N. 2001. Corporate Governance and Merger Activity in the US: Making Sense of the 1980s and 1990s. National Bureau of Economic Research Working Paper n.8220.

Kilian, L. 2008. The economic effects of energy price shocks. Journal of Economic Literature, 46, 871-909.

Kyrtsou, C., Malliaris, A.G., and Serletis, A. 2009. Energy sector pricing: On the role of neglected nonlinearity. Energy Economics, 31, 492-502.

Mitchell, M.L., and Mulherin, J.H. 1996. The impact of industry shocks on takeover and restructuring activity. Journal of Financial Economics, 41, 193-229.

Monge, M., and Gil-Alana, L. A. 2016. Fractional integration and cointegration in merger and acquisitions in the US petroleum industry. Applied Economics Letters, 23, 701-704.

Naccache, T. 2011. Oil price cycles and wavelets. Energy Economics, 33, 338-352.

Nelson, R.L. 1959. Merger movements in American industry, 1895-1956. NBER Books.

Percival, D.B., and Walden, A.T. 2000. Wavelet methods for time series analysis. Cambridge University Press.

Petitt, B.S., and Ferris, K.R. 2013. Valuation for mergers and acquisitions. Financial Times Press.

Ramsey, J.B. 2002. Wavelets in economics and finance: past and future. Studies in Nonlinear Dynamics and Econometrics, 6.

Resende, M. 1999. Wave behaviour of mergers and acquisitions in the UK: a sectoral study. Oxford Bulletin of Economics and Statistics, 61, 85-94.

Schreiber, T., and Schmitz, A. 1996. Improved surrogate data for nonlinearity tests. Physical Review Letters, 77, 635-638.

Shleifer, A., and Vishny, R. 1990. Equilibrium short horizons of investors and firms. American Economic Review, 80, 148-153.

Town, R. J. 1992. Merger Waves and the Structure of Merger and Acquisition Time-Series. Journal of Applied Econometrics, 7, 83-100.

Chapter 4

U.S. shale oil production and WTI prices behaviour

The aim of this paper is to relate the shale oil revolution in the United States with WTI oil price behavior. Since the development of the combination of horizontal drilling techniques together with hydraulic fracturing in the 1970s, known as shale oil, oil markets have undergone a significant transformation with the unexpectedly strong rise in the United States production affecting oil prices. The goal of this paper is two-fold: first, we analyze the relationship of total United States crude oil production and WTI crude oil prices by studying its performance in the time-frequency domain applying wavelet tools for its resolution. Using wavelet methodologies, we observe a shift to higher frequencies of the wavelet coherency for the time period 2003-2009 and lower frequencies for the period 2009-2014. The results also indicate that during the period 2003-2009 the U.S. oil production and WTI oil prices time series are in phase; they move together, with total United States oil production leading. During the period 2009-2014 oil production and WTI oil prices time series are out of phase (negatively correlated), suggesting that oil production increases precede a decrease in WTI oil prices. In the second part of the paper and to give greater credibility to the results obtained through the wavelet transform, we analyze the behavior of WTI crude oil before and after the shale oil boom in the United States employing methodologies based on long run dependence. The results indicate that mean reversion takes place only for the data corresponding to the first subsample, ending at 2003. For the second subsample, as well as for the whole sample, lack of mean reversion is detected with orders of integration equal to or higher than 1 in all cases.

4.1 Introduction

The production of shale oil[1] consists in horizontal drilling and the hydraulic fracturing of underground rock formations containing deposits of crude oil that are trapped within the rock. This process is used to extract crude oil that would be impossible to release through conventional drilling methods.

The boom production of shale oil in United States is an example of a technological change in a single industry in one country affecting international trade worldwide.

The evolution of United States oil production was in decline until the early 1970s. This trend was only briefly reversed by the development of the Alaskan oil fields in the late 1970s. According to Kilian (2016a), the expansion of United States shale oil takes place between 2003 and 2013 stimulated by high conventional crude oil prices resulting in this technology becoming competitive. According to Clements and Cummings (2016) the global oil market witnessed a period of stable and high prices with crude averaging over USD 110bbl between 2011 and mid-2014. During this period, there were geopolitical turbulences in Libya, Iraq and Iran that led to reduced exports, creating a market supply shortage. United States tight oil reduced the gap thanks to technological advances in horizontal funding techniques which were funded by high oil prices and low financing costs through credits. November 2008 was the reversal date of this trend in the United States. It can be shown that this reversal is largely due to U.S. fracking. Figure 1 plots the crude oil production at the Bakken, Eagle Ford, Haynesville, Marcellus, Niobrara, Permian and Uttica shale oil plays. According to the Energy Information Administration report (May 2016), the seven regions previously mentioned account for 92% of domestic shale oil production growth in United States.

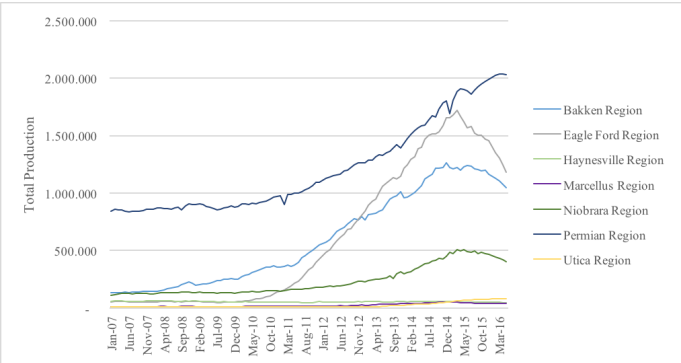

Figure 1: Oil production of selected U.S. shale plays

[1] According to Mănescu and Nuño (2015) the definition provided by the Energy Information Administration (EIA) and the International Energy Agency (IEA) is that shale oil is the "tight oil" or "light, tight oil". The term tight oil does not have a specific technical, scientific, or geologic definition. Tight oil refers to oil produced from very low-permeability shale, sandstone, and carbonate formations.

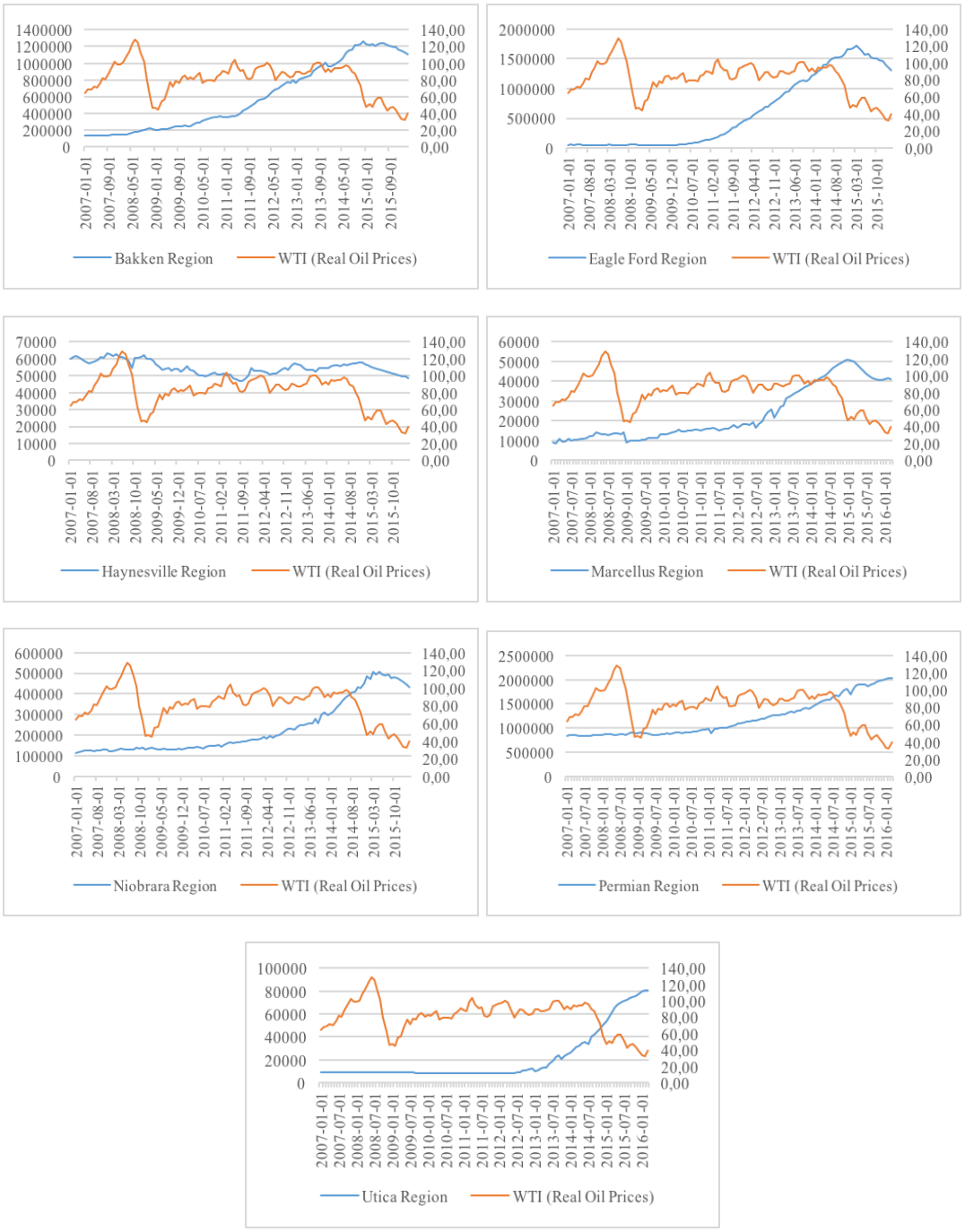

Figure 2: U.S. shale oil production by region and the behaviour of WTI crude oil prices

.

Figure 2 plots the crude oil production at the Bakken, Eagle Ford, Haynesville, Marcellus, Niobrara, Permian and Uttica shale oil and the WTI crude oil price behaviour during the period 2007-2016.

Following Kilian (2016a), the production of shale oil increased exponentially until growth became linear. In March 2014 the United States economy produced on average 8.2 millions of barrels/day (mbd) and imported 7.3 mbd. Of the total 15.5 mbd of crude oil, 3.6 mbd were produced from shale oil, accounting for half of the United States oil production and only a quarter of the total quantity of oil has been used by the United States economy.

Kilian (2016b) argues that the increase of shale oil production in the United States has displaced the Arab oil producing countries and their crude oil exports. This fact has occurred because United States refineries have increasingly exported refined products such as gasoline or diesel made from domestically produced crude oil.

The high oil prices in recent years made shale oil exploration economically viable. However, there were several factors which ensured that the shale oil revolution took place in the United States and not elsewhere. According to Alquist and Guenétte, (2014) there was a history of shale gas exploitation, legal incentives for land owners and an advanced oil production infrastructure. In the early 19th century, the technology necessary for shale oil exploration started to be developed and was perfected during the 1980s. Also, the United States has legal and institutional features that make the economic environment attractive for the extraction of unconventional oil, and have infrastructures that consist of a large number of state-of-the-art drilling rigs, an extensive pipeline network, and associated refineries.

According to Covert (2014) and related to the flow of shale oil, there is evidence of significant productivity gains in fracking that could further lower the cost of recovering shale oil and raise future estimates of recoverable shale oil.

From a different perspective, Sharenow and Worah (2013) showed that shale oil could provide a rebalancing global supply. The United States shale and eventually shale production globally, combined with production from Canada's oil sands, could potentially increase energy balances for the first time since the oil spikes of the 1970s, leading to the development of new reserve basins. Killian (2016a) argues that this has implications for the price of oil because the United States oil industry has been able to blend heavy crudes and shale oil in the right proportion to imitate mid-grade crude oil of type traditionally imported and refined along the Gulf Coast.

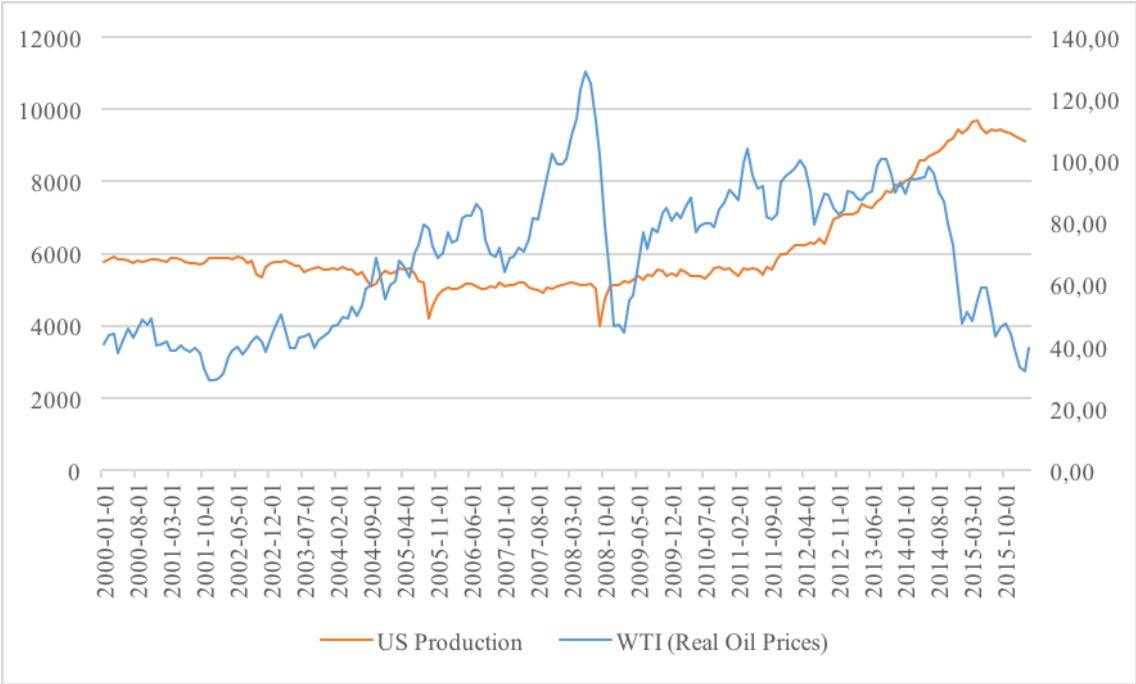

Figure 3: Total U.S. oil production and the behaviour of WTI crude oil prices.

Figure 3 illustrates the total United States oil production and the behaviour of WTI crude oil prices.

It is common in the literature to utilize Fourier analysis to analyse the different relations at different frequencies, omitting the time information, despite it being difficult to identify structural changes with this type of analysis. In this chapter we analyse the relationship of total United States oil production and WTI crude oil prices by studying its dynamic in the time-frequency domain through the application of wavelet tools for its resolution. To complement this and to give further credibility to the results obtained by the wavelet transform, we analyse the behaviour of WTI crude oil before and after the shale oil boom in the United States, employing methodologies based on long run dependence or long memory using the date break cited by the literature and by our wavelets results. In addition, we employ the methodology suggested in Gil-Alana (2008) to estimate breaks in the context of fractional integration.

Under the hypothesis that shale oil production affects WTI oil prices and according to Kilian (2016a) the evolution of the United States oil price is determined by the increases in shale oil production. The development of the United States refining, pipeline and rail infrastructure are important to understand and forecast the evolution of the domestic price of oil in the United States. There are others factors that Baumeister and Kilian (2016) mentioned such as oil supply shocks, demand shocks and shocks to oil price expectations. In this research we use the variables related with crude oil production in United States and WTI crude oil prices because we want to study

how the overproduction related with the shale oil affects WTI behaviour.

The contributions of the paper are twofold. First, we use a methodology based on a time-frequency technique that it is able to analyse the evolution of the different frequency components of the time series overtime. Applying the wavelet transform it is possible to detect the evolution in time of the low frequency. This low frequency is related with the trend or long run component in the time series. Also, applying the wavelet transform we can detect the evolution overtime of the high frequency components related to seasonality or the short run component, as well asthe rapid changes in the time series[2]. We use wavelets to analyse the relationship between WTI oil prices and total oil production in the U.S. for the time period 2000-2016. Following Aguiar-Conraria and Soares (2011a,b), two tools are used to analyse the impact of crude oil production on the crude oil prices: the wavelet coherency and the wavelet phase-difference. The wavelet coherence is a localized correlation coefficient in the time-frequency space. The information on the delay between the oscillations of two time-series is the phase-difference. These concepts developed by Aguiar Conraria were previously examined in Naccache (2011), analysing the relationship between oil price and the economy. The analysis is performed in the time-frequency domain, using wavelet analysis. Following these authors, we use this methodology for three reasons. First, stationarity is not required in the wavelet analysis (in our case, oil prices are non-stationary). On the other hand, we can study how relations evolve between time and frequencies. And the last reason is related with the energy markets and the research by Kyrtsos et al. (2009). They argue that several energy markets display consistent non-linear dependencies. Second, in this chapter we use some recently developed methods based on the concepts of long run dependence and long memory using fractional integration techniques (Gil-Alana and Hualde, 2009). The methodology used in the second part of the research is similar to the one applied in Monge et al. (2016). Fractional integration is more general than the standard methods that use exclusively integer orders of differentiation (i.e., AR(I)MA).

The rest of the paper is structured as follows. Section 2 reviews the oil supply and the implications on the WTI crude oil price behaviour in the U.S.. Section 3 presents the methodology applied in the paper. In Section 4 we discuss the main empirical results, while Section 5 concludes.

[2]Hogan and Lakey (2005) examined the relationship between time-frequency and time-scale (wavelets) methods.

4.2 Is the shale oil supply behind the behaviour of WTI crude oil prices?

In the last decade, global oil markets have enjoyed a greater supply due to non-conventional sources of oil production in the United States and the Canadian Oil Sands combined with the production of biofuels.

According to the Bank of Canada (2015), if shale oil production were one-third of current oil production and the expected increase in global shale oil production were able to reach two-thirds of oil production, this increase could become uneconomical. In line with Benes et al. (2015), the cost of non-conventional oil production is likely to decline as new technologies will reduce the cost exploration and extraction.

Baumeister and Kilian (2016) basing their study on an alternative methodology, were unable to pin down the quantitative role of fracking. In their research they provide a strong evidence that a slowdown in the global demand for oil was a major contributor to this specific oil price decline, along with shocks to global oil production and oil price expectations.

Baffes et al. (2015) mentioned that the "unconventional" U.S. oil production differs from conventional ones, because they have a shorter life-cycle, around 2.5-3 years from the start until full extraction. Krane and Agerton (2015) and McCracken (2015) argue that oil supply from these sources tends to be more elastic to price changes than from conventional sources, even in the short term.

Another important factor mentioned by Baffes et al. (2015) is that OPEC does not have a legal clause on how to intervene when market conditions warrant, thus, allowing it to respond flexibly to changing circumstances. Also, these authors mentioned that changes in supply are due to the expansion of oil production in the United States, causing concerns regarding about supply disruptions to almost disappear. Furthermore, OPEC's policy has played a dominant role in explaining how the recent plunge in prices has been due to supply shocks.

To give consistency to this explanation, Arezki and Blanchard (2015)documented that demand related factors only contribute to20-30 percent of the decline and the supply related factors, and OPEC's decision not to cut supplies were more important in driving the fallin oil prices. Also, Hamilton (2014) explains that only two-fifths of the decline in oil prices in the second half of 2014 was due to weak global demand. Baumeister and Kilian (2016) conclude in their research report that more than half of the oil price decline reflects the cumulative effects of earlier oil supply and demand shocks and, among the remaining half, the most influential shock was associated with the weakening global economy while positive oil supply shocks were limited between June and Decem-

ber 2014.

4.3 Methodology

4.3.1 Wavelet analysis

The wavelet transform offers localized frequency decomposition, providing information about frequency components. Wavelets have significant advantages over basic Fourier analysis when the series under study is stationary –see Gençay et al., (2002), Percival and Walden (2000) and Ramsay (2002). In our research we use continuous wavelet analysis tools, mainly wavelet coherence, measuring the degree of local correlation between two-time series in the time-frequency domain, and the wavelet coherence phase differences.

The continuous wavelet transform

The continuous wavelet transform of a time series $x(t)$, with respect to the wavelet ψ, is a function $WT_x(a,\tau)$ defined as:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x_t \psi^*_{a,\tau}(t)\, dt \tag{4.1}$$

where $WT_x(a,\tau)$ are the wavelet coefficients of $x(t)$ at a certain scale a and a shift τ, where,

$$\psi^*_{a,\tau} = \frac{1}{\sqrt{a}}\, \psi^* \left(\frac{t-\tau}{a} \right) \tag{4.2}$$

is the complex conjugate of the wavelet function ψ. The parameter a is a scaling factor that controls the stretching factor of the wavelet and τ is a location parameter in time. Then, $WT_x(a,\tau)$, is going to be a matrix of time series. The scaling factor a is a positive real number that simply means stretching it (if $a > 1$), or compressing it (if $a < 1$). If a is positive, we assume that we are using an analytic or progressive wavelet, i.e., its Fourier transform is defined on the positive frequency axis, $\Psi(\omega) = 0$ when $\omega < 0$.

The lower the value of the scaling factor, the higher frequency components are reflected in the continuous wavelet transform, thus we are dealing with the short-run components of the signal. As the scaling factor increases, we deal with lower frequency components of the time series, we focus on the long-run components. Then, the continuous wavelet transform is a multidimensional

transform; from one time series we obtain a matrix of time series that show different frequency components (depending on the scaling factor) of the original one.

If the wavelet function ψ is complex, then the wavelet transform $WT_x(a,\tau)$ will also be complex, with amplitude,$|WT_x(a,\tau)|$, and phase, $\phi_x(a,\tau)$. The real part of the wavelet transform, $\Re\{WT_x\}$, and its imaginary part, $\Im\{WT_x\}$ define the phase or phase-angle of the wavelet transform:

$$\phi_x = Arctan\left(\frac{\Im m\{WT_x\}}{\Re e\{WT_x\}}\right) \tag{4.3}$$

The phase of a given time-series x_t is measured in radians, ranging from $-\pi/2$ to $+\pi/2$. Then, the phase is also a matrix containing the angle of each frequency component of the original time series. The phase will be used to extract conclusions of the synchronism between two time series, applying the wavelet coherency and the phase difference between time series (Aguiar-Conraria and Soares, 2011a, 2011b and 2014).

The wavelet or mother wavelet used to analyze the time series must satisfy certain technical conditions to provide effective time-frequency location properties (Daubechies, 1992). First, it has to be a function of finite energy, $\int_{-\infty}^{+\infty} \psi(t)\,dt = 0$. There are many different wavelet families, but the election of a certain wavelet will depend on the application itself.

Related to time localization properties, we can normalize the wavelet function so that $\int_{-\infty}^{+\infty} |\psi(t)|^2\,dt = 1$. $|\psi(t)|^2$ defines a probability density function, and therefore we can obtain the mean, μ_ψ, and the standard deviation, σ_ψ, of this distribution. They are called the center and the radius of the wavelet, respectively. If we consider the Fourier transform of the mother wavelet, $\Psi(\omega)$, in a similar way we can calculate its mean and standard deviation, μ_Ψ and σ_Ψ.

These quantities define the Heisenberg box in the time-frequency plane: $[\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi] \times [\mu_\Psi - \sigma_\Psi, \mu_\Psi + \sigma_\Psi]$. We say that Ψ is localized around the point (μ_ψ, μ_Ψ) of the time-frequency plane with an uncertainty given by $\sigma_\psi\sigma_\Psi$. In our context, the Heisenberg's uncertainty principle establishes that $\sigma_\psi\sigma_\Psi \geq 1/2$.

The Morlet wavelet,

$$\psi(t) = \pi^{1/4} e^{i\omega_0 t} e^{-t^2/2} \tag{4.4}$$

is a complex valued wavelet, so we will be able to measure the synchronism between two time series. This wavelet has optimal time-frequency concentration, in the sense that $\sigma_\psi\sigma_\Psi = 1/2$. Therefore, using this wavelet, we have the optimum trade off between time and frequency resolution. On the other hand, the Morlet can be considered as a wavelet (with finite energy, defined as before) when

the frequency parameter $\omega_0 = 6$. For this value of the Morlet wavelet, the wavelet scale, a, satisfies the inverse relation $f \approx 1/a$, as the rest of the most used mother wavelets.

Wavelet and cross wavelet power spectrum, and wavelet coherency

The wavelet power spectrum (WPS) or the scalogram of a time series $x(t)$, as it is called, is the squared amplitude of the wavelet transform, that is: $WPS_x(a,\tau) = |WT_x(a,\tau)|^2$. The wavelet power spectrum let us know the distribution of the energy (spectral density) of a time-series across the two-dimensional time-frequency representation.

While the wavelet power spectrum shows the variance of a time-series in the time-frequency plane, the cross wavelet power spectrum (CWPS) of two time-series and shows the covariance between these time-series in the time-frequency plane:

$$CWPS_{xy}(a,\tau) = |WT_x(a,\tau)WT_y(a,\tau)^*| \tag{4.5}$$

where the * represents the complex conjugate, as before.

Therefore, the complex wavelet coherency between two time-series $x(t)$ and $y(t)$ is defined as the ratio of the cross-spectrum and the product of the power spectrum of both series:

$$WCO_{xy} = \frac{SO(WT_x(a,\tau)WT_y(a,\tau)^*)}{\sqrt{SO(|WT_x(a,\tau)|^2)SO(|WT_y(a,\tau)|^2)}} \tag{4.6}$$

where SO is a smoothing operator in both time and scale. Without the smoothing operator, the wavelet coherency would be always one at all times and scales (see Aguiar-Conraria et al. (2008) for details).

As the WCO_{xy} is a matrix of complex time series, we can split it again into amplitude and phase, $WCO_{xy} = |WCO_{xy}|\, e^{i\phi_{xy}}$. The amplitude matrix is the wavelet coherency, WC_{xy} and the angle ϕ_{xy} is called the phase difference between both time series:

$$\phi_{xy} = Arctan\left(\frac{\Im m\{WCO_{xy}\}}{\Re e\{WCO_{xy}\}}\right) \tag{4.7}$$

ϕ_{xy} is the phase difference between time series $x(t)$ and $y(t)$, and tells us about the synchronism between those time series. ϕ_{xy} ranges from $-\pi$ to π.

On the one hand, if $\phi_{xy} = 0$ then both time series move in phase. This will mean that both time series increases or decreases their values at the same time. If $\phi_{xy}\epsilon(-\frac{\pi}{2}, 0)$, they move in phase but

time series $x(t)$ is leading; if $\phi_{xy}\epsilon(0, \frac{\pi}{2})$, time series $y(t)$ is leading. Therefore, in these cases we can find that one time series anticipates the increase or decrease of the other one. On the other hand, a phase difference of π or $-\pi$ indicates an anti-phase relation, when one time series increases, the other one is decreasing in time. Finally, if $\phi_{xy}\epsilon(-\frac{\pi}{2}, -\pi)$, both time series are out of phase but $x(t)$ is leading; if $\phi_{xy}\epsilon(\frac{\pi}{2}, \pi)$, $y(t)$ is leading. In this case this means that one time series has a time delay with respect to the other one.

Significance tests, Monte Carlo simulations

To check the statistical significance of the wavelet coherency, WC_{xy}, we rely on Monte Carlo simulations (Schreiber and Schmitz,1996). We model each time series as an ARMA(p,q) process where $p = q = 1$, with no pre-conditions. Then we assess the statistical significance of the amplitude, not of the phase. The phase difference is not tested as there is no agreement in the scientific community about how to define the procedure. We should only take into account the phase difference when the amplitude of the wavelet coherency is statistically significant.

4.3.2 Fractional integration

We will also use techniques based on the concept of fractional integration, which means that number of differences required to render a series $I(0)$ stationary may be a fractional value rather than an integer. A given time series $X(t)$, $t = 1, 2...$ is said to follow an integrated of order d process (and denoted as $X(t) \approx I(d)$) if

$$(1 - L)^d X(t) = U(t), \qquad t = 1, 2, ..., \tag{4.8}$$

where d can be any real value, L is the lag-operator ($LX(t) = X(t-1)$) and $U(t)$ is $I(0)$, defined for our purposes as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Thus, $U(t)$ may display some type of time dependence of the weak form, i.e., the type of an AutoRegressive Moving Average (ARMA) form such that, for example, if $U(t)$ is ARMA (p,q), $X(t)$ is said to be ARFIMA (p,d,q).

Based on the specification in (4.8) different features can be observed depending on the value of d. Thus, if $d = 0$ in (4.8), $X(t) = U(t)$ and the process is said to be short memory or $I(0)$. In this case, if $U(t)$ is ARMA, the autocorrelations decay exponentially fast. On the other hand, if $d > 0$ the process is said to be long memory, so-named due to the high degree of association between observations which are far distant in time. In this context, if $d < 0.5$ the process is still covariance

stationary and the autocorrelations decay hyperbolically fast. As long as d is smaller than 1, the process is mean reverting with shocks disappearing in the long run, contrary to what happens with $d \geq 1$ where shocks are expected to be permanent, i.e. lasting forever.

We estimate the fractional differencing parameter d by means of both parametric and semiparametric techniques. In the parametric approach, we use the Whittle function in the frequency domain (Dahlhaus, 1989), while in the semiparametric case, we use a Gaussian semiparametric method that also uses the Whittle function on a band of frequencies that degenerates to zero (Robinson, 1995).

Also, based on the fact that long memory may be produced by the existence of breaks that have not been taken into account, we also conduct the methodology proposed in Gil-Alana (2008) that allows for breaks still in the context of fractional integration. In doing so, we provide evidence of a break at the end of 2003, which is consistent with Kilian (2016a), where he identifies that the expansion of United Statesshale oil starts after 2003 stimulated by the high prices of conventional crude oil, thereby making this technology competitive.

4.4 Empirical results

4.4.1 Data

The data examined in this work correspond to U.S. Crude Oil Production and WTI crude oil prices in the United States over the period 2000:01-2016:03. The WTI crude oil prices data was obtained from the Federal Reserve Bank of St. Louis[3]. The database was in nominal prices (dollars as currency units), and we have deflated to real prices. We have used the Producer Price Index for All Commodities from the Federal Reserve Bank of St. Louis[4]. The base year to obtain the new crude oil prices is 2011.

Furthermore, we used monthly data of the U.S. Crude Oil Production (thousands barrels per day) over the period 2000:01-2016:03 obtained from DataStream Database.

4.4.2 Empirical results

We first estimate the wavelet coherency between the monthly quantity of total U.S. oil production and the WTI crude oil prices. We rely on Monte Carlo simulations to test if the similitude of the

[3]Spot Oil Price: West Texas Intermediate, retrieved from FRED, Federal Reserve Bank of St. Louis. `https://research.stlouisfed.org/fred2/series/OILPRICE/`.

[4]US. Bureau of Labor Statistics, Producer Price Index for All Commodities, retrieved from FRED, Federal Reserve Bank of St. Louis `https://research.stlouisfed.org/fred2/series/PPIACO/`.

wavelet coherency is statistically significant. We compute the complex wavelet coherence matrices between a surrogate for WTI crude oil prices and a surrogate for the total crude oil production. We do 1000 simulations modelling both time series as an ARMA (p, q) process, with no pre-conditions on p and q, with $p = q = 1$.

We estimate the wavelet coherency for frequencies corresponding to periods between 1.5 to 4 and 4.5 to 8 years.

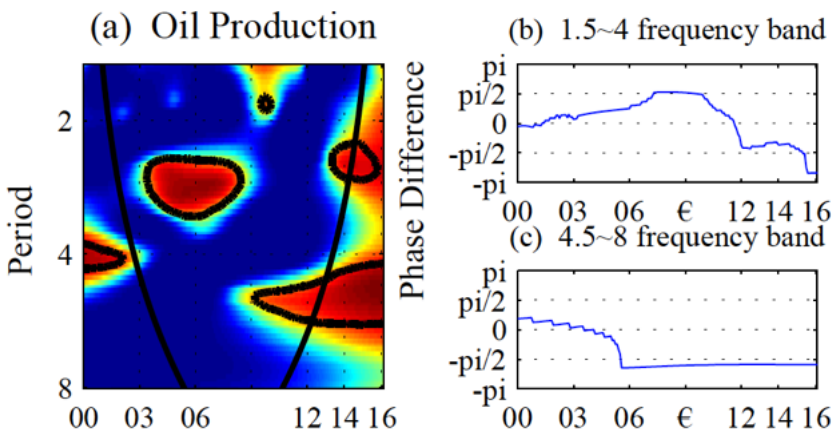

Figure 4: Wavelet Coherency and phase-difference between Total U.S. Oil Production and WTI crude oil price.

Note: On the left: Wavelet Coherency between Total U.S. Oil Production and WTI. On the right: Phase-difference between Total U.S. Oil Production and WTI at $1.5 \backsim 4$ *year (top) and* $4.5 \backsim 8$ *year (bottom) frequency bands.*

In Figure 4 we display the empirical results. On the left panel (a) we have the wavelet coherency between oil production and WTI crude oil prices[5]. On the right hand side, we have the phase-differences: on the top (b) we have the phase-difference in the 1.5 - 4 year frequency band; at the bottom (c), we have the phase-difference in the 4.5 - 8 year frequency band. The regions surrounded by the black contour are the high coherency regions with significant values at 5%.

Analysing the wavelet coherency between oil production and WTI crude oil prices, we appreciate that the regions with higher coherency are between 2003 and 2014 corresponding to the wavelet scales of periods from the 1.5 to 7 year band. We focus our phase difference analysis on two frequency bands: 1.5-4 and 4.5-8 years.

[5]Coherency ranges from blue (low coherency) to red (high coherency). The cone of influence is shown with a thick line, which is the region subject to border distortions.

To analyse the wavelet coherency graph, we have to focus on the regions of high coherency of the chart. In those regions we can observe the phase difference of the frequency band to extract some conclusions.

In the 1.5-4 year band, we identify a region of high coherency between 2003 and 2009, in the frequency bands between 2.5 and 3.5 years with a corresponding phase difference in this band between 0 and $\pi/2$. This result suggests that U.S. oil production and WTI oil prices time series are in phase, they move together, with total oil production leading.

We can find also a region of high coherency between 2009 to 2014 in the 4.5-8 year band, specifically between the 5 and 6 year frequency bands. The phase difference of that period stays between $-\pi/2$ and $-\pi$, suggesting that U.S. oil production and WTI oil prices time series are out of phase (negative correlated) with oil production oil leading. This suggests that the oil production increases precede a decrease on WTI oil prices. This coincides with Kilian (2016a) in the sense that the evolution of the U.S. price of oil is determined by increases in shale oil production.

From this wavelet coherency figure, we can observe a change across time in the common frequency bands between crude oil production and WTI; higher frequencies between the years 2003 and 2009 suggest that the influence in this period of time is a short-term relationship, reaching a maximum at the 3 year frequency band. This means that the crude oil production influence WTI oil prices faster that in preceding years. On the other hand, the relationship of both time series in the 2009 to 2014 period had a long term component, i.e., a lower frequency band of approximately between 5 to 6 years, suggesting a longer term impact of the crude oil production over the WTI crude oil prices.

Next we move to the long memory part of the paper, and taking into account that some authors argue that fractional integration (and even long memory, in a more general context) can be a spurious phenomenon caused by the presence of as structural break that had not been taken into account (Diebold and Inoue, 2001; Granger and Hyung, 2004) we perform first the approach suggested in Gil-Alana (2008), finding evidence in favour of a break at December 2003. Thus, we separate the whole dataset in two different subsamples, one from January 2000 to December 2003, and the second from January 2004 until the end of the sample. This is in line with the research conducted in Kilian (2016a) where he identifies that the expansion of U.S. shale oil starts after 2003 stimulated by high conventional crude oil prices, resulting in this technology becoming competitive.

Using fractional integration methods the results are presented across Tables 1 - 5. Tables 1 and 2

focus on a parametric approach, and the model considered is

$$y_t = \beta_0 + \beta_1 t + X_t, \quad (1-L)^d X_t = U_t, \quad t = 1, 2, ... \tag{4.9}$$

Under the assumption of white noise errors (in Table 1) and Bloomfield's (1973) autocorrelated disturbances (in Table 2). The latter is a non-parametric approach of modeling $I(0)$ processes that produce autocorrelations decaying exponentially as in the ARMA case. In both cases, we display the results of the estimates of d for the three standard cases examined in the literature of i) no deterministic terms ($\beta_0 = \beta_1 = 0$ a priori in (4.9)), ii) an intercept (β_0 unknown and $\beta_1 = 0$ a priori) and iii) an intercept with a linear trend (β_0 and β_1 unknown). We present the results for the two subsamples along with those corresponding to the whole dataset.

Starting with the results based on white noise errors (Table 1), we observe that in both cases of prices and production, the results for the whole sample are very similar to those corresponding to the second subsample; thus, for prices, the estimate of d is 1.25 for the whole sample and 1.28 for the data starting in 2004, and in both cases the unit root null hypothesis is rejected in favor of $d > 1$; however, for the data corresponding to the first subsample, the estimated value of d is about 0.81 and the unit root null cannot be rejected. Focusing now on production, the estimates of d are smaller than 1 in the three cases and the unit root null cannot be rejected in any of the three cases, however, once more, lower values are obtained for the data in the first subsample.

Series	No det. terms	An intercept	A linear time trend
Prices (total)	1.17 (1.04, 1.34)	**1.25 (1.12, 1.42)**	1.25 (1.12, 1.42)
Prices (1st subsample)	0.97 (0.78, 1.27)	**0.81 (0.60, 1.19)**	0.81 (0.60, 1.19)
Prices (2nd subsample)	1.16 (1.03, 1.35)	**1.28 (1.13, 1.47)**	1.28 (1.13, 1.47)
Production (total)	0.96 (0.88, 1.07)	**0.97 (0.91, 1.05)**	0.97 (0.91, 1.05)
Prod. (1st subsample)	0.93 (0.75, 1.21)	**0.73 (0.47, 1.18)**	0.70 (0.36, 1.18)
Prod. (2nd subsample)	0.93 (0.83, 1.07)	**0.96 (0.89, 1.05)**	0.95 (0.88, 1.05)

Table 1: Estimates of d based on white noise disturbances.

Series	No det. terms	An intercept	A linear time trend
Prices (total)	0.84 (0.64, 1.15)	**0.96 (0.79, 1.25)**	0.96 (0.79, 1.25)
Prices (1st subsample)	0.71 (0.33, 1.16)	**0.39 (0.06, 0.79)**	0.39 (0.06, 0.79)
Prices (2nd subsample)	0.91 (0.69, 1.24)	**0.96 (0.74, 1.34)**	0.96 (0.74, 1.33)
Production (total)	0.94 (0.81, 1.11)	**1.01 (0.93, 1.12)**	1.01 (0.92, 1.13)
Prod. (1st subsample)	0.78 (0.35, 1.23)	**0.10 (-0.23, 0.53)**	-0.24 (-0.68, 0.43)
Prod. (2nd subsample)	0.87 (0.72, 1.08)	**0.99 (0.89, 1.13)**	0.99 (0.88, 1.15)

Table 2: Estimates of d based on autocorrelated (Bloomfield) disturbances.

Looking now at the results based on autocorrelated errors, the values are substantially smaller, especially for those corresponding to the first subsample, but they are consistent with those presented above for the case of white noise errors, with lower degrees of integration during the first subsample. In fact, for prices, the estimate of d in the first subsample is found to be 0.39, and the hypothesis of mean reversion ($d < 1$) cannot be rejected in this case, although it is rejected in the second subsample and for the whole dataset. For production, the same result holds, and the estimate of d for the first subsample is even smaller (0.10) being close to 1 for the second subsample and the whole dataset.

Due to the disparity of the results depending on the specification of the error term, we also conduct the analysis with a semiparametric approach, where no functional form is imposed on the $I(0)$ error term $U(t)$.

Table 3 displays the results for the whole sample. We observe that the unit root is almost never rejected for prices, this hypothesis being rejected in favor of $d > 1$ for production with all bandwidth numbers[6].

[6] We use a selected group of bandwidth numbers. The choice of the bandwidth clearly shows the trade-off between bias and variance: the asymptotic variance is decreasing with m while the bias is growing with m.

m	Prices	Production	Lower 95%	Upper 95%
8	0.842	1.500**	0.709	1.290
9	0.778	1.500**	0.725	1.274
10	0.787	1.500**	0.739	1.260
11	0.772	1.378**	0.752	1.247
12	0.802	1.348**	0.762	1.237
13	0.790	1.375**	0.771	1.228
14	0.778*	1.363**	0.780	1.219
15	0.823	1.280**	0.787	1.212

Table 3: Estimates of d using a semiparametric method for the whole dataset.

m	Prices	Production	Lower 95%	Upper 95%
5	0.630*	0.202*	0.632	1.367
6	0.800	0.361*	0.664	1.335
7	0.950	0.277*	0.689	1.310
8	0.773	0.410*	0.709	1.290
9	0.673*	0.488*	0.725	1.274
10	0.655*	0.500*	0.739	1.260
11	0.720*	0.500*	0.752	1.247
12	0.745*	0.500*	0.762	1.237

Table 4: Estimates of d using a semiparametric method for the first subsample.

m	Prices	Production	Lower 95%	Upper 95%
6	0.554*	1.500**	0.664	1.335
7	0.679*	1.500**	0.689	1.310
8	0.766	1.487**	0.709	1.290
9	0.742	1.349**	0.725	1.274
10	0.811	1.418**	0.739	1.260
11	0.784	1.284**	0.752	1.247
12	0.775	1.150	0.762	1.237
13	0.781	1.095	0.771	1.228

Table 5: Estimates of d using a semiparametric method for the second subsample.

Table 4 focuses on the first subsample and here, evidence of mean reversion ($d < 1$) is obtained in many cases for prices and in all cases for production. Very different results are obtained in the results corresponding to the second subsample, support being found for the unit root or even $d > 1$ in the majority of the cases.

For the first subsample we conclude that there was a shock in the crude oil production and price will recover by itself over time with no need for a strong policy measures since the series will tend to revert to its trend sometime in the future. This behavior, however, is not observed with the data starting at 2004 or when the whole dataset is used. For these cases, shocks will have permanent effects and strong policy measures must be adopted to recover the original trends.

4.5 Concluding Remarks

In this research, we have analyzed the shale oil revolution and its effects on WTI oil price behavior. Since the development of the combination of horizontal drilling techniques together with hydraulic fracturing, known as shale oil, in the 1970s, oil markets have undergone a significant transformation with the unexpectedly strong rise in US production affecting the oil prices.

It is very common to utilize methodologies based on Fourier analysis to analyse the different relations at different frequencies, omitting the time information, despite it being difficult to identify structural changes with this type of analysis. Hence we also use methodologies based on long run dependence or long memory processes.

First, we analyze the relationship of total U.S. crude oil production and WTI crude oil prices by studying its dynamics in the time-frequency domain applying wavelet tools for its resolution. Analyzing the wavelet coherency we appreciate that the regions with higher coherency are between 2003 and 2014 corresponding to the wavelet scales of periods from the 1.5 to 7 year band. We focus our phase difference analysis on two frequency bands: 1.5-4 and 4.5-8 years. Analyzing the regions of high coherency inthe chart, we identify a region of high coherency in the 1.5 - 4 year band between 2003 and 2009, in frequency bands between 2.5 and 3.5 years with a corresponding phase difference in this band between 0 and $\pi/2$. This result suggests that U.S. oil production and WTI oil prices time series are in phase, they move together, with total oil production leading.

We can find also a region of high coherency between 2009 to 2014 in the 4.5-8 year band, specifically between the 5 and 6 year frequency bands. The phase difference of that period stays between $-\pi/2$ and $-\pi$, suggesting that oil production and WTI oil prices time series are out of phase (negatively correlated) with production oil leading. This suggests that the oil production increases precede a

decrease in WTI oil prices. This coincides with Kilian (2016a) in that the evolution of the U.S. price of oil is determined by the increases in shale oil production.

From this wavelet coherency figure, we can observe a change across time in the common frequency bands between crude oil production and WTI; higher frequencies between the years 2003 and 2009 suggest that the influence in this time period is a short-term relationship, reaching a maximum at the 3 year frequency band. This means that the U.S. crude oil production influences WTI oil prices faster than in the preceding years. On the other hand, the relationship of both time series in the 2009 to 2014 period had a long term component, i.e., a lower frequency band of approximately between 5 to 6 years, suggesting a longer term impact of the crude oil production over the WTI crude oil prices.

In the second part of the paper, we use fractional integration techniques to analysethe behavior of WTI crude oil before and after the shale oil boom in the U.S.. We chose the subsamples according to the methodology proposed in Gil-Alana (2008) for structural breaks in the context of fractional integration. The break date was found at the end of 2003, consistent with the results obtained in Kilian (2016a). The most notorious feature observed here is that mean reversion is detected in both production and prices series with the data ending at 2003. However, with data starting in 2004 or when the whole dataset is used, we notice the lack of mean reversion, with orders of integration equal to or higher than 1 in all cases.

Testing the hypothesis that shale oil production affects WTI oil prices, the evolution of the United States price of oil is determined by the increases in shale oil production. Also, the development of the United States refining, pipeline and rail infrastructure are important to understand and forecast the evolution of the domestic price of oil in the United States. There are others factors mentioned by Baumeister and Kilian (2016) such as oil supply shocks, demand shocks and shocks to oil price expectations. We have only taken into account the crude oil production in the United States and WTI crude oil prices because this research has mainly focused on how overproduction of shale oil affects WTI oil price behaviour. The influence of other variables using similar methodologies to those employed in this chapter will be examined in future papers.

4.6 References

Aguiar-Conraria, L., Azevedo, N., Soares, M.J. 2008. Using wavelets to decompose the time-frequency effects of monetary policy. Physica A: Statistical Mechanics and its Applications, 387, 2863-2878.

Aguiar-Conraria, L., Soares, M.J. 2011a. Oil and the macroeconomy: using wavelets to analyze old issues. Empirical Economics, 40, 645-655.

Aguiar-Conraria, L., Soares, M.J. 2011b. Business cycle synchronization and the euro: a wavelet analysis. Journal of Macroeconomics, 33, 477-489.

Aguiar-Conraria, L., Soares, M.J. 2014. The continuous wavelet transform: moving beyond uni- and bivariate analysis. Journal of Economic Surveys, 28, 344-375.

Alquist, R., Guénette, J.D. 2014. A blessing in disguise: the implications of high global oil prices for the north american market. Energy Policy, 64, 49-57.

Arezki, R., Blanchard, O. 2015. Seven questions about the recent oil price slump. Energia, 36, 2-10.

Baffes, J., Kose, M.A., Ohnsorge, F., Stocker, M. 2015. The great plunge in oil prices: Causes, consequences, and policy responses. Policy Research Note No.1, World Bank.

Bank of Canada. 2015. Monetary policy report January 2015. Bank of Canada.

Baumeister, C., Kilian, L. 2016. Understanding the decline in the price of oil since June 2014. Journal of the Association of Environmental and Resource Economists, 3, 131-158.

Benes, J., Chauvet, M., Kamenik, O., Kumhof, M., Laxton, D., Murula, S., J. Selody. 2015. The future of oil: geology versus technology. International Journal of Forecasting, 31, 207-221.

Clements, M., Cummings, A. 2016. U.S. shale: the saviour and the scourge of the oil market. SYZ Wealth Management.

Covert, T.R. 2014. Experiential and social learning in firms: the case of hydraulic fracturing in the bakken shale (Job Market Paper). Working Paper.

Cuestas, J.C., Gil-Alana, L.A. 2016. Testing for long memory in the presence of non-linear deterministic trends with Chebyshev polynomials. Studies in non-linear dynamics and econometrics, 20, 57-74.

Dahlhaus, R. 1989. Efficient parameter estimation for self-similar process, Annals of Statistics, 17, 1749-1766.

Daubechies, I. 1992. Ten lectures on wavelets. Society for Industrial and Applied Mathematics, Philadelphia.

Diebold, F.X., Inoue, A. 2001. Long memory and regime switching, Journal of Econometrics, 105, 131-159.

Gençay, R., Selçuk, F., Whitcher, B. 2002. An introduction to wavelets and other filtering methods in finance and economics. Academic Press.

Gil-Alana, L.A. 2008. Fractional integration and structural breaks at unknown periods of time. Journal of Time Series Analysis, 29, 163-185.

Gil-Alana, L.A., Hualde, J. 2009. Fractional integration and cointegration. An overview with an empirical application. The Palgrave Handbook of Applied Econometrics, 2, 434-472.

Granger, C.W.J., Hyung, N., 2004. Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. Journal of Empirical Finance, 11, 399-421.

Hamilton, J. 2014. Oil prices as an indicator of global economic conditions. Econbrowser.

Hogan J., Lakey, J. 2005. Time-frequency and time-scale methods: adaptive decompositions, uncertainty principles, and sampling. Birkhäuser, Boston.

Kilian, L. 2016a. The impact of the shale oil revolution on U.S. oil and gas prices. Review of Environmental Economics and Policy. Forthcoming.

Kilian, L. 2016b. The impact of the fracking boom on Arab oil producers. Working Paper.

Krane, J., Agerton, M. 2015. Effects of low oil prices on U.S. shale production: OPEC calls the tune and shale swings. Baker Institute Research Paper.

Kyrtsos, C., Malliaris, A.G., Serletis, A. 2009. Energy sector pricing: on the role of neglected nonlinearity. Energy Economics,31, 492-502.

McCracken, R. 2015. Shale oil's response to prices may call for industry re-evaluation. Energy Economist, Platts.

Monge, M., Gil-Alana, L.A., Perez de Gracia, F. 2017. Crude Oil Price Behaviour Before and After Military Conflicts and Geopolitical Events. Energy, 120, 79-91

Naccache, T. 2011. Oil price cycles and wavelets. Energy Economics,33, 338-352.

Percival, D.B., Walden, A.T. 2000. Wavelet methods for time series analysis. Cambridge University Press.

Ramsey, J. B. 2002. Wavelets in economics and finance: past and future. Studies in Nonlinear Dynamics and Econometrics,6, 1-28.

Robinson, P.M. 1995. Gaussian semi-parametric estimation of long range dependence. Annals of Statistics, 23, 1630-1661.

Schreiber, T., Schmitz, A. 1996. Improved surrogate data for nonlinearity tests. Physical Review Letters,77, 635-638.

Sharenow, G.E., Worah, M.P. 2013. Shale oil: a deep dive into implications for the global economy and commodity investors. $http://www.pimco.com/en/insights/pages/shale-oil-a-deep-dive-into-implications-for-the-global-economy-and-commodity-investors.aspx$.

Chapter 5

Conclusions

The four research papers written in this doctoral thesis attempts to better understanding oil market behaviour.

In the thesis' first paper, *Crude Oil Price Behaviour Before and After Military Conflicts*[1], our objective and focus has been first to analyse the statistical properties of a real oil prices by using unit roots and fractional integration methods, and then to understand the behaviour of oil prices before and after military conflicts and geopolitical events since the Second World War.

The results suggest that the real oil prices and its logarithm transformations are nonstationary I(1), while the first differences are stationary I(0). I also estimated the differencing parameter d in terms of a fractional model. In the first case, I analyze the real oil price of the WTI's series and its time trend. It is worth noting that since the estimated value of d is significantly below 1 the series seems to be mean reverting, meaning that shocks will be transitory and will disappear by themselves in the long run, though it will take some time to recover its original trend.

Using the approach suggested in Gil-Alana (2008) that divides the sample into different subsamples with different deterministic trends and different differencing parameters for each subsample, we detect two significant breaks, one at October 1973 and the other one at October 1990.

Focusing in the volatility (measure in terms of absolute and squared returns) the results indicate evidence of stationarity (and long memory in case of the absolute returns). We also observe several outliers, corresponding to different episodes of violence. Removing these outliers, the same results were obtained in terms of the estimates of d.

In the second part of our empirical work, I focus on the subsamples according to the different conflicts. There are six conflicts and the first thing we do is to examine if there is a different degree of integration before and after the breaks. First, I take the same number of observations (60) before and after the conflicts and I estimate d in the levels of the log-prices, the squared and

[1] Monge, M., Gil-Alana, L.A., Perez de Gracia, F. 2017. Crude Oil Price Behaviour Before and After Military Conflicts and Geopolitical Events. Energy, 120, 79-91.

the absolute returns. We cannot find any systematic pattern before and after the conflicts, and noting that in the sub-periods I could have incorporated subsequent conflicts due to the proximity of one to another, I also considered different sizes for each subsample, avoiding the interpolation with other conflicts. Once more, the results did not show up any significant difference before and after the conflicts.

Finally, I estimate d for subsequent sub-samples increasing in size incorporating one conflict each time. We observe here a significant monotonic increase in the estimated values of d with the conflicts, implying a continuous increase in the degree of persistence of the series. However, this evidence is not so clear in the case of the absolute returns.

In the second and third paper, *Fractional Integration and Cointegration in Mergers and Acquisitions in the U.S. Petroleum Industry*[2] and *Are Mergers and Acquisitions in the Petroleum Industry affected by Oil Prices?*[3], I contribute to the literature on crude oil price behavior and examine how this affects mergers and acquisitions in the petroleum industry in the U.S. We analyze the relationship of these two series by studying its dynamic in the time and time-frequency domain, respectively, using data from January 1980 to June 2012. In the second paper, we employ methodologies based on fractional integration and cointegration. First I show that the two individual series display a high degree of persistence though the series seem to be mean reverting with shocks disappearing in the very long run. Testing the hypothesis of (fractional) cointegration, we see that this is rejected and thus, we consider, as a potential specification, a regression model in which lagged oil prices appear as an explanatory variable in the analysis of M&A data. The results indicate that an increase in the crude oil price produces a signicant increase in the M&A data between 2 and 3 months after the initial shock. The third paper, employs wavelet tools, observing a shift to higher frequencies of the wavelet coherency during the mid-1990s and late 2000s. The results also indicate that during the mid-1990s and late-2000s an increase in mergers and acquisitions took place that was led by the increase in WTI crude oil prices, which is in line with the results reported in the second paper.

The paper *U.S. Shale Oil Production and WTI Prices Behaviour*[4], analyzes the relationship of total United States crude oil production (including shale oil production) and WTI crude oil prices by studying its performance in the time-frequency domain applying wavelet tools for its resolution. The results indicates a shift to higher frequencies of the wavelet coherency for the time period

[2] Monge, M., Gil-Alana, L.A. 2016. Fractional integration and cointegration in merger and acquisitions in the US petroleum industry. Applied Economics Letters, 23, 701-704.

[3] Monge, M., Gil-Alana, L.A., Pérez de Gracia, F. and Rodríguez Carreño, I. 2017. Are Mergers and Acquisitions in the Petroleum Industry affected by Oil Prices?. Energy Sources, Part B: Economics, Planning and Policy, 12, 420-427.

[4] Monge, M., Gil-Alana, L.A., Perez de Gracia, F. (Forthcoming). U.S. Shale Oil Pro duction and WTI Prices Behaviour. Energy.

2003-2009 and lower frequencies for the period 2009-2014. The results also indicate that during the period 2003-2009 the U.S. oil production and WTI oil prices time series are in phase; they move together, with total United States oil production leading. During the period 2009-2014 oil production and WTI oil prices time series are out of phase (negatively correlated), suggesting that oil production increases precede a decrease in WTI oil prices. In the second part of the paper and to give greater credibility to the results obtained through the wavelet transform, we analyze the behavior of WTI crude oil before and after the shale oil boom in the United States employing methodologies based on long run dependence. The results indicate that mean reversion takes place only for the data corresponding to the first subsample, ending at 2003. For the second subsample, as well as for the whole sample, lack of mean reversion is detected with orders of integration equal to or higher than 1 in all cases.