Business School

WORKING PAPER SERIES

Working Paper

2014-121

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Oil Price and Financial Markets: Multivariate Dynamic Frequency Analysis

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Abstract

The aim of this paper is to study the degree of interdependence between oil price and stock market index into two groups of countries: oil-importer countries and exporter ones. To this end, we propose a new empirical methodology allowing a time-varying dynamic correlation measure between the stock market index and the oil price series. We use the frequency approach proposed by Priestley and Tong (1973), that is the evolutionary co-spectral analysis. This method allows us to distinguish between short-run and medium-run dependence. In order to complete our study by analyzing long-run dependence, we use the cointegration procedure developed by Engle and Granger (1987). We find that interdependence between the oil price and the stock market is higher in exporters' markets than the importers' ones.

Keywords**:** oil prices, stock markets, evolutionary co-spectral analysis

JEL Classifications: C14, C22, G12, G15, Q43

1. Introduction

Energy markets have been recently marked by considerable price movements. In particular, from 2001 to 2010, energy prices in international exchange platforms have been rising strongly, and record high prices for oil have been accompanied by important volatility and sudden decrease. This high volatility makes oil one of the major macro-economic factors causing unstable economic conditions for stock markets around the world **(**see Table 1 and 2 in the Appendix 1). Oil price movements show some important peaks and troughs during the period under study here. The main peaks are observed between 2007 and 2008. Another peak is observed in June 2009, where prices increased by more than 60% since the January 2009 price levels. All these changes are linked to aggregate demand-side oil price shocks. The first one occurred during the Asian economic crisis, the second took place in 2000, where interest rates decreased significantly creating a bust in the housing market and construction industries.

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The third one took place in the period 2006–2007, a result from the rising demand of oil from China and the fourth demand-side oil price shock took place in the global financial crisis of 2008 (see Figure 1 in the Appendix).

How these price movements impact the economy? Theoretically, there are several transmission channels. First, the price of a share being equal to its discounted future cash flow, rising oil prices can increase the interest rate to limit inflationary pressure, tighten the cost of doing business, put pressure on output prices thus decreasing profits (Jones et *al.*, 2004). High interest rates also make bond investments more attractive than stock ones (Chittedi, 2012). Financialization of oil markets and intensive oil trading can also be factored in (Creti et *al.*, 2013). All these effects generally trigger a negative relationship between oil and stock markets, which parallels the one between high oil prices and macroeconomic indicators.

Given that the roots of the link between oil and stock markets are of different nature, it is therefore interesting to explore whether the comovements between oil and stock price emerge in a given time frame, either in the short or in the long term.

Moreover, while there is a sizeable empirical literature on oil and stock markets, less is known about this relationship in the context of oil importing versus oil exporting countries. Most of the studies focus on oil importing countries, for instance the U.S. However, specific effects on different set of countries are worth investigating. For instance, an increase of oil prices negatively influences the economy of importing countries. When oil price rises, they can experience strong negative consequences and economic recession (Ferderer, 1996). Instead, an increase in the oil prices influences positively oil exporting countries' economies. Nevertheless, a decrease in the oil prices exhibits a negative relationship with economic growth of oil producers and can generate political and social instability (Yang and *al.*, 2002).

Our study tackles the issues of oil and stock market interdependence in oil exporting and importing countries by measuring the interaction between oil price and stock markets indices according a frequency approach that is the evolutionary co-spectral analysis as defined by Priestley and Tong (1973). Then, we complete our analysis through a cointegration analysis à la Engle-Granger (1987).

While existing studies applies either VAR or volatility analysis, we choose the evolutionary co-spectral analysis as it presents several advantages. First, this kind of analysis does not impose any restrictions or pre-treatment of the data (as it is the case of volatility analysis, for instance, which requires the series to be stationary or cointegration techniques which can be only applied to time series data integrated of order one). Second, it does not have an "end-point problem": no future information is used, implied or required as in band-pass or trend projection methods. In addition, the evolutionary co-spectral analysis gives a robust frequency representation of non-stationary process. Finally, the most important advantage of frequency analysis consists of providing information about the time horizon of the interdependence between two series: the analysis endogenously delivers whether the variables under investigation present short, medium or long-term interdependence. This additional information allows understanding which cycles and periods are more synchronized than others. The frequency of our data (monthly) avoids us to obtain long-run dependence through spectral approach.[4] For this reason, we complete our analysis by using the cointegration approach to look at longer terms phenomena.

Our study clearly shows changes in co-movements between oil prices and stock markets, thus partially contradicting the results of the studies that focus on the negative relationship between oil prices and stock market returns. Overall, our analysis shows two main findings. Oil price shocks in periods of world turmoil or during fluctuations of the global business cycle (downturn or expansion) seem to have a significant impact on the relationship between oil and stock market prices, both in oil importing and oil exporting countries. In exporting countries, our analysis unveils higher and multiple peaks which coincide with very important events (as oil price crisis that has occurred in 2008). In the case of importing countries the pattern of interaction is clearly smoothed compared to exporting countries. All other oil price shocks originated by OPEC's productions cuts, hurricanes etc., do not seem to have a significant impact on the coherence between oil and stock markets in importing countries. In any case, the interdependency between oil and stock markets is not very strong in the short run (that is 10 months in our study), but it is revealed more clearly in the medium run (3 years and one quarter). According the cointegration analysis, we have showed that the long run relationship is significant for all studies importing countries and non significant for some cases of exporting countries. Loosely, speaking the long run and medium run relationship has

[4] The frequency approach allows to study 7 frequencies $\frac{\pi}{20}, \frac{4\pi}{20}, \frac{7\pi}{20}, \frac{\pi 10}{20}, \frac{13\pi}{20}, \frac{16\pi}{20}, \frac{\pi 19}{20}$. The shift from the frequency domain to the time domain takes place through the following formula: $\frac{2\pi}{\lambda}$, where λ is the frequency. The smaller frequency gives us information about the bigger span relationship. In other, the frequency $\frac{\pi}{20}$ corresponds to $\frac{2\pi}{\frac{\pi}{20}}$ months = 3 years and one quarter, whereas $\frac{10\pi}{20}$ refers to 10 months time frame. Therefore, with monthly data, we cannot go beyond 3 years and one quarter limit.

a similar pattern.

This paper is organized as follows. Section 2 summarizes the literature and compares our approach to existing studies. Section 3 presents the empirical methodology and the data. Section 4 details our results, and section 5 concludes.

2. Related Literature

The relationship between oil price and real economic activity has been widely investigated. Hamilton (1983) concludes that positive oil price shocks are a substantial cause for economic recession in the US. After this work, oil prices dynamics has motivated many studies, among them the ones focusing on the links between oil and stock prices. Most papers, devoted to oil-importing countries, show a negative relationship between oil prices and stock markets activities. One of the first paper exhibiting this relationship is Sadorsky (1999), who shows that oil prices shocks have symmetric effects on the economy, positive shocks have a greater impact on stock markets and economic activity than do negative oil price shocks. Since this seminal paper, other studies have either confirmed this finding (as for instance Basher et al, 2010; Chen, 2009; Elder and Serletis, 2010; Jones and Kaul, 1996; Kilian and Park (2009); Masish et *al.*, 2011; Wei, 2003) or pointed out that the impact of oil price on stock markets can be weakly significant (Aspergis and Miller, 2009; Miller and Ratti, 2009). In the following, we detail some of the empirical models on that topic.

Hammoudeh et *al.* (2004) examines the long-run interaction between five GCC stock markets (Bahrain, Kuwait, Oman, Saudi Arabia, and UAE) and three global factors (oil spot price indices, US 3-month Treasury bill rate, and S&P index). They apply cointegration tests and a Vector Error Correction model to weekly data from February 1994 to December 2004. The authors find that oil price movements do not have direct effects on any GCC stock markets, while the latter counts for less than 4% of the variations in oil prices after a 20 week period.

Using a multi-factor approach, Syed and Sadorsky (2006) study the impact of oil price changes on emerging stock market. They argued that oil price risk impacts stock price returns. Narayan and Narayan (2012) use the EGARCH method to model daily data of crude oil prices and conclude that shocks influence constantly and asymmetrically the volatility over the long-term period. Asymmetric effect indicates that positive shocks affect oil price differently than negative shocks. Chiou and Lee (2009) examine the asymmetric effects of WTI daily oil prices on Standard&Poor 500 stock returns. Using the Autoregressive Conditional Jump Intensity model with expected, unexpected and negative unexpected oil price fluctuations, they find that high fluctuations in oil prices have asymmetric unexpected effects on stock returns. Malik and Ewing (2009) rely on bivariate GARCH models to estimate the volatility transmission between weekly WTI oil prices and equity sector returns, finding evidence for spillover mechanisms. Choi and Hammoudeh (2010) extend the time-varying correlations analysis by considering commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index. They show that commodity correlations have increased since 2003, limiting hedging substitutability in portfolios. Finally, Arouri and Nguyen (2010) use a GARCH model to inspect the effect of oil prices on European sector returns rather than only on aggregate stock market index returns. They conclude that oil prices tend to exercise a significant influence on various European sectors; however, the magnitude and the direction of the effect differ from one sector to another.

All the above mentioned models do not consider different group of countries on the basis of the weight of oil in their economy. A few papers tackle this issue. Bjornland (2009) shows that a 10% increase in oil price result in 2.5% of stock market index increase in Norway, an oil-exporting country. Yoon and Park (2011) and Park and Ratti (2008) argue that the negative effect of oil price on stock markets only holds for oil importing countries, but their analysis is limited to a few countries (Norway, Korea, Saudi Arabia and Russia). Filis et *al.* (2011) investigate time-varying correlations between Brent oil prices and stock markets on both oil importing and oil exporting countries. Using multivariate asymmetric DCC-GARCH approach, they find that the conditional variances of oil and stock prices do not differ for oil importing and oil exporting economies. However, time-varying correlations depend on the origin of the oil shocks: the response from aggregate demand-side shocks is much greater than supply-side shocks originated by OPEC's production cuts. Wang et al. (2012) use Vector Auto Regressive analysis impulse response analysis to investigate the impact of oil demand and supply shocks in several oil-importing and oil-exporting countries. The author show that stock markets of oil importing countries react to oil supply shocks, but the effect is short lived. Demand shock affect stock market of both group of countries. Concerning specifically oil exporting countries, Al Janabi and *al.* (2010) use bootstrap test for causality to study non-normal financial data with time-varying volatility. They conclude that oil prices do not tend to affect these stock markets and thus oil prices cannot be used as predictors for the Gulf Cooperation Council stock markets. More recently, Arouri and Rault (2011) study the impact of oil prices shocks on Gulf countries, with a boostrap panel cointegration model, and provide evidence that the stock market performance of the Gulf markets is affected by positive oil price shocks. Similar results were also documented by Bashar (2006) and Hammoudeh and Aleisa (2004).

Our paper takes a novel perspective in assessing the links between oil prices and stock markets. We use a technique which has not yet been used so far in that context, that is evolutionary co-spectral analysis which is a time frequency approach. Contrary to time series models, our approach allows for a representation of non-stationary series without any risk of misspecification. Indeed, differently from traditional time series model-such as ARMA, Multivariate GARCH (CCC, DCC…), evolutionary spectral analysis does not depend on assumption on the data. The evolutionary spectral analysis does not show an "end-point problem": no future information is used, implied or required as in band-pass or trend projection methods. The most important contribution with respect to traditional time series analysis consists of the decomposition of series on two dimensions, that is frequency and time occurrence of the dependence. This allows to study time series according to different horizons, for instance short and medium-term. To complete the long run relationship between oil price and stock markets, we employ the cointegration approach of Johanson and Engle (1987). Therefore, we aim at complementing the existing studies to uncover whether the results of the previous literature are robust to model specification, in particular in the dynamic dimension of the oil-stock market relationship when importing and exporting countries are accounted for.

3. Empirical analysis and data

As mentioned in the introduction, our objective is to measure the dynamic interaction between oil price series and stock market index for oil importer and exporter countries. The short-run and the medium-run interaction between these series is measured according to a frequency approach based on the theory of evolutionary co-spectral analysis of Priestley and Tong (1973). We measure co-movement between series by the coherence function. We then propose a time-varying measure of this variable. Concerning the long-run interaction, we propose the Engle and Granger (1987) procedure of cointegration (see appendix 3).

3.1 Theory of the evolutionary Co-spectral (Priestley and Tong: 1973)

According to Priestley (1965), a non-stationary discrete[5] process or a continuous[6] process can be written as equation (1). Priestley and Tong (1973) extend the theory of the evolutionary spectral analysis of Priestley (1965–1966), to the case of a bivariate non-

[5] A discrete process corresponds to a process of which the value of T is countable. Indeed, a time series is considered as a discrete process.

[6] A continuous process is a process used to describe the physical signal.

stationary process. In this sub-section, we summarize this theory.

Consider, for example, a bivariate continuous parameter process $\{X(t), Y(t)\}$, in which each component is an oscillatory process. Each component can be written as follows:

$$X(t) = \int_{-\infty}^{+\infty} A_{t,x}(w_1)\, e^{iwt}\, dZ_x(w_1) \tag{1}$$

$$Y(t) = \int_{-\infty}^{+\infty} A_{t,y}(w_2)\, e^{iwt}\, dZ_y(w_2) \tag{2}$$

where

$$E[dZ_x(w_1)\, dZ_x^*(w_2)] = E[dZ_y(w_1)\, dZ_y^*(w_2)]$$
$$= E[dZ_x(w_1)\, dZ_y^*(w_2)] = 0 \qquad for\ w_1 \neq w_2$$
$$E[|dZ_x(w_1)|^2] = d\mu_{xx}(w), \quad E[|dZ_y(w_1)|^2] = d\mu_{yy}(w), \quad and$$
$$E[dZ_X(w_1)\, dZ_y^*(w_1)] = d\mu_{xy}(w)$$

with $[.]^*$ denoting the conjugate function of $[.]$.

Let F_x, F_y denote respectively the families of oscillatory functions as: $\{\varphi_{t,x}(w_1) \equiv A_{t,x}(w_1)e^{iwt}\}, \{\varphi_{t,x}(w_1) \equiv A_{t,x}(w_1)e^{iwt}\}$. Priestley and Tong (1973) define the evolutionary power cross-spectrum at time t with respect to the families F_x, F_y, $dH_{t,XY}(w)$ by

$$dH_{t,XY}(w) = A_{t,X}(w)\, A_{t,Y}^*(w)\, d\mu_{XY}(w) \tag{3}$$

Further, if $\{X(t), Y(t)\}$ is a bivariate stationary process, so that $F_x\, and\, dF_y$ may be chosen to be the family of complex exponentials, namely $F_x \equiv F_Y \equiv \{e^{iwt}\}$, $dH_{t,XY}(w)$ reduces to the classical definition of the cross-spectrum. Thus, for each t, we may write

$$dH_{t,XY}(w) = E[A_{t,X}(w)\, dZ_X(w)\, A_{t,Y}^*(w)\, dZ_Y^*(w)] \tag{4}$$

Priestley and Tong (1973) extend the above relation to the case of a non-stationary bivariate process where the amplitudes are time-dependent; correspondingly, the cross-spectrum is also time-dependent. Clearly, $dH_{t,XY}(w)$ is complex-valued, and, by virtue of the Cauchy–Schwarz equality, we have immediately that

$$|dH_{t,XY}(w)|^2 \leq dH_{t,XX}(w)\, dH_{t,YY}(w) \quad \text{for each } t \text{ and } w \tag{5}$$

If the measure $\mu_{XY}(w)$ is absolutely continuous with respect to the Lebesgue measure, we can write, for each t:

$$dH_{t,XY}(w) = h_{t,XY}(w)dw \tag{6}$$

and $h_{t,XY}(w)dw$ may then be termed the evolutionary cross-spectral density function.

3.1.1 Estimation of the evolutionary Co-spectral density function

The evolutionary cross-spectral density function estimation, which we develop here, is an extension of Priestley and Tong (1973) from the estimation of the evolutionary spectral density function in the univariate case, such as developed by Priestley (1965–1966). In our analysis, we are interested in time series as discrete process.[7] We analyse two pairs of series-oil price series and stock market index of a country. Therefore, we detail the procedure to estimate the evolutionary cross-spectral density function.

Let a non-stationary discrete bivariate process $\{X(t), Y(t)\}$ have the Gramer representation for each $-\pi \prec w \prec \pi$:

$$X_t = \int_{-\pi}^{\pi} A_{t,X}(w) e^{iwt} dZ_X(w) \quad \text{and} \quad Y_t = \int_{-\pi}^{\pi} A_{t,Y}(w) e^{iwt} dZ_Y(w)$$

with

$$E[dZ_x(w_1)\, dZ_x^*(w_2)] = E[dZ_y(w_1)\, dZ_y^*(w_2)]$$
$$= E[dZ_x(w_1)\, dZ_y^*(w_2)] = 0 \quad \text{for } w_1 \neq w_2$$
$$E[|dZ_x(w_1)|^2] = d\mu_x(w), \quad E[|dZ_y(w_1)|^2] = d\mu_y(w), \quad \text{and}$$
$$E[dZ_X(w_1)\, dZ_y^*(w_1)] = d\mu_{xy}(w)$$

By virtue of the Cauchy–Schwarz inequality, we can write that:

$$|dH_{t,XY}(w)|^2 \leq dH_{t,XX}(w)\, dH_{t,YY}(w)$$

And $dH_{t,XY}(w) = h_{t,XY}(w)dw$ for each t and w

where $h_{t,XY}(w)dw$ may then be termed the evolutionary cross-spectral density function.

The estimation of the evolutionary cross-spectral density function needs two filters. For the discrete univariate process, Priestley (1966) gives two relevant windows. These are relevant filters and they are tested by several works, such as Ahamada and Boutahar (2002). For the

[7] For more details on continuous process, see Ftiti (2010).

discrete bivariate process, Priestley and Tong (1973) adopt the same choice, that is:

$$g(u) = \begin{cases} \dfrac{1}{2\sqrt{h\,\pi}} & if \ \ |u| \leqslant h \\ 0 & if \ \ |u| \ > h \end{cases} \qquad W_v = \begin{cases} \dfrac{1}{T'} & if \ \ |v| \leqslant \dfrac{T'}{2} \\ 0 & if \ |v| \ > \dfrac{T'}{2} \end{cases} \tag{7}$$

Then, the estimation of the evolutionary cross-spectral density function is as follows:

$$\hat{h}_{t,\,XY}(w) = \sum_{v \in Z} W_{T'}(v) U_X(w, t-v) \ U_Y(w, t-v) \tag{8}$$

with

$$U_x(t,w) = \sum_{u \in Z} g(u)\, X(t-u)\, e^{-i\,(t-u)w}\, d \tag{9}$$

$$U_Y(t,w) = \sum_{u \in Z} g(u)\, Y(t-u)\, e^{-i\,(t-u)w}\, d \tag{10}$$

In this paper, we take $h = 7$ and $T' = 2$. We make the same choice[8] as Artis et al. (1992), Priestley (1995), Ahamada and Boutahar (2002), Essaadi and Boutahar (2008).

According to Priestley (1988), if we have $E(\hat{h}(w)) \approx h_t(w)$, $\mathrm{var}(\hat{h}(w))$ decreases when T' increases. $\forall\ (t_1, t_2)$, $\forall (w_1, w_2)$, $\mathbf{cov}(\hat{h}_{t_1}(w_1), \hat{h}_{t_2}(w_2)) = 0$, if at least one of the following conditions (i) or (ii) is satisfied.

(i): $|w \pm w'|$ a e w n s ea $\| w_1 \pm w_2 |$ ... $|\Gamma(w)|^2 |$

(ii): $|S - t|$ i m s b o t h o f h a a e $\{w(u)\}$

In order to respect conditions (i) and (ii), we choose $\{t_i\}$ and $\{w_j\}$ as follows:

$t_i = \{1 + 20(i-1)\}_{i=1}^{I}$ Where $I = \left[\dfrac{T}{20}\right]$ and T the sample size

$$w_j = \left\{ \frac{\pi}{20}(1 + 3(j-1)) \right\}_{j=1}^{7}$$

To respect the *(ii)* condition, we inspect instability in these frequencies; $\frac{\pi}{20}, \frac{4\pi}{20}, \frac{7\pi}{20}, \frac{\pi 10}{20}, \frac{13\pi}{20}, \frac{16\pi}{20}, \frac{\pi 19}{20}$.

[8] This choice of values is justified by the fact that they respect the conditions (i) and (ii).

We finally have a co-spectral density function in 7 frequencies. However, we retain only two frequencies reflecting respectively short-term and medium-term. Indeed, the first frequency $\frac{\pi}{20}$ traduces the medium-term interdependence and the frequency $\frac{4\pi}{20}$ traduces the short-term one. The shift from the frequency domain to the time domain takes place through the following formula: $\frac{2\pi}{\lambda}$, where λ is the frequency. For example, the frequency $\frac{\pi}{20}$ corresponds to $\frac{2\pi}{\frac{\pi}{20}}\ months = 3\ years$ and one quarter, whereas $\frac{2\pi}{\frac{4\pi}{20}}$ refers to 10 months time frame.

3.1.2 Coherence Function

According to Priestley and Tong (1973), the evolutionary cross-spectral density function may be written as:

$$h_{t,XY}(w) = C_{t,XY}(w) - i\,Q_{t,XY}(w) \tag{11}$$

$$\begin{aligned} C_{t,XY}(w) &= R\{h_{XY}(w_j, t)\} \\ Q_{t,XY}(w) &= \mathrm{Im}\{h_{XY}(w, t)\} \end{aligned} \tag{12}$$

and the real-valued functions $C_{t,XY}(w)$ and $Q_{t,XY}(w)$ termed the evolutionary co-spectrum and the evolutionary quadrature spectrum, respectively. If the measures $\mu_{XX}(w)$ and $\mu_{YY}(w)$ are absolutely continuous, Priestley and Tong (1973) similarly define the evolutionary auto-spectral density functions, $h_{XX}(w_j,t)$, $h_{YY}(w_j,t)$.[9] The coherency function is defined by the following expression:

$$\begin{aligned} C_{t,XY}(w) &= \frac{\left|h_{t,XY}(w)\right|}{\left\{h_{t,XX}(w)\,h_{t,YY}(w)\right\}^{1/2}} \\ &= \frac{\left|E[d\,Z_Y(w)\,d\,Z_X^*(w)]\right|}{\left\{E\left|d\,Z_X(w)\right|^2\,E\left|d\,Z_Y(w)\right|^2\right\}^{1/2}} \end{aligned} \tag{13}$$

Priestley and Tong (1973) interpret $C_{t,XY}(w)$ as the modulus of the correlation coefficient between $d\,Z_X(w)$ $d\,Z_Y(w)$ or, more generally, as a measure of the linear relationship between corresponding components at frequency w in the processes $\{Y(t)\}$ and $\{X(t)\}$.

The estimation of the coherency function is based on the estimation of the cross-spectral density function between two processes $\{Y(t)\}$ and $\{X(t)\}$ and the estimation of the auto-spectral density function of each process. So, the estimation coherency can be written as

[9]For more details see Ftiti (2010).

follows:

$$\hat{C}_{t,XY}(w) = \frac{\left|\hat{h}_{t,XY}(w)\right|}{\left\{\hat{h}_{t,XX}(w)\,\hat{h}_{t,YY}(w)\right\}^{1/2}} \tag{14}$$

3.3 Data description

In this study, we use monthly data for oil prices and stock market indices. The sample consists of oil-importing (US, Italy, Germany, Netherland and France) and exporting countries (Emirate Arab Units, Kuwait, Saudi Arabia and Venezuela). To select the sample, we have adopted two criteria: (i) the presence of a well-established stock market and (ii) a rank in the top 20 oil-importers and exporters countries.

The Brent crude oil index is used as it accounts for the 65% of the world oil daily production (IMF, 2010). The data range from 03/09/2000 to 03/12/2010 and have been extracted from Federal Reserve Bank of Saint Louis and Datastream Database. The time horizon depends on data availability and includes, in addition to the major economic crisis and political events such as the different monetary and financial crises in Asian and Latin American and Middle East region, the first and the Gulf war, the Russian economic crisis and the terrorist attack in US. This will allows making important conclusion regarding the link between the dynamic of oil prices and the financial market returns.

4. Empirical findings and discussions

4.1. Oil price and stock market movement

Figure 1 in the Appendix presents the Brent crude oil prices, in dollars, from September 2000 to October 2010 in levels. The series appears to have a non-stationary behavior in the sense that it does not converge towards its long term means while the series in first difference fluctuates around zero and seems to be stationary. Figures 2 and 3 describe stock market indices during the period under analysis respectively for oil exporting and oil importing countries.

Fig 2. Stock Market indices of Oil-Exporting Countries

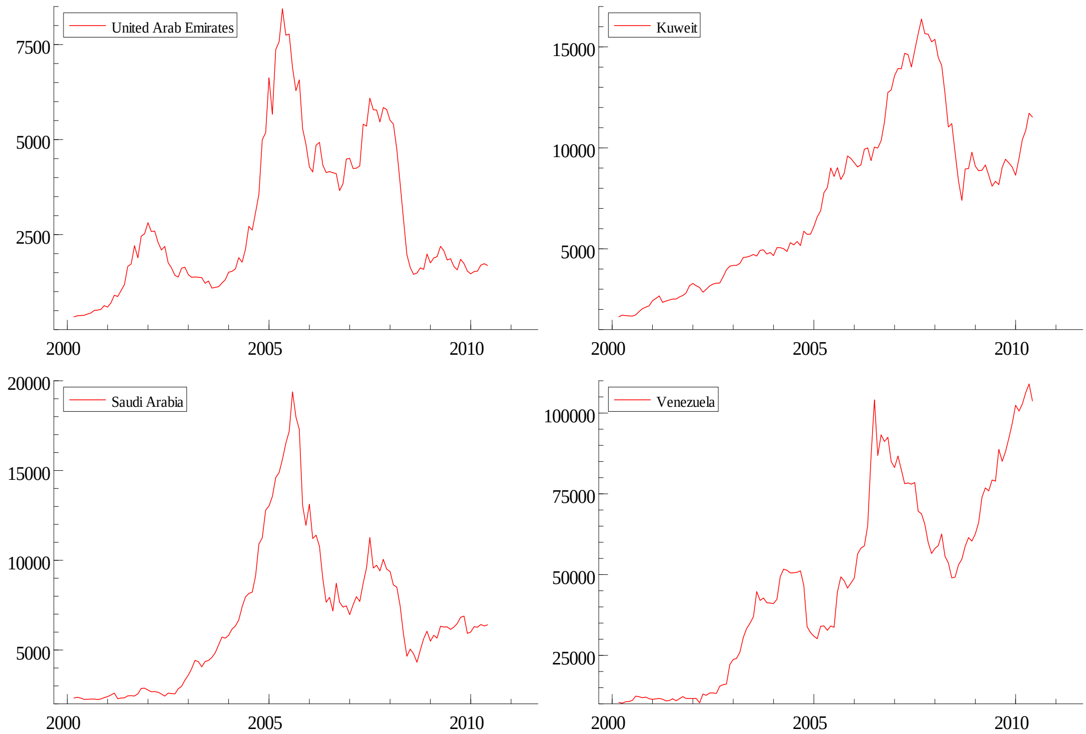
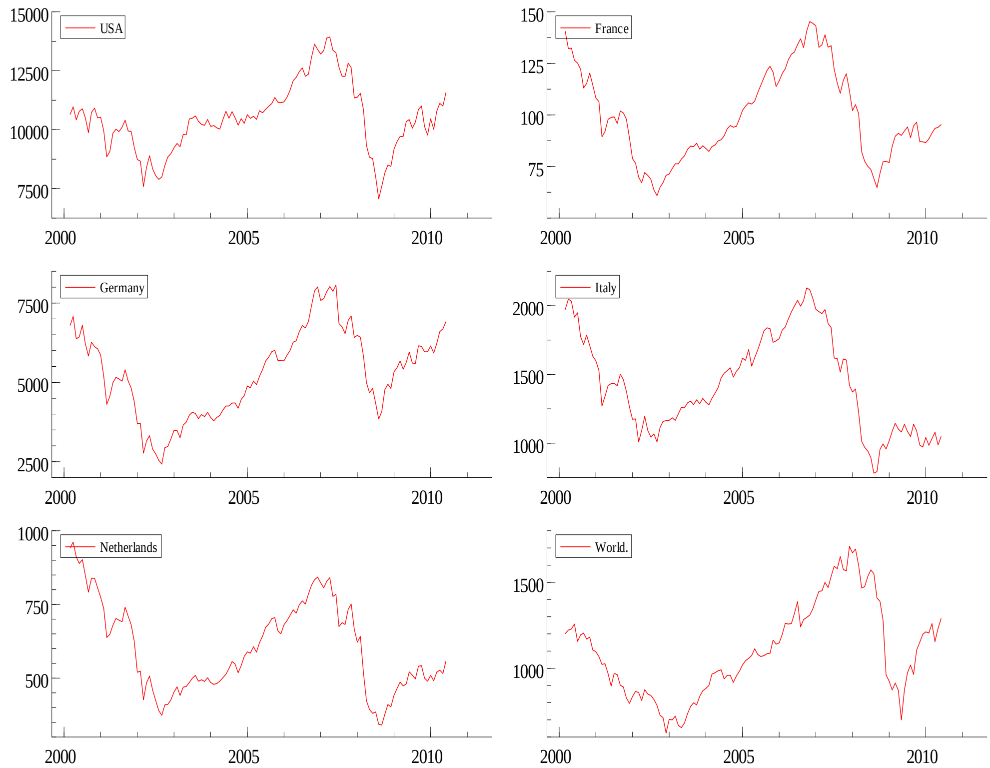


Fig 2. Stock Market indices of Oil-Exporting Countries



Taking into account the peaks and troughs of oil prices and the events that have taken place during our period of study, the relation between oil and stock market indexes exhibit some noteworthy aspects.

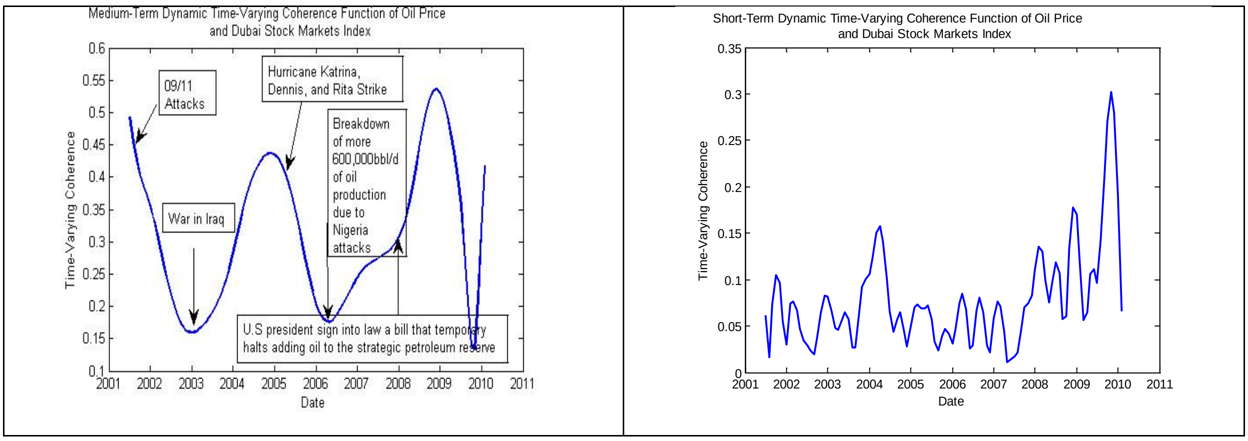
First, in exporting countries (Figure 2), we remark that stock markets have the same movement of oil prices fluctuation under the sub-period 2000-2005. We observe a period of oil price and stock market prices increase. However, for the sub-period 2005–2010, oil prices were increasing constantly. In addition, the period 2005 until mid-2007 is characterized mainly by a continuous oil price increase, as well as increased stock market prices. During mid-2006 until early 2007, when an oil price trough is observed, stock markets also exhibited a decrease in their price levels. Moreover, during 2007 until 2009, both oil prices and stock indexes are bullish. Finally, after the sub-period 2008-2009, both oil and stock market prices experienced a bearish performance. Venezuela exhibits a slightly different pattern, given a weaker development of its financial markets.

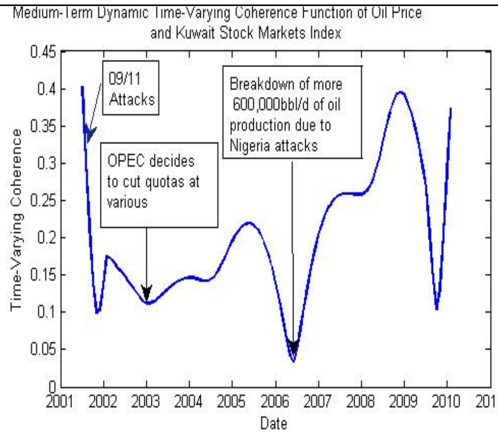
As preliminary result, we notice that the visual inspection of the series does not provide a clear distinction between stock market performance and oil prices on oil-importing and oil-exporting countries. However, we observe that stock indices of importing countries (Figure3) do not move in the same direction with oil prices. For example, during the sub-period 2000-2003, oil prices exhibited an increase, whereas the majority of the stock markets showed a decrease. For the sub-period 2007-2008, stock prices decrease when the oil prices were increasing constantly.

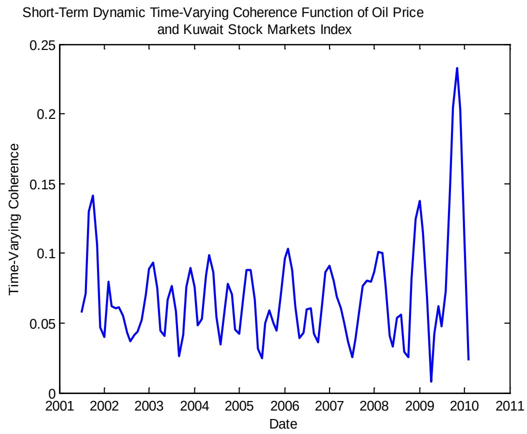
4.2 The results of dynamic coherence: short and medium terms dependence

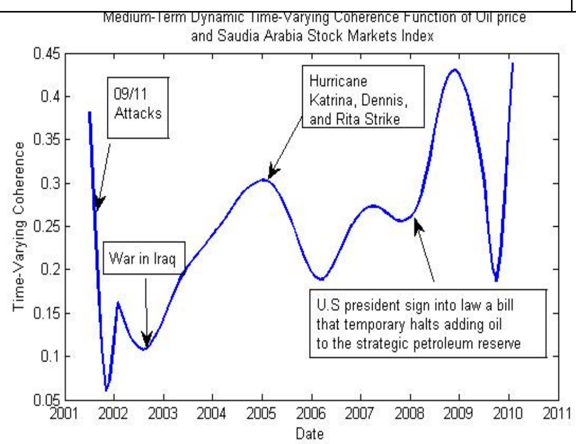
The analysis resulting from the time-varying coherence functions as computed from equation (14) between each stock market index and the Crude oil prices is shown in Figures 4 and 5, for oil-exporting and importing countries respectively.

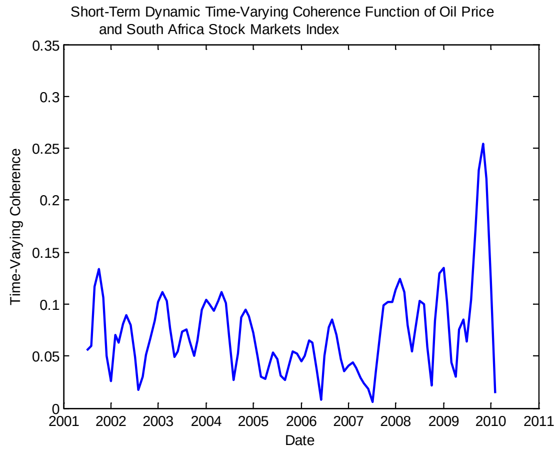
Figure 4: the dynamic coherence functions between stock market index and Oil price of exporting countries

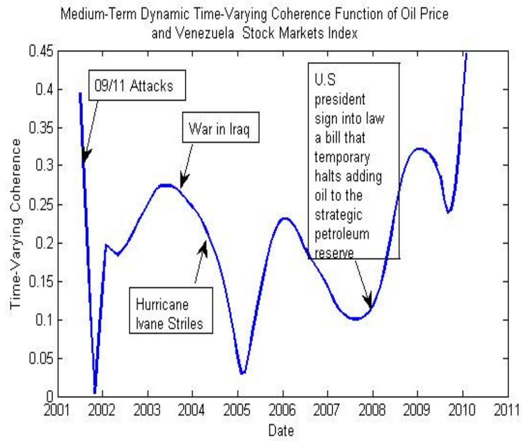


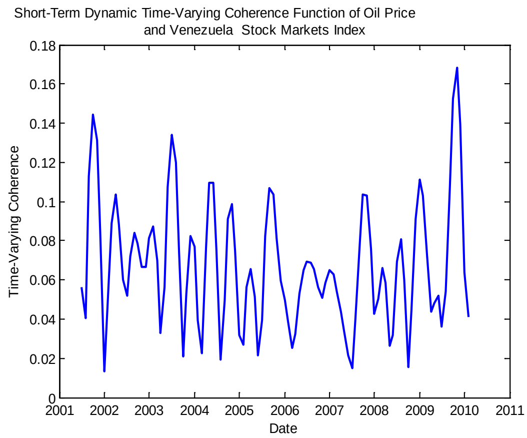

Medium-Term Dynamic Time-Varying Coherence Function of Oil Price
and Kuwait Stock Markets Index
Time-Varying Coherence
Date
09/11 Attacks
OPEC decides to cut quotas at various
Breakdown of more 600,000bbl/d of oil production due to Nigeria attacks

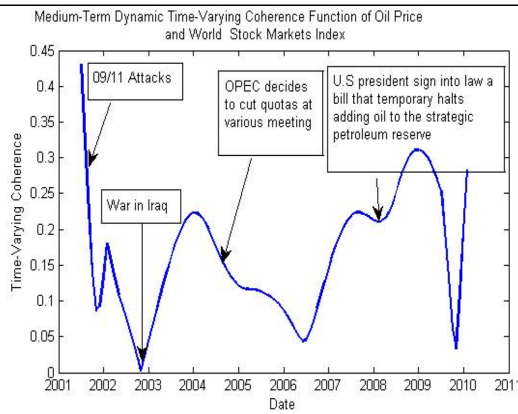

Short-Term Dynamic Time-Varying Coherence Function of Oil Price
and Kuwait Stock Markets Index
Time-Varying Coherence
Date


Medium-Term Dynamic Time-Varying Coherence Function of Oil price
and Saudia Arabia Stock Markets Index
Time-Varying Coherence
Date
09/11 Attacks
War in Iraq
Hurricane Katrina, Dennis, and Rita Strike
U.S president sign into law a bill that temporary halts adding oil to the strategic petroleum reserve


Short-Term Dynamic Time-Varying Coherence Function of Oil Price
and South Africa Stock Markets Index
Time-Varying Coherence
Date


Medium-Term Dynamic Time-Varying Coherence Function of Oil Price
and Venezuela Stock Markets Index
Time-Varying Coherence
Date
09/11 Attacks
War in Iraq
Hurricane Ivane Striles
U.S president sign into law a bill that temporary halts adding oil to the strategic petroleum reserve


Short-Term Dynamic Time-Varying Coherence Function of Oil Price
and Venezuela Stock Markets Index
Time-Varying Coherence
Date


Medium-Term Dynamic Time-Varying Coherence Function of Oil Price
and World Stock Markets Index
Time-Varying Coherence
Date
09/11 Attacks
War in Iraq
OPEC decides to cut quotas at various meeting
U.S president sign into law a bill that temporary halts adding oil to the strategic petroleum reserve

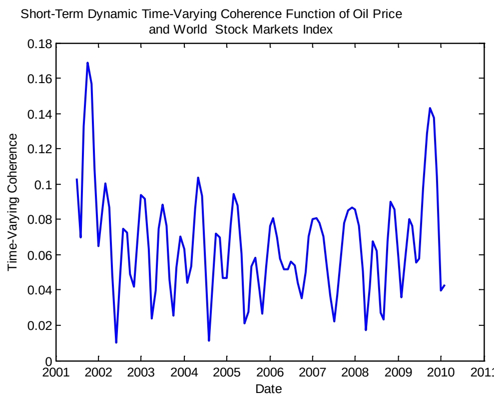
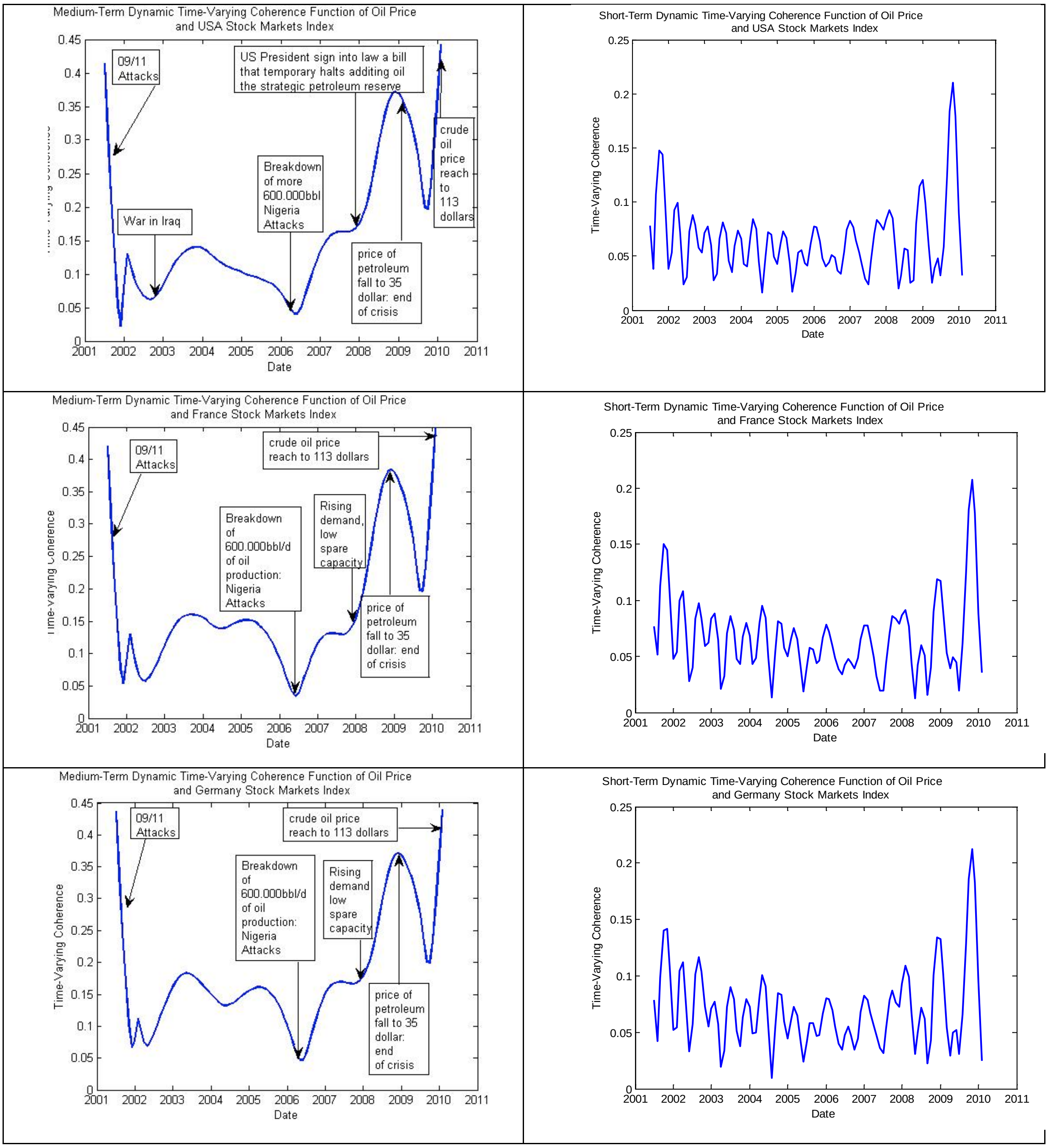
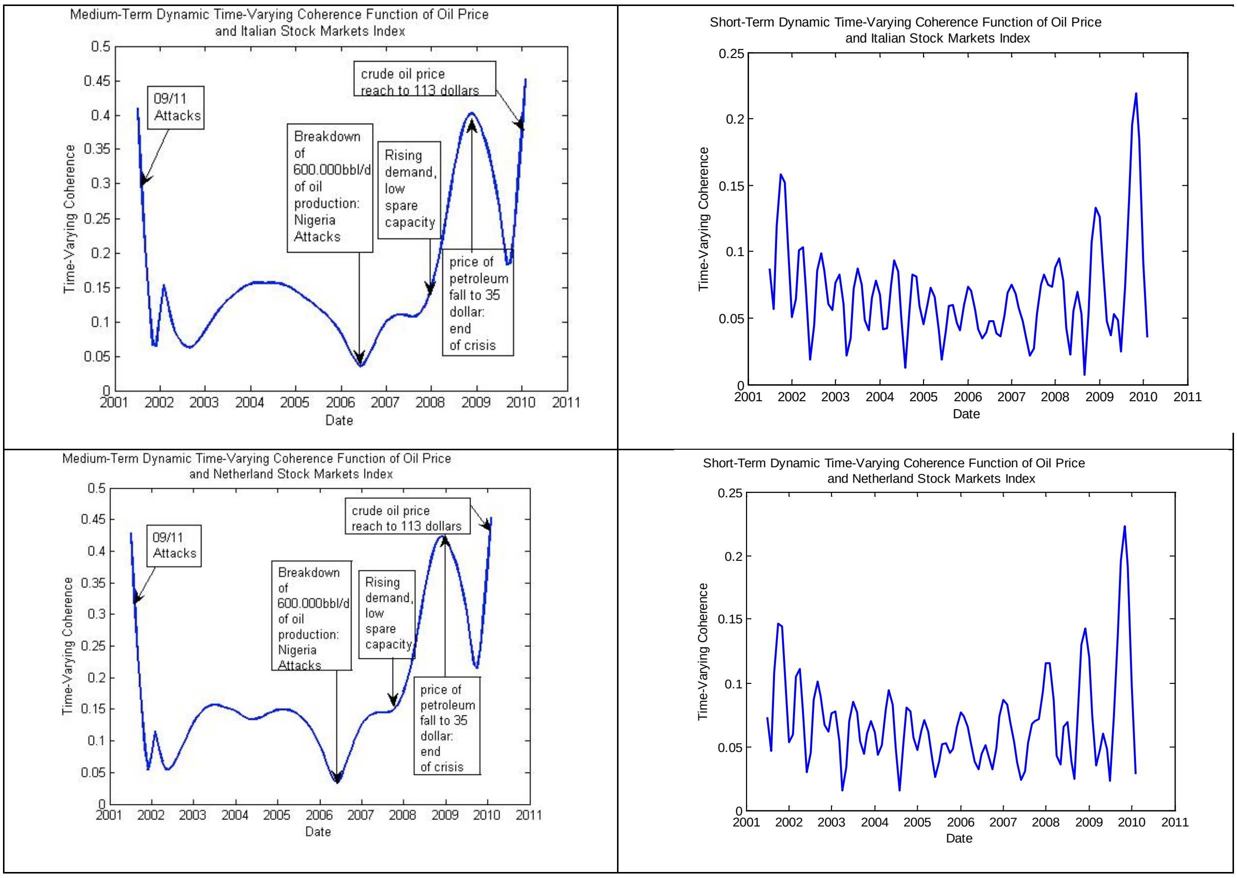

Short-Term Dynamic Time-Varying Coherence Function of Oil Price
and World Stock Markets Index
Time-Varying Coherence
Date

Figure 5: The dynamic coherence functions between stock market index and oil price of importing countries





According to the graphs in Figures 4 and 5, we observe a divergence between the medium-term interdependence of and the short-term one. More precisely, for all studied markets (exporting and importing ones), the interdependence between oil prices and stock market indices is less important in the short term than in the medium term. In the short term, the average interdependence does not exceed 10%, while in the medium-term, on average, it reaches more than 40%. Hence, for both importing and exporting countries, stock market indices react weakly to transitory fluctuations of oil price (short-term interdependence). Stock market indices for all countries, instead, react strongly to persistent fluctuations of oil price (medium-term interdependence).

In the short-run, there is no difference in the pattern of dynamic coherence function between exporting and importing price. The dynamic interaction between oil price and stock market indices is weak in the short-run, but it rises slightly in crisis period. In fact, the short-run dynamic of stock market, for both importing and exporting countries, does not depend strongly on oil price in stable periods. However, in crisis periods, stocks markets are affected by oil price, even though this interdependency is not very strong in the short-run. For example, we observe a rise in the short-run coherence pattern around the occurrence of some exogenous shocks (see Tables 1 and 2 in the Appendix).

The nature of dynamic interaction is different in medium-term. According to Figures 4 and 5, we observe a higher interdependence, in the medium-run, between oil price and stock market indices of all countries. However, there is some difference in the pattern between exporting and importing countries. Indeed, for exporting countries (Figure 4), we have different regimes in the time-varying dynamic coherence; nevertheless, there is a fewer periodicity (or fewer regimes) for the case of importing countries. In other words, exporting countries experience higher and multiple peaks which coincide with very important events (such as the 2008 oil price crisis). Moreover, in the case of importing countries the pattern of interaction is clearly smoothed compared to exporting countries. We conclude that stocks markets indices in exporting countries are more interdependent to oil price than importing countries, as in the former countries stock markets are dominated by oil companies, much larger than other listed companies.[10] This effect is novel with respect to the results obtained by Wang et *al.* (2012).

Concerning exporting countries, we observe a peak in coherence pattern observed around the year 2001 for all countries (40%). This high level of coherence between oil and stock market prices is due to the rapid increase in the housing market and construction industry, a result of decreasing interest rates worldwide in 2000. In addition, the 2001 attack can explain the higher coherence level observed in this period.

In 2003 there is a relatively less high of the coherence pattern in the case of exporting countries (Dubai, Kuwait and South Africa). This result is explained by the war in Iraq in Mars 2003 and PdVSA Strike in Venezuela. We observe a breakdown, for all exporting countries, in coherence pattern at the date of 2006. We explain this decrease in interdependence between oil price and stock market index by the military attack in Nigeria which caused the shutting down of more than 600 000 billion barrel per day.

Another period of interest is the one running from 2006 until mid 2008, characterized by high oil prices due to rising demand, mainly by China. The coherence level shows an increasing and positive pattern for all countries. This aggregate demand-side oil price shock has a positive effect on stock markets (both in oil-importing and oil-exporting countries), as it signals an increase in world trade. These findings are in line with Hamilton (2009b) and Kilian and Park (2009), who suggest that aggregate demand-side oil price shocks, originated

[10] This phenomenon can be attenuated by the fact that oil-exporting countries depend on export revenues that decline smoothly, due to the low demand elasticity of oil demand (Bjornland, 2009; Park and Ratti, 2011).

by world economic growth, have a positive impact on stock prices.

From mid-2006 and early 2009, the coherence pattern rises sharply and reaches a higher value (higher than 40%) for all stock markets, both in exporting and importing countries. The main event in this period is the global financial crisis initiated from the export of US mortgages to the rest of the world, as asset backed securities, which can be regarded as an aggregate demand-side oil price shock (International Energy Agency 2009). The higher interaction between oil and stock market prices can be explained by the fact that such crisis caused stock markets to enter bearish territories and caused oil prices to decline heavily, as also documented by Creti et *al.* (2013).

There are only three periods of noteworthy higher or lower coherence between oil prices and stock markets for exporting countries. These are the early 2000 until 2001 (aggregate demand-side oil price shocks — higher coherence), 2003-2005 higher coherence (aggregate demand-side oil price shocks — higher coherence), and 2007–2008 (aggregate demand-side oil price shock — positive correlation). The years 2003-2005 represent the sole period showing little difference[11] between importing and exporting countries in term of coherence pattern of oil and stock market prices.

The explanation of such findings can depend on the boom that the housing market experienced in 2000 creating a positive environment for world markets and at the same time a high demand for oil, driving the prices of both markets to higher levels. The 9/11 terrorist attack and the second war in Iraq also created significant uncertainty in all economies, causing similar movements in their stock markets and thus similar coherence with oil prices. In addition, the Chinese growth and its impact in the world trade caused euphoria in all stock markets regardless the country of origin. Similarly, the last world financial crisis influenced all stock market similarly and thus their co-movements.

Our analysis shows two main findings. Oil price shocks in periods of world turmoil or during fluctuations of the global business cycle (downturn or expansion) seem to have a significant impact on the relationship between oil and stock market prices, regardless the status of the market (i.e. belonging to an oil-importing or oil-exporting country). However, all other oil price shocks originated by OPEC's productions cuts, hurricanes etc., do not seem to have a significant impact on the coherence between oil and stock markets in importing countries.

[11] The coherence level of importing countries is smoother compared to those of exporting countries during 2003-2005 periods.

Moreover, aggregate demand-side oil price shocks (housing market boom, Chinese economic growth, and the latest global financial crisis) cause a significant higher correlation between stock market prices and oil prices. Important precautionary demand side oil price shocks (i.e. second war in Iraq, terrorist attacks) tend to cause higher coherence but with a less magnitude compared to aggregate demand-side oil price shocks. The origin of the shock seems to be an important determinant of the correlation magnitude between oil prices and stock markets, as long as the oil shocks originate from major events of world turmoil, such as wars or changes in the phase of the global business cycle.

Overall, the results of the previous literature are confirmed concerning the impact of oil shocks on stock markets of oil-importing and oil-exporting countries, whereas for the case of supply shocks our findings show some aspects that have been neglected so far. In particular, we stress the role of crisis periods in the oil prices as drivers of the co-movements between oil and stock markets. Moreover, distinguishing the pattern of interdependence in the short-term frame (10 months) with respect to the medium-term one (3 years and one quarter), we show that oil price shocks mainly have medium-lived effects on stock markets, a result that complements the existing ones.

4.3 Engle and Granger (1987) results of cointegration procedure: Long term dependence

Table 1: The results of cointegration analysis are given in the following table (tab.3)

$X_{2,t}$	T-statistics	Critical value[12] (0.05%)	Critical value (0.01%)	Conclusion
Exporting countries				
Dubai SMI	-1.20545	-3.38763	-3.73	No long-run relationship
Kuwait SMI	-3.89567*	-3.38763	-3.73	There is a long-run relationship
South-Africa SMI	-2.73657	-3.38763	-3.73	No long-run relationship
Word SMI	-3.54224**	-3.38763	-3.73	There is a long-run relationship
Venezuela SMI	-3.88861*	-3.38763	-3.73	There is a long-run relationship
Importing countries				
USA SMI	-4.40545*	-3.38763	-3.73	There is a long-run relationship
France SMI	-4.15022*	-3.38763	-3.73	There is a long-run relationship
Germany SMI	-3.89326*	-3.38763	-3.73	There is a long-run relationship
Italia SMI	-3.76216*	-3.38763	-3.73	There is a long-run relationship

[12] Critical value for MacKinnon for two variables.

Netherland	-3.45421*	-3.38763	-3.73	There is a long-run relationship

We find that the cointegration relationship is stronger in the case of importing countries than in the case of exporting one. Indeed, in all studied importing countries the cointegration relationship is identified with a 1% significant level. However, for the case of exporting countries, long run relationship is identified only for two cases (Kuwait, Venezuela). This result traduces that the long-run relationship (equilibrium) between stock markets and oil price is identified for all studies importing countries and on some-not all- importing countries.

The existence of the cointegration relationship between stock market and oil price traduce the persistent effect of oil shocks on the financial markets. Therefore, our results note that oil shocks are more persistent in the case of importing than exporting countries.

For the case of importing countries, our results traduce the persistent of oil demand shocks, which is explained by the high consumption of these countries (USA, France, Italy, Netherland and Italy). We suggest that higher oil consumption leads to a stronger negative impact of high oil price on national economy, offsetting the positive effects of economic growth more rapidly. On the other hand, the long run response of stock market returns in oil-exporting countries to oil supply shocks seem to be mitigated. While the short-term price elasticity of crude oil is almost non significant (Fig 4 and Fig 5), its long-term price elasticity is much higher (e.g., Hamilton, 2009). This suggests that an increase in oil supply, which is followed by a decrease in oil price, does not induce an increase in oil demand in the short term and thus leads to less profits and stock market declines in oil-exporting countries. However, if the oil price shock persists over a long period of time, this may trigger higher oil demand in oil-importing countries, which leads to more profits and stock market inclines in oil-exporting countries. The absence of long run relationship between oil price and stock market for the case of Dubai and South Africa can be explained by a higher diversification of their economy and therefore their weak part of oil production on their GDP.

5. Conclusion

The paper investigates the issues of oil and stock market interdependence in oil exporting and importing countries by measuring the interaction between oil price and stock markets indices according the evolutionary co-spectral analysis as defined by Priestley and Tong (1973). The dataset consists of monthly stock and oil prices from oil importing countries (US, Italy, Germany, Netherland and France) and oil exporting countries (Emirate Arab Units, Kuwait Saudi Arabia and Venezuela), from 03/09/2000 to 03/12/2010. Our analysis does not impose any kind of restrictions or pre-treatment of the data (as it is the case of volatility analysis, for instance, which requires the series to be stationary or cointegration techniques which can be only applied to time series data integrated of order one). Moreover, no future information is used, implied or required as in band-pass or trend projection methods. In addition, the evolutionary co-spectral analysis gives a robust frequency representation of non-stationary process. Finally, the most important advantage of frequency analysis consists of providing information about the time horizon of the interdependence between two series: the analysis deliver as result whether the variables under investigation present short, medium or long-term interdependence. This additional information allows understanding which cycles and periods are more synchronized than others.

For all studied markets studied, the interdependence between oil prices and stock market is shown to be a medium-term phenomenon. Moreover, while there is substantial homogeneity of the interdependence patterns within the two groups of countries under investigation, our analysis shows that high oil prices deriving from demand shocks move together with stock prices, especially in exporting countries. Supply shocks cause higher coherence only in exporting countries. Therefore, in terms of diversification potential, oil is not always countercyclical with respect to stock markets, as generally predicted by the previous literature. Oil can have this role in importing countries, when high oil prices originate from supply shocks. At the opposite, if the shock originates from demand, oil prices and stock market tend to move together, with a strength that varies demanding on the origin of the shock, in both importing and exporting countries. In such scenario, oil does not have a save heaven role to counteract changing returns of a portfolio of stocks in none of the countries studied.

References

Ahamada I., Boutahar M. (2002), Tests for covariance stationarity and white noise, with application to Euro/US Dollar exchange rate, Economics Letters, 77, pp. 177-186.

Al-Janabi, Hatemi-J A and Irandoust, (2010) Modeling Time-Varying Volatility and Expected Returns: Evidence from GCC and MENA Regions, Emerging Markets Trade and Finance, 46(5), 39-47.

Arouri, M. E. H., & Nguyen, D. K. (2010). Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade. Energy Policy, 38, 4528−4539.

Arouri, M. E. H., & Rault, C. (2011). Oil prices and stock markets in GCC countries: Empirical evidence from panel analysis. International Journal of Finance and Economics. doi:10.1002/ijfe.443

Artis M. J., Bladen-Hovell R. & Nachane D.M. (1992), Instability of Velocity of Money, a

New Approach Based on the Evolutionary Spectrum, CEPR Discussion Paper, n° 735.

Aspergis, N. and Miller, S.M, 2009, Do structural shocks affect stock prices? Energy Economics 31, 569-575

Bashar, A. Z. (2006). Wild oil prices, but brave stock markets! The case of GCC stock markets. Operational Research, 6(2), 145−162.

Bjornland, H. C., (2009), Oil price shocks and stock market booms in a oil-exporting country, Scottish Journal of Political Economy 56, 232-254.

Chen, S. S. (2009). Do higher oil prices push the stock market into bear territory? Energy Economics, 32(2), 490−495.

Chittedi, K.R., 2012, Do oil prices matters for Indoan Stock Markets? An Empirical Analysis, Journal of Applied Economics and Business Research, 2(1), 2-10

Chiou, J.S., Lee, Y.H. (2009), Jump dynamics and volatility: Oil and the stock markets, Energy 34(6), 788-796.

Choi, K., Hammoudeh, S. (2010), Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment, Energy Policy 38(8), 4388-4399.

Creti, A., Joets M., Mignon V., (2013) "On the links between stock and commodity markets' volatility", Energy Economics, Vol. 37, pp. 16-28

Elder, J. Serletis, A. 2010, Oil price uncertainty, Journal of Money, Credit and Banking, 42, 1137-1159.

Federer, J. P. (1996), "Oil Price Volatility and the Macroeconomy." *Journal of Macroeconomics*, Winter 1996, *18*(1), pp. 1-26.

Filis, G., Degiannakis, S., Floros, C. (2011), Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries, International Review of Financial Analysis 20(3), 152-164.

Ftiti, Z. 2010. "The macroeconomic performance of the inflation targeting policy: An approach based on the evolutionary co-spectral analysis (extension for the case of a multivariate process)." *Economic Modelling* 27:468–476.

Hamilton, D.J (2009a). Understanding crude oil prices. *The Energy Journal*, 30(2), 179-206.

Hamilton, D.J (2009b). Causes and consequences of the oil shock of 2007-08. *Brooking papers on Economic Activity*, spring, 215-261.

Hamilton, James D. (1983), Oil and the Macroeconomy Since World War II, *Journal of Political Economy*, 91, 228-248.

Hammoudeh, S., Dibooglu, S. & Aleisa, E. (2004), Relationships among U.S. oil prices and oil industry equity indices, *International Review of Economics and Finance* 13(4), 427-453.

Hammoudeh, S., & Aleisa, E. (2004), Dynamic relationship among GCC stock markets and NYMEX oil futures, *Contemporary Economic Policy*, 22, 250-269.

Jones, C. & Kaul, G., (1996), Oil and stock markets, *Journal of Finance*, 51, 463-491.

Jones, D. W., Paul N. L, & Inja K. P. (2004), Oil Price Shocks and the Macroeconomy: What Has Been Learned Since 1996? *The Energy Journal* 25(2), 1-32.

Jung H. & Park G. (2011), Stock markets reaction to oil price shocks: A comparison between an oil-importing economy and an oil-exporting economy, *Journal of Economic Theory and Econometrics*, 22, 1-29.

Kilian, L. & Park, C. (2009), The impact of oil price shocks on the U.S market. *International Economic Review*, 50, 1267-1287.

Masih, R. Peters & S., Mello L.D., (2011), Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea, *Energy Economics*, 33, 975-986.

Malik, F. & Ewing, B.T. (2009), Volatility transmission between oil prices and equity sector returns, *International Review of Financial Analysis*, 18, 95-100.

Miller, J. I., & Ratti, R. A. (2009), Crude oil and stock markets: stability, instability, and bubbles. Energy Economics, 31(4), 559-568.

Narayan, S. & Narayan, P.K (2012), Do the US macroeconomic conditions affect Asian stock markets?, *Journal of Asian Economics*, 23(6), 669-679.

Park, J., & Ratti, R. A. (2008), Oil prices and stock markets in the U.S. and 13 European countries. *Energy Economics*, 30, 2587−2608.

Priestley, M. B. (1965), Evolutionary spectra for non stationary process. *Journal of Royal statistic society. ser.* B, 27, 204-237.

Priestley, M. B. (1966), Design relations for non stationary processes. *Journal of Royal statistic society. ser.* B, 28, 228-240.

Priestley M. B. (1969), A Test for Non-Stationary of Time Series. *Journal of Royal Statistical Society*, 31, 140-149.

Priestley, M. B. & Tong, H. (1973), On the analysis of bivariate non-stationary processes. *Journal of royal statistic society. ser.* B, 35, 135-166.

Priestley, M. B. (1981). Spectral Analysis and Time Series. *Academic Press*, New York.

Priestley M. B. (1988). Non-Linear and Non-Stationary Time Series Analysis. *Academic Press*, London.

Priestley M. B. (1996), Wavelets and time-dependent spectral analysis. *Journal of Time Series Analysis*, 17(1), 85-103

Sadorsky, P. (1999), Oil price shocks and stock market activity, *Energy Economics* 21, 449-469.

Syed B. & Sadorsky, P. (2006), Day-of-the-week effects in emerging stock markets, *Applied Economics Letters*, 13(10), 621-628.

Wang Y. & Wu C. & Yang L. (2012), Oil price shocks and stock market returns: Evidence from oil-importing and oil-exporting countries, Working paper SSRN, available at Electronic copy available at: http://ssrn.com/abstract=2189575.

Wei, C. (2003), Energy, the stock market, and the Putty Clay investment model, *American Economic Review*, 93, 311-323.

Yang, C.W. Hwang, M.J. & Huang, B.N. (2002), An analysis of factors affecting price volatility of the US Oil market, *Energy Economics*, 24, 107-119.

Yoon, K. H. & Ratti, R. A., (2011), Energy price uncertainty, energy intensity and firm investment, *Energy Economics*, 33(1), 67-78.

Appendix 1

Table 1: Oil price chronology from 2000 to 2010: main events

Months	2000	2001	2002	2003	2004	2005	2006	2008	2009	2010
01			OPEC decides to cut quotas		OPEC decides to cut quotas at various meeting			Rising demand, low spare capacity		
02							Breakdown of more 600,000bbl/d of oil production due to Nigeria attacks			
03	OPEC oil agree to increase the oil production			War in Irak						
04										
05								U.S president sign into law a bill that temporary halts adding oil to the strategic petroleum reserve		
06										
07										
08						Hurricane Katrina, Dennis, and Rita Strike				
09		09/11 Attacks			Hurricane Ivane Striles			Hurricane Gustav strikes		
10				OPEC decides to cut quotas at various						
11										
12			PdVA Strike in Venezuela					OPEC decides to cut quotas.		

Source: US Energy Information Administration.

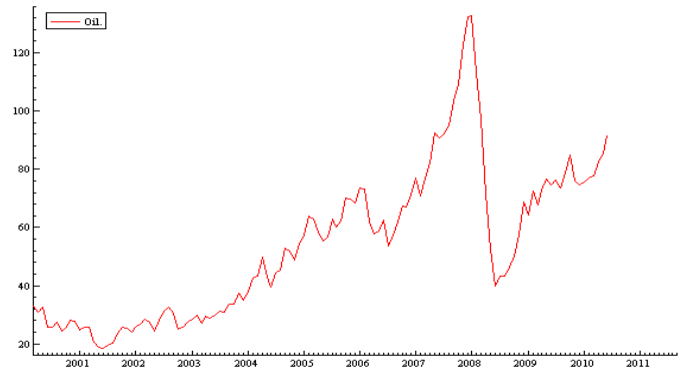
Table 2: Oil price shock origin and their main events

Events	Year	Oil price shock origin
Housing Market boom	2000	Aggregate demand side
09/11 Attacks	2011	Precautionary demand
PdVSA worker's strike	2012	Supply side
Second war in Iraq	2003	Precautionary demand
Chinese economic growth	2006-2007	Aggregate demand side
Global financial crisis	2008	Aggregate demand side
Golbal debt crisis	2010	Aggregate demand side

Sources: Kilian's (2009) and Hamilton (2009a,b) findings

Appendix 2

Fig 1. Brent crude oil price, in dollars, from 2000 to 2010



Appendix 3

Cointegration procedure: *Engle-Granger (1987) approach*

Engle and Granger (1987) have proposed an approach to check for the relationship between time series analysis. Their approach is based on the following steps:

1. The first step consists to test whether the studied series are integrated in the same order, for example I(1). To do this, we use in our analysis classical stationary tests, the ADF, PP, and KPSS. The results of these tests confirm that all studies series are I(1).

2. The second step Estimate the long-run relationships, i.e., run regression between two variables $X_{1,t}$ *and* $X_{2,t}$ (Eq. 15). Then, we save regression residuals. In our analysis $X_{1,t}$ represents the oil price and $X_{2,t}$ represents the stock market index for each studied country.

$$X_{1,t} = \beta_0 + \beta_1 X_{2,t} + u_t \qquad (15)$$

3. The third step is to test whether the residuals are stationary using again the standard tests employed on the first step. The procedure is the same as in the step 1.). If we are able to reject the null hypothesis about the unit root, we can conclude that the variables in (X1) and (X2), respectively, are cointegrated of the orders CI(1,1).