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PRICE VOLATILITY TRANSMISSION BETWEEN OPEC AND NON-OPEC OILS, A WAVELET BASED APPROACH.

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ABSTRACT

The importance of measuring volatility cannot be ignored. Equally important is to understand how volatility is transmitted between markets and assets. Using the wavelets methodology, this study seeks to analyze at different frequencies, the direction and magnitude of volatility transmission in the crude oil produced by OPEC countries and other producing and exporting countries that are not part of this organization (non-OPEC. This approach contributes to the literature identifying the crude oil volatility in different frequencies and in its origin, the producing countries. This way is possible to provide information for Energy Policy Makers, investors and researchers about the two groups of suppliers, helping them to define strategies of purchase, trade, storage and hedging.

Key-words: Price volatility transmission, OPEC and non-OPEC crude oils behavio, Frequency analysis.

1. INTRODUCTION

Since the 1986 oil price shock, the behavior of these prices has become a daily concern for governments and investors. Trading in crude oil also changed, attracting numerous types of market participants, not just the parts with commercial interests, but also those who treat oil as a form of investment. In recent years the role negotiation became even wider and accessible. At the same time, there is a relatively easy access to several markets, particularly European and North American markets.

On the world stage of oil, OPEC (Organization of Petroleum Exporting Countries) plays a central role in discussions about pricing and supply global demand. Founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela, in 2013 has 14 members, all major world producers. Aiming to coordinate and unify petroleum policies of member countries, ensuring fair and stable prices for the producing countries, an efficient and regular supply of petroleum to consuming nations and a fair return for those investing in the industry (OPEC, 2012).

Despite having approximately 78% of proven world reserves of oil (OPEC Annual Statistical Bulletin, 2012), all member countries are considered underdeveloped and are located mostly in the Middle East and North Africa, regions of great political instability and social. In this context one should note the five major shocks in oil prices due to this instability: 1956 with the nationalization of the Suez Canal, 1973 with the Yom Kippur War, 1979 due to the Iranian revolution and 1991 with the Gulf War I.

The majority of OPEC members are located in regions of great political instability, social and economic. As it is known, the Gulf region is very rich in oil resources, being responsible for about 60% of U.S. imports of crude oil. Successive wars, terrorists attacks and every kind of instability is directly reflected on crude oil price.

However it must be considered that seven of the 15 largest oil producers are outside of OPEC (EIA, 2012). In 2006 these countries were: Russia, USA, China, Mexico, Canada, Norway and Brazil. However many non-OPEC producers are faced with wells that are rapidly depleting. Some major producers such as the United States, Mexico and Norway, have experienced a decline in production in recent years. However, the overall figures for non-OPEC producers are reinforced by significant increases in production in Brazil, Canada, and Russia.

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The importance of measuring volatility cannot be ignored. Equally important is to understand how volatility is transmitted between markets and assets. In oil markets, agents often have exposure to a large number of different types of crude oil, with different prices and volatilities and enabling them to build portfolios consisting of different varieties of this commodity.

Notable paper verified these questions about international crude oil markets. Weiner (1991) results suggested that the world oil market is far from unified and crude oil prices do not move together around the world. However, more studies tend to support that oil markets behave like one common market (Adelman (1992); Gulen (1999); Ewing and Harter (2000); Engle and Granger; (1987), Bachmeier and Griffin (2006))

From a different point of view Salisu and Fasanya (2012) employed the tests developed by Liu and Narayan (2010) to detect structural breaks in data series. This evidence suggests that oil volatility is not uniform in time presenting persistence and leverage effects. This kind of evidence shows some necessity of investigate crude oil volatility from a time variable point of view since its behavior is changed because of the considered time window.

Therefore, using the wavelets methodology, this study seeks to analyze at different frequencies, the price volatility relations in the crude oil produced by OPEC countries and other producing and exporting countries that are not part of this organization (non-OPEC). This way you can understand the functioning of this important market and answer the following question: How volatility behaves in relations between the different types of oil and how it is transmitted between OPEC members and non-OPEC producers?

This approach brings two main contributions to the literature: (1) We present the OPEC and non-OPEC volatilities correlations in different frequencies and (2) present the price volatility transmission between these producers. This way is possible to provide information for Energy Policy Makers, investors and researchers about the two groups of suppliers, helping them to define strategies of purchase, trade, storage and hedging.

This paper is structured as follows. Section 2 provides a review of the selected studies and aims to demonstrate how the wavelets methodology can bring a new perspective to this issue. In Section 3 we describe the data and period analyzed, and present the econometric model developed in this paper. The application, estimation and comparison with previous studies are presented in Section 4 with some tables and figures. In Section 5 we draw some important policy conclusions about the volatility relations among crude oil producers' countries.

2. WAVELETS APPLICABILITY

The interaction of a variable with the changes of the environment may result in a universe of relationships, difficult to be observed and understood In this sense, the filtering methods in finance and economics are useful tools to identify certain features and behavior of time series. Decomposing the series is possible to extract seasonality, trends and noise. Thus, Wavelets are an interesting methodology to decompose time series in different frequencies and reveal more information.

The method uses a wavelet basic function called mother wavelet, which is expanded and contracted to capture local characteristics in time and frequency. The wavelet filter is long in time when capturing low frequency events, and short in time when capturing events of high frequency. Through combinations to expand and contract the "mother wavelet", you can capture all the information present in a time series (Gençay et al., 2002). Thus, the wavelet fits through a range of frequencies, to capture and locate features events that are local in time. This makes this method an excellent tool for time series analysis, especially non-stationary.

Capobianco (2003) investigated this potential for decomposing financial volatility processes. The results indicate that wavelets and derived functional dictionaries may play an important role in detecting hidden features and the dependence structures.

Looking to demonstrate the contributions of wavelet methodology to correlations analysis, Razdan (2004) studied the correlations between Bombay stock index (BSE) and National stock index (NSE). As known the traditional correlation coefficient between these indices is $r = 0.9931$, indicating that the BSE index is strongly correlated with NSE index. However using the Wavelet correlation coefficient he was capable to show that this correlation changes as the time scale, including

International Journal of Research In Social Sciences

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being negative. This found highlights the applicability of wavelets in reveal new information.

Souza and Silva (2010), employed wavelet analysis to remove high frequency price movements of oil price, then using hidden Markov model, they were capable to forecast the probability distribution of the price return accumulated over the next days and infer future price trends.

Power and Turvey (2010) analyzed the long-range dependence in the volatility of 14 commodities futures prices including crude oil. Using wavelets to decompose in time scales and Hurst coefficient, was not possible to reject the null hypothesis that the long memory parameter *H* has been constant over the entire sample characterizing no long-range dependence. Unlike the findings of Alvarez-Ramirez et al (2008) were no evidences of the existence of a trend in the time-varying Hurst coefficient for any of the commodity futures.

Wavelets can be especially useful to investigate reanalyze old questions with divergent results, given its capacity to revel more time-series information. Benhmad (2012) used a wavelet approach to study the linear and nonlinear Granger causality between the real oil price and the real effective U.S. Dollar exchange rate. The series decomposition reveled seven frequency bands with different causality relations each. This approach show that previous studies were capable to detect only the relation present at the analyzed frequency, and the wavelets decomposition expand the researched universe.

Several papers had divergent results when analyzed the relationship between crude oil price changes and stock market returns. Combining wavelet analysis and Markov Switching Vector Autoregressive (MS-VAR) model to explore the Impact of the crude oil shocks on the stock market returns for UK, France and Japan, Jammaz & Aloui (2010), shows the efficiency of wavelet to filtering series and determining the behavior of the stock market volatilities. Applying this technique, they were able to extract the driving dynamics of crude oil prices and to bring out past events that were not originally visible.

Using wavelets methodology we are able to identify the behavior of crude oil volatility in different frequencies. This approach can be especially meaningful to understand the transmission direction; supplying market participates with more precise information.

3. METHODOLOGY

3.1 Wavelets filtering methodology

According to Gençay et al. (2002) a wavelet $\psi(t)$ is a function of time (t) wich obeys two basic rules, known as *wavelet admissibility condition*. The first condition ensures that $\psi(f)$ goes to zero quickly as $f \rightarrow 0$. This first condition can be expressed by

$$\int_{-\infty}^{\infty} \psi(t)dt = 0, \qquad (1)$$

The second condition imposed on a wavelet function is unit energy, that is,

$$\int_{-\infty}^{\infty} |\psi(t)|^2 \, dt = 1, \qquad (2)$$

In order to quantify the function change at a particular frequency and at a certain point in time the mother-wavelet $\psi(t)$ is dilated and translated,

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) \qquad (3)$$

Where: u and s are, respectively, the time location and scale parameters or frequency ranges. The continuous wavelet transform (CWT) is a function $W(u,s)$ which is obtained by projecting the original function $x(t)$ in the mother wavelet $\psi_{u,s}(t)$,

$$W(u,s) = \int_{-\infty}^{\infty} x(t)\psi_{u,s}(t)dt. \qquad (4)$$

In order to assess variations in large-scale basis (ie a low frequency), a large value for s must be chosen, and vice versa. Applying CWT for a continuous location and scale parameters of a function, it is possible to extract a set of "basic" components.

3.2 Transmission and Granger causality

The Granger causality test (1961) has

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International Journal of Research In Social Sciences

www.ijsk.org/ijrss

been applied in several economic and financial studies, as an efficient methodology to detect the direction of transmissions whether of prices, currency exchange rates or volatilities. Wang (2010) analyzed the volatility transmission between U.S. industries. Using causality tests, the results showed that the industrial base, producing machinery, can be a source of risk that can affect virtually all other sectors. Their results indicate that traditional sectors like oil and automobile apparently not seem to have great influence on other major sectors. Bentzen (2007) used high frequency data and causality tests to investigate the relationship between WTI, Brent and Dubai. The results demonstrate bidirectional transmissions, which highlights the globalization of this market. He et al. (2010) investigated the relationship between economic activity and oil prices. They found strong evidence of Granger causality between these variables. Other applications of Granger causality test can also be found in Hong (2001), Bubak et. al (2011) Nishiyama (2011).

According Tsay (2008), the Granger causality test is based on the assumption that the future cannot cause the past nor the present . Thus, if Y comes after X, then Y cannot cause X. Likewise if X precedes Y, that does not mean that X causes Y. Thus the test looks for an evidence of any of the following events: i) X causing Y (X → Y), ii) Y cause X (Y → X), iii) bi causality (Y → X and X → Y).

Thus, the test Granger causality checks whether information contained in a time series explain the occurrence of variations in the other series. Formally, in the current study, the causality test is represented as follow,

$$x_{t,l} = \alpha + \sum_{i=1}^{k} \alpha_{x,i} x_{t-i} + \sum_{i=1}^{k} \alpha_{y,i} y_{t-i} + \varepsilon_{x,t} \quad (5)$$

$$y_{t,l} = \beta + \sum_{i=1}^{k} \beta_{x,i} x_{t-i} + \sum_{i=1}^{k} \beta_{y,i} y_{t-i} + \varepsilon_{y,t} \quad (6)$$

where $x_{t,l}$ and $y_{t,l}$ represent the volatility, squared return, of the OPEC and non-OPEC crude oil price, in time *t* and in the frequency *l*, $\varepsilon_{x,t}$ and $\varepsilon_{y,t}$ are white noise. Do not reject the null hypothesis $H_0 = \alpha_{y,1} = \alpha_{y,2} = ... = \alpha_{x,k} = 0$, in the regression equation (5) implies that the volatility of OPEC crude oil prices do not Granger cause the volatility of the price of non-OPEC crude oil. Similarly, do not reject the null hypothesis, $H_0 = \beta_{x,1} = \beta_{x,2} = ... = \beta_{x,k} = 0$, in the regression equation (6) implies that the volatility of non-OPEC do not Granger cause the OPEP crude oil volatility.

To perform this study we analyzed weekly average prices ($ / barrel) weighted by the volume exported by OPEC member countries and other producing and exporting countries not members of the organization these indices are released by the U.S. Energy Information Administration (EIA) considering the following countries and varieties of crude oil (Table 1). The sample period extends from January 3, 1997 to September 30, 2011, totaling 768 observations.

OPEC	**non-OPEC**
Abu Dhabi Murban Spot Price FOB	Australia Gippsland Spot Price FOB
Algeria Saharan Blend Spot Price FOB	Brunei Seria Light Spot Price FOB
Angola Cabinda Spot Price FOB	Cameroon Kole Spot Price FOB
Asia Dubai Fateh Spot Price FOB	Canadian Par Spot Price FOB
Ecuador Oriente Spot Price FOB	Canada Heavy Hardisty Spot Price FOB
Mediterranean Sidi Kerir Iran Heavy Spot Price FOB	Canada Lloyd Blend Spot Price FOB
Mediterranean Sidi Kerir Iran Light Spot Price FOB	China Daqing Spot Price FOB
Iraq Kirkuk Netback Price FOB	Colombia Cano Limon Spot Price FOB
Kuwait Blend Spot Price FOB	Egypt Suez Blend Spot Price FOB
Libya Es Sider FOB Spot Price	Gabon Mandji Spot Price FOB
Neutral Zone Khajji Spot Price FOB	Indonesia Minas Spot Price FOB
Nigeria Bonny Light Spot Price FOB	Malaysia Tapis Blend Spot Price FOB
Europe (Forcados, Nigeria) Spot Price FOB	Mexico Isthmus Spot Price FOB
Qatar Dukhan Spot Price FOB	Mexico Maya Spot Price FOB
Saudi Arabia Heavy Spot Price FOB	Europe (Ekofisk, Norway) Blend Spot Price FOB
Saudi Arabia Light Spot Price FOB	Oman Blend Spot Price FOB
Saudi Arabia Medium Spot Price FOB	Mediterranean (Russia, Urals) Spot Price FOB
Venezuela Bachaquero	

International Journal of Research In Social Sciences

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OPEC	non-OPEC
17 Spot Price FOB Venezuela Bachaquero 24 Spot Price FOB Venezuela Tia Juana Light Spot Price FOB	Europe (UK) Brent Blend Spot Price FOB

Table 1: Crude oil used in the composition of OPEC and non-OPEC averages

Note: FOB denotes Free on Board, price without additional costs as insurance or taxes.

Where p_t and pt_{-1} are the crude oil prices indexes in time *t.* According to Gençay et al. (2002) this is an efficient proxy for volatility, once its represent the price fluctuations in time, respecting present estimation error, being ideal to be decomposed by Wavelets.

4. RESULTS

As known, stationary is an important assumption when using methods of time series analysis as

In this work the squared log-return are chosen to represent the volatility once it can be considered an efficient measure of dispersion behavior, been calculated according to equation (7):

$$(\log(p_t / p_{t-1}))^2 = (r_t)^2 \tag{7}$$

the main characteristics of volatility. Furthermore, how it is not an estimation, does not

Granger causality tests. Thus, we applied Aumented Dickey-Fuller with GLS constant (ADF-GLS) and KPSS tests in the square of the logarithm of the price return series.

Augmented Dickey-Fuller (GLS) test			KPSS test	
Variable	Test Statistic	p-value: Z(t)	Test Statistic	Critical value 5%
OPEC	-3.8171	0.0001	0.1173	0.462
Non-OPEC	-3.5656	0.0003	0.1171	0.462

Table 2: ADF-GLS and KPSS stationary tests.

The ADF-GLS and KPSS confirm the absence of unit root, allowing its statistical modeling.

Figure 1 show the original volatility series behavior. It is possible to verify that volatility is not constant in time, besides there are strong volatilities clusters

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International Journal of Research In Social Sciences

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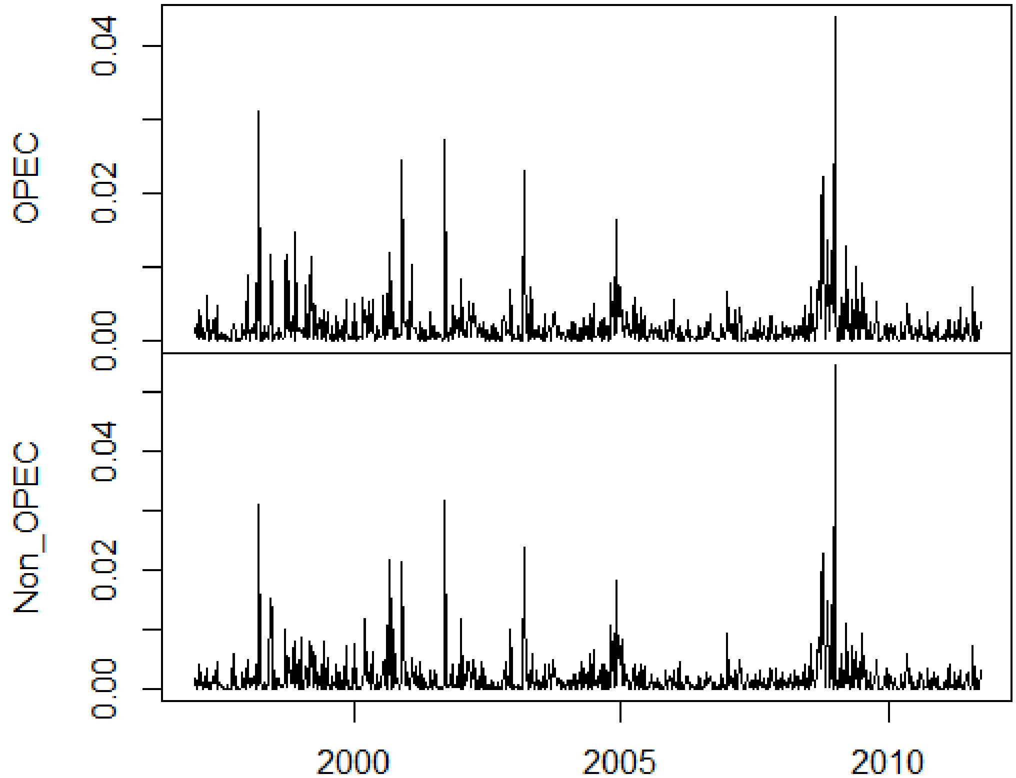

Figure 2: Original volatility series behavior

This evidence suggests that volatility is certain moments, but does spread over time. Around to 2001 it can be perceived a volatility spike, referring to September 11 terrorist attacks. In March 2003, the second Gulf War brought more instability to crude oil production. Close of 2005, can be observed more volatility again, caused by uncertainty of Iraq situation, its electoral process and increase in violence, judgment of Saddan Hussein and conflicts between Israel and Palestine. After some years of stability, the crude oil volatility reached record levels, due to 2008 financial crisis. This analysis reinforces the well know stylized fact that, volatility seems to be restricted to times when the market gets good or bad news.

According to Table 3, both OPEC and non-OPEC crude oils volatilities, present very close to zero means, been little higher for non-OPEC. The same occurs with variance and the others indicators, suggesting that non-OPEC volatility is higher and oscillates more than OPEC. The positive skewness is a characteristic of volatility since it is always positive. The kurtosis analysis shows that non-OPEC distribution present heavier tail, what is consistent with the variance behavior.

	OPEC crude oil	**non-OPEC crude oil**
observations	767	767
Mean	0.001774	0.001971
Variance	0.000011	0.000015
Standard deviation	0.003372	0.003910
Skewness	5.823168	6.074777
Kurtosis	49.985038	56.380140

Table 3: Descriptive statistic of OPEC and non-OPEC squared returns.

International Journal of Research In Social Sciences

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As know the OPEC is responsible for most crude oil production, and how it is an Organization, all members take decisions together, unlike what occurs for non-OPEC countries, which do not have a coordinated policy. This regulation from OPEC side can offers some stability to the market. This supply regulation is perceived for market agents and it has a little reflex in the descriptive statistics.

Besides, OPEP countries are more traditional producers and exporters and their reserves capacity is already know, while non-OPEP countries has most part of their reserves discovered during the last few years, and the annual extracted volume is not stable yet (a good example is Brazil, with huge reserves in the pre-salt layer, but due to technical complexity and high costs, they remain unexplored). Despite of seven of the 15 largest oil producers do not belong to OPEC, non-OPEP countries are not big exporters, they consume the most part of this production, and maybe that's can be one of reason why their prices are more volatile.

In order to capture more information, OPEC and non-OPEC volatility series were decomposed using the Daubechies Wavelet LA(8). According to Gençay (2002) the LA(8) present the better fit to financial series behavior, especially when one works with volatility. By applying this formula, we decomposed in eight frequencies, D1 to D8, due to series lenght, considering frequencies of 1, 2, 4, 8, 16, 32, 64 and 128 weeks respectively. Figure 3 shows the behavior of the wavelet decomposed series.

The frequencies descriptive statistics for OPEC and non-OPEC are presented in Table 4 and Table 5 respectively. The decreasing standard deviation of OPEC and non-OPEC shows that in low frequency the series oscillates less, being more constant.

	D1	D2	D3	D4	D5	D6	D7	D8
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
St.dev.	0.0021	0.0015	0.0012	0.0007	0.0007	0.0008	0.0007	0.0005
Skewness	2.3582	1.2937	0.7972	0.4710	1.0023	0.9296	0.9124	0.1532
Kurtosis	29.081	15.653	7.8281	2.4630	4.4679	2.5996	0.9124	-0.109

Table 4: OPEC frequencies descriptive statistics.

	D1	D2	D3	D4	D5	D6	D7	D8
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Variance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
St.dev.	0.0025	0.0017	0.0014	0.0009	0.0008	0.0009	0.0008	0.0005
Skewness	1.9878	1.0145	1.0059	0.0901	1.1811	0.9228	0.9122	0.0882
Kurtosis	37.332	14.457	9.6055	3.0776	5.9191	2.3422	1.3087	-0.279

Table 5: non-OPEC frequencies descriptive statistics.

As occurs in the original data, skewness is always positive and decrease from D1 to D8, the same occurs with kurtosis, due to long term of low-frequencies, decrease the presence of outliers and the series become smoother. The variance is 0.000 in all frequencies which according to Fan and Gençay (2010) is due to the unit energy property and indicates that the series are stationary after the decomposition. Figure 3 shows the behavior of the wavelet decomposed series.

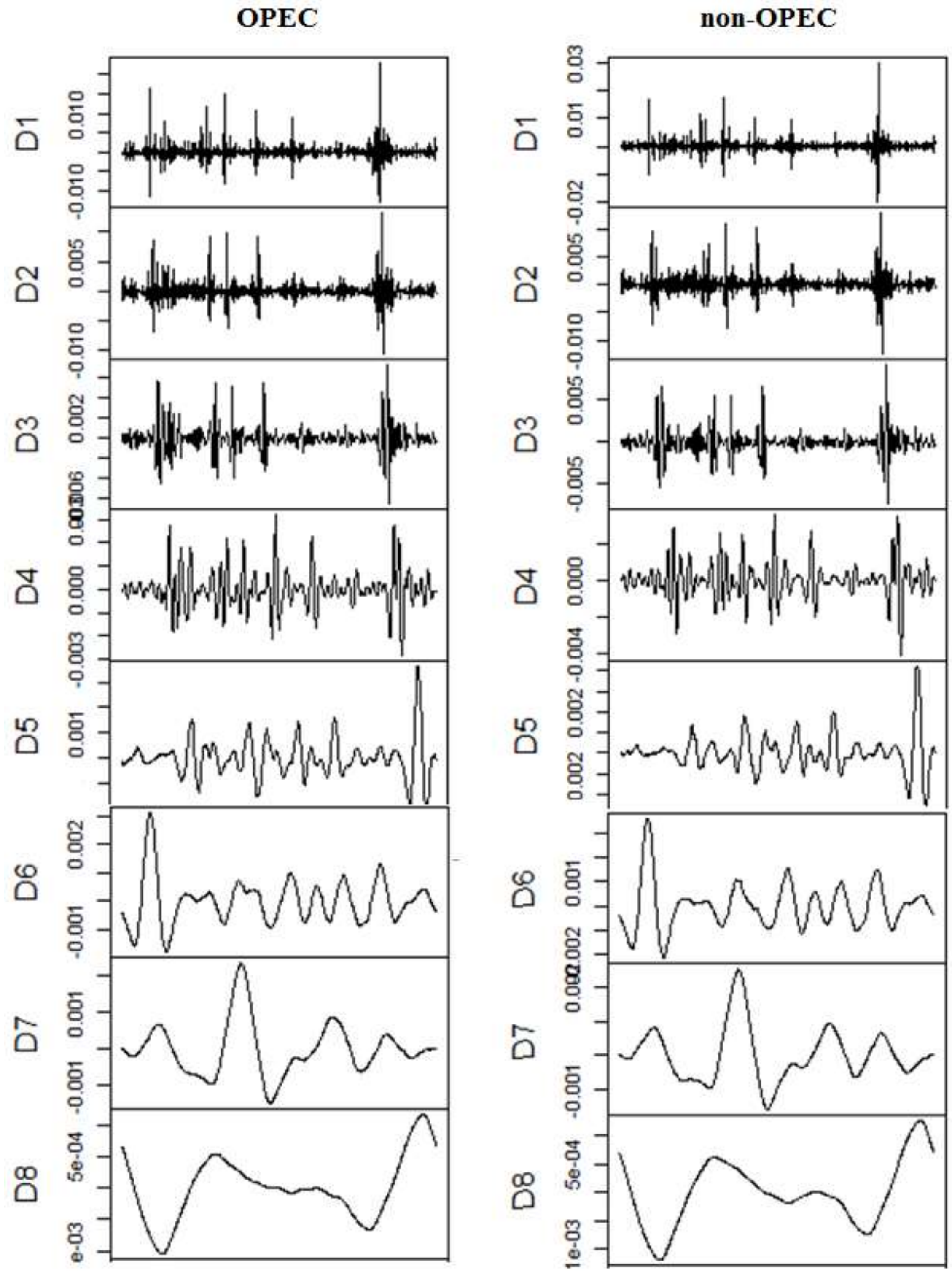

Figure 3: Wavelet decomposed OPEC and non-OPEC volatilities.

The decomposed series present a different behavior from the originals series. Despite the high frequencies (D1, D2 and D3) to present volatility clusters as well as the original series, the low frequencies D4; D5; D6; D7 and D8 reveals that both crude oil volatilities spread over time. As can

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International Journal of Research In Social Sciences

www.ijsk.org/ijrss

be observed, wavelet decomposition reveals that crude oil volatility does not keep isolated in one single event, it is capable to contaminate the following periods. This means that considering longer periods of observation ,

once the series are strike by bad or god news, volatility does not come back to the level before keeping their effects on the market. From a different point of view Jin et al. (2012) conclude that only large shocks will increase expected conditional volatilities. This can be confirmed for wavelet decomposition, once the volatility seems to be embodied in futures periods.

This result can bring new information to oil market agents. Long-term investors can be subject to volatility effects for long periods, while short-term investors are subject only to volatility. That does not mean that short-term investors are less exposed to risk, but means that long-term investors must to monitor events for longer periods.

The relations between OPEC and non-OPEC volatilities can be analyzed by the wavelet correlation coefficient (WCC) perspective. The WCC is estimated according to equation (18) shows the correlation in each frequencies.

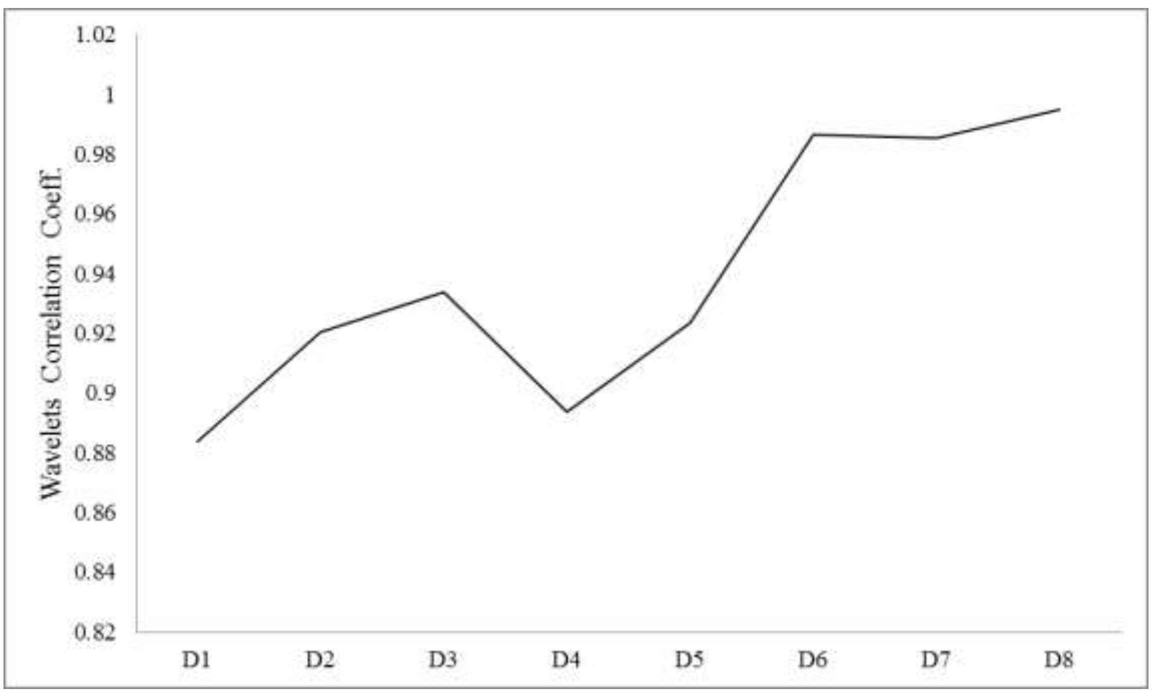

Figure 4: Wavelet correlation coefficient for OPEC and non-OPEC price volatilities

International Journal of Research In Social Sciences

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As can be observed the correlations grows in the lower frequencies. In D1 we found the lower correlation (r*=0.8838), and in the lower frequency, D8 we found the higher correlation (0.9950). This evidence shows that the correlation, besides strong, is not constant over time and points to the existence of volatility adjustment mechanisms. In short term the volatility is not the same for OPEC and non-OPEC crude oils, however we can say that in long term the volatility spreads for both oils contaminating them equally.

In order to understand the volatility dynamic, between OPEC and non-OPEC we analyzed the volatility transmission from Granger causality viewpoint. Based on this perspective is it possible to observe if one of those suppliers have enough power to determine the market volatility. The causalities are performed for each frequency Table 6 shows the results for all eight tested frequencies

Table 6: Granger causality tests in each frequency.

h_0	$x \xrightarrow{no} y$		$y \xrightarrow{no} x$	
	χ^2 statistic	p-value	χ^2 statistic	p-value
D1	72.099	0.011	69.418	0.018
D2	84.489	0.002	86.751	0.001
D3	95.665	0.002	83.877	0.023
D4	96.188	0.002	117.24	0.000
D5	131.73	0.000	117.91	0.000
D6	178.65	0.000	168.83	0.000
D7	275.19	0.000	207.37	0.000
D8	420.73	0.000	223.88	0.000

Note: Where x and y are OPEC and non-OPEC volatilities, and the arrow represent the Granger causality direction.

Confirming the already found by wavelets decomposition, the volatility is not recluse to the cluster, spreading over several periods, the Akaike criterion indicated between 50 and 70 lag to be considered in the estimations, confirming it. For all eight analyzed frequencies the null hypothesis, (OPEC does not cause non-OPEC and non-OPEC does not cause OPEC) are rejected, showing strong bi-causal relations between OPEC and non-OPEC volatilities. This means that OPEC and non-OPEC producers influence each other, and none of them have enough power, for alone, to determine market volatility. This relation confirm the observed by Bachmeier and Griffin (2006), suggesting that crude oil market is unified and behaves like one common market. As well as in Malik and Hammoudeh (2007), the Granger causality results suggest that shocks can spillover from one country to another, since according to Ewing and Malik (2013) the oil producers share information.

As is known, the most part of crude oil market instability comes from political instability and events in Middle East, however seams that non-OPEC have power to cushion the volatility generated for those events. Considering that non-OPEC is not an Organization, with central power and coordinate decisions about crude oil production, can be considered surprising that they can influence the OPEC crude oil volatility. Here again, it must be remembered that seven of 15 largest oil producers do not belong to OPEC and, in the last decade, the production of non-OPEC countries increased considerably, representing 10,5 million of barrels per day, or 25% of world crude oil production. Furthermore the non-OPEC reserves outnumber the OPEC ones in the proportion of 2 to 1 (OPEC, 2011).

These evidences can be especially useful to energy policy makers determine their suppliers. Non-OPEC countries are less subject to political instability since the most of them are not involved in endless conflicts. The continuous non-OPEC production growth can bring excellent perspective to big consumers as United States. Improve domestic production and sign contracts with non-OPEC countries can be a good alternative to stay less subject to crude oil volatility, cushioning bad news.

Another important political and economic conclusion comes from the fact that non-OPEC even not being an Organization and still be able to influence the crude oil volatility. If important non-OPEC producers and consumers as United States, Canada, Norway, Brazil, Russia, Mexico and China have coordinate oil policy this influence could be stronger.

CONCLUSIONS

Since its foundation, OPEC is in the center of crude oil supply, its decisions and policy has determined the market volatility. Especially in the last three decades, crude oil market has gone through many turbulent periods. Conflict, terrorist attacks and financial crises have increased the market volatility. At the same time, new reserves have been discovered, and new countries have gained important roles in this scenario, and now seven of the 15 largest oil producers do not belong to this organization.

To understand the role of OPEC and non-OPEC crude oil in the market volatility, this study employed the Wavelets methodology to decompose the series and realize a detailed frequency analysis of volatility transmission in this market. It's possible to observe that crude oil volatility is not restrict clusters, the frequency analysis reveal that it spreads over time contaminating futures periods.

The correlation between OPEC and non-OPEC price volatilities is not constant, changing in each frequency. It is possible to observe that the wavelet correlation coefficient grows in the lower frequencies pointing to the existence of volatility adjustment mechanisms, which are confirmed by the volatility transmission analysis.

The strong bi-causal relation between OPEC and non-OPEC crude oil volatilities confirms the found by Bachmeier and Griffin (2006), and show evidences that non-OPEC has e has as much force as OPEC to influence the market volatility, suggesting volatility spillovers between both. Considering that non-OPEC is not an Organization, with central power and coordinate decisions about crude oil production, can be considered surprising that they can influence the OPEC crude oil volatility. If important non-OPEC producers and consumers have coordinate oil policy this influence could be stronger.

The increasing participation of non-OPEC countries in the oil production can be the reason behind this behavior. Those evidences can be especially useful to energy policy makers determine their suppliers, since Non-OPEC countries are less subject to political instability since the most of them are not involved in endless conflicts.

To improve this research, we suggest the use of structural breaks and copula function to model the volatility. The absence of longer series, with previous periods is a limitation of this study, since was not possible to verify if this behavior was the same before 1997.

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