Energy commodities and advanced stock markets: A Post-crisis approach

Nikolaos Stoupos[1][2] and Apostolos Kiohos[3]

Abstract

The debate between the stock markets and the energy markets is a research matter which has always concerned the academia across the globe. This study attempts to answer the question whether there are realized linkages and volatility responses between the energy markets (crude oil and natural gas) and the stock market indices in five advanced economies during the post-global financial crisis era of 2008. Firstly, we took the impact of 166th OPEC meeting into consideration which as a matter of fact, represents the commencement of four continuous cycles of OPEC oil output policy for the 21st century. The results highly support that in the long run, there are strong dynamics between the energy markets and the developed stock markets. Every stock index indicates high resilience against the long-term volatility responses of each energy commodity. Furthermore, the prices of oil and gas seem to greatly influence the Japanese stock market index.

Keywords: realized volatility-dynamics, advanced stock markets, OPEC, energy commodities, market risk analysis

JEL: C13, C58, G15, G17, Q47

[1]Post-Doc Research Fellow, Department of International and European Studies, University of Macedonia, Egnatia 156, 54006, Thessaloniki, Greece, nikostoupos@gmail.com, (corresponding author)
[2]Adjunct Senior Lecturer, Department of Economics, University of Patras, Uni Campus, 26504, Patras, Greece.
[3]Assistant Professor, Department of International and European Studies, University of Macedonia, Egnatia 156, 54006, Thessaloniki, Greece, akiohos@uom.gr, akiohos@otenet.gr

1.Introduction

The existence of a correlation between oil pricing and stock market valuations has been a point of contention among economists, academics and traders for decades. Energy commodities and their financial derivatives have historically been used as alternative investments when investors wish to hedge, speculate or rebalance their portfolio.

Conventional financial wisdom alludes to the presence of a definite correlation between oil and stock price. Contrarians to this idea have stated that oil and equities complement one another on a cyclical basis (Chandler, 2014). Regarding the relationship between oil and stock pricing, conventional wisdom states that these two assets have an inverse correlation. In simplest terms, the relationship is as follows: a) as oil prices rise, equities valuations are driven down and b) as oil prices fall, equities valuations are driven up. Alternatively, these two assets operate as a substitute in financial terms.

Consequently, the underlying assumption adopted by this view is that when oil prices increase, energy prices rise as a whole. This fact leads to the emergence of a systemic inflation, increasing the sunk costs absorbed by companies during the execution of everyday business operations. As a result, traders and investors are prompted to sell off corporate stock and drive share price down (Verdickt *et al.* 2019).

Under these circumstances, the behavior of the stock markets significantly affects the portfolio management, asset and firm valuations, investment decisions, and other issues addressed by the finance literature. The volatility of the stock indices is considered as the principal factor which will influence the investors and the portfolio managers in order to re-assess the investments and hedge the investment risk. One rationale for using oil and natural gas price fluctuations as a factor affecting stock prices is that, in theory, the value of stock equals the discounted sum of expected future cash-flows. These cash-flows are affected by macro-finance variables and the financialization of the markets which in turn, may be impacted by oil or gas price alterations.

The main purpose of this research is to examine realized linkages and volatility (short- and long-term) between two energy commodities (crude oil and natural gas) and five advanced stock markets during the post-crisis era (after the end of the 2008 financial crisis) by exploring the impact of the OPEC agreement on 27/11/2014. More specifically, OPEC announced that it would mainly focus on preserving its market share instead of maintaining a $100-115/barrel price range. This shift in policy suggests that OPEC will no longer act as the swing oil producer. Instead, the marginal cost producers of unconventional oil are increasingly playing this role. The deep price decline also coincided with a sharp appreciation of the U.S. dollar, which trends to be negatively associated with U.S. dollar prices of commodities, including oil (Zhang *et al.,* 2008; Akram, 2009).

Moreover, this date actually represented the initiation of the first stage of the four continuous cycles of OPEC oil output policy for the 21st century. The fourth cycle is expected to complete until the end of 2020, since OPEC has decided to target the level of global oil stocks to bring them down to 'normal' levels (May 2017). According to the Oxford Institute for Energy Studies (2017), since 2013, global oil supply balances have experienced four short-run cycles in line with the moving dynamics of OPEC's oil output policy.

The first cycle took place from November 2013 to March 2015, where the large oil supply overhung and OPEC opted to leave it to the price mechanism to clear the imbalance. During the second cycle (April 2015 to May 2016), OPEC's pursuit of a high output – low price strategy aimed at driving high-cost oil production out of the market. At the same time, the third cycle lasted one year (June 2016 to April 2017), where OPEC shifted in its output policy and followed a long journey towards reaching an agreement on the output cuts with the oil producers inside and outside the bloc. The fourth cycle (May 2017 to December 2020) was related with OPEC's strong commitment to the agreement and its decision to target the level of global oil stocks by bringing them down to 'normal' levels.

As a matter of fact, the OPEC announcement on 27/11/2014 directly terminated a period of five consecutive years after the end of the financial crisis of 2008 where the price of crude oil price was maintained between 100 and 115 price per barrel. Meanwhile, the advanced stock markets (e.g. America, Europe and Eastern Asia) faced an increasing period of value. Therefore, it has become very thought-provoking to study the impact of this OPEC policy on energy and advanced stock markets from a more academic perspective. The research examines stock market indices from France, Germany, Japan, the UK and the US. To answer the research query, the Fractionally Co-Integrated Error Correction model (FCECM) and the Asymmetric

Component GARCH are used in order to produce empirical results. In specific, the study utilizes the FCECM as the mean equation and the AC-GARCH as the conditional variance equation. (Degiannakis and Floros, 2015).

The Fractionally Co-Integrated Error Correction model (FCECM) (Caporin *et al.* 2013) exhibits a higher fit of the data by improving the accuracy of realized dynamics instead of the classic Error Correction Model (Engle and Granger, 1987). For instance, Dolatabadi *et al.* (2016) analyze spot and futures commodity prices by implementing the fractionally co-integrated VAR model. At the same time, Barunik and Dvorakova (2015) explore fractional cointegration relationship between daily high and low stock prices.

Additionally, the implementation of AC-GARCH model (Engle and Lee, 1999) simultaneously reveals the short- and long-term volatility as well as the volatility persistence, the volatility clustering and volatility asymmetry. The AC-GARCH model also provides highly accurate results in intraday data (Sun and Yu, 2020). The use of realized volatility inherits all stylized facts that have been established for volatility in earlier latent variable specifications, most notably long-range dependence (Hillebrand and Medeiros, 2010).

The findings reveal that the advanced stock market indices be positively influenced by the oil/gas prices which essentially occurs due to hedging, speculation and arbitrage choices in the short-run. The effect of natural gas prices is quite anemic. On the other hand, the crude oil prices have a negative long-term impact on the developed stock market indices. The volatility persistence of stock market indices against the shocks of energy commodities prices is extremely high in the long-run and largely sensitive in the short-run. Lastly, the relationship between stock markets indices and oil/gas prices is based on the theory of conventional wisdom and the transmission mechanism of stock valuation channel.

The present research has been organized into several sections. Section 2 describes the relevant theoretical background between stock and energy commodities prices. Section 3 unveils the most recent literature review regarding the relationships between stock markets and energy markets. Section 4 displays the dataset analysis. Section 5 includes the methodology of the paper, and Section 6 presents the empirical evidence (preliminary and advanced econometric tests). Section 7 concludes the paper by presenting our implications.

2. Theoretical Background

2.1 Uncertainty Channel

According to Brown and Yucel (2002), the linkages between energy commodities prices and the stock markets profitability are influenced through the transmission of the uncertainty channel. The increase of energy commodities prices could create the uncertainty levels in the global economy since they affect plenty of macroeconomic factors, such as inflation, GDP and total consumption. When the oil prices increase, companies mitigate the demand for irreversible investments. Thus, this event decreases the expected cash flows. Additionally, households' consumption is negatively influenced by the increasing oil prices due to the rising uncertainty. Household increase their savings rather than consume (Degiannakis, *et al.*, 2018a). A massive reduction on consumption levels has a significant impact on the total turnover of companies which thereby dampens their economic growth prospects and total earnings. Accordingly, lower earnings lead to a fall of stock prices.

2.2 Fiscal Channel

The transmission of the fiscal channel predominantly interests economies which are based on the exports of energy commodities (oil, natural gas). These economies use their oil/gas revenues in order to finance their physical and social infrastructure (Emami and Adibpour, 2012). Higher energy commodities price transfer funds from economies which import energy resources to the oil/gas exporting economies. Assuming that the needs of oil/gas importing economies could not easily change mainly due to their structure, an increase of cash flows and total sales of energy sector companies is expected. Therefore, higher profitability of these companies will increase the price of their stocks and the stock market will enter into a bullish period (Degiannakis, *et al.*, 2018b). On the other hand, assuming that the needs of oil/gas importing economies could easily change mainly due to substitution of energy resources, a decrease of cash flows and total turnover of energy sector's firms will be observed. Hence, lower profitability of the energy sector will eventuate. In this case, stock markets will react negatively and the stock prices will decline.

2.3 Stock valuation channel

The most direct channel between oil/gas prices and stock markets is relied on the stock valuation channel. According to Degiannakis *et al.* (2018b), oil prices could influence (positively or negatively) the prospective cash flows of a company. This widely depends on the nature of a firm (oil/gas-consumer or oil/gas-producer). An increase of oil/gas prices will raise the production cost of and oil/gas-consumer company (no substitution effect exists among production factors) (Basher and Sadorsky, 2006). As an immediate result, higher production cost leads to a fall of profitability and expected cash flows. In contrast, an increase of oil/gas prices will positively influence the prospective cash flows and total earnings of oil/gas-producer company. In summary, it is expected that a bearish behavior on the stocks will take place for oil/gas-consumer firms, when oil price rises. On the other hand, a bullish attitude on the stocks will occur for oil/gas-producer companies.

3. Literature Review

The interrelationship between energy markets and the stock markets is always a field of considerate academic and professional interest due to the strong impact of oil and natural gas on the modern global economy. Ghouri (2006), Park Ratti (2008) and Ding *et al.* (2016) claimed the significant negative impact of oil prices on stock markets in Eastern Asia, the US and the EU. According to Gatfaoui (2019), this relationship between stock and energy markets plays an impactful role on the performance and the risk of investors' portfolio. Similar evidence was provided by Rehman *et al.* (2019) regarding portfolio diversification benefits. Additionally, other researchers support that energy commodities prices influenced asymmetrically the stock prices of different business industries (Arouri and Nguyen, 2010; Nicolau and Palomba, 2015; Nadal *et al.* 2017). The dissymmetric effect of oil or natural gas prices occurs also on stock market indices which are located in different countries due to the structure of their economy (Fang and Egan 2018; Chang *et al.* 2020). For instance, Balcilar *et al.* (2019) suggest that the effect of energy commodities prices is different between emerging and developed economies. The negative impact of energy commodities on stock markets as well as its duration is also based on oil supply shocks (Chai *et al.* 2011, Ewing *et al.* 2018), financial crises (Wen *et al.* 2018;

Bampinas and Panagiotidis 2017) and official announcements/agreements of OPEC countries (Huang *et al.* 2018).

Despite the important relationship between oil and stock prices, volatility linkages are also a significant research matter. For instance, Basta and Molnar (2018) and Sarwar *et al.* (2020) found that there is a substantial co-movement between the volatilities of the oil and stock markets. Subsequently, Angelidis *et al.* (2015) endorsed the idea that oil price returns and volatility possess the power to forecast the state of the US stock market returns and volatility. On the other hand, other researchers attempt to study the sensitivity of stock markets volatility against the shocks of energy commodities volatility (Diebold and Yilmaz 2012; Kang *et al.* 2015; Zhang *et al.* 2017). The sensitivity of stock prices volatility is concretely determined by miscellaneous factors. Degiannakis *et al.* (2013) examined this time-varying relationship between returns of oil price and industrial sector indices. Their findings report that the correlation between industrial sectors returns and oil price returns is determined by the origin of the oil price shock and the type of industry. Antonakakis *et al.* (2017) defended that both stock market returns and volatility suggest that connectedness varies across different time periods. Similar findings are presented by Filis (2014) and Degiannakis *et al*. (2018a) regarding economic/financial uncertainty and supply-side oil shocks. Furthermore, other researchers approved the there is strong correlation and clearly and systematically time-varying between oil volatility and stock markets volatility (Broadstock and Filis 2014).

The sensitiveness of stock prices volatility due to the external shocks of energy commodities price volatility is more vulnerable and less persistent in the emerging stock markets (Ahmed 2018; Bouri *et al.* 2019).

In addition, plenty of researchers studied the use of energy commodities and their derivatives on portfolios' allocation and construction (Chatrath *et al.* 2012; Basher *et al.* 2018; Ali *et al.* 2020). Their results confirm the prime role of energy commodities regarding the strategies of hedging, safe-haven and diversification.

Gatfoui (2016) studied the joint role of gas and oil markets on the stock markets. He implied that there is a definite combined link prevailing between the natural gas and crude oil markets. On the other hand, Batten *et al.* (2017) claimed that the price determination of these two energy commodities is independent and there were no joint dynamic linkages on the stock markets.

Considering the available literature, the majority of previous researchers focused on the relationship between stock and energy markets by studying the impact of financial uncertainty and economic crises. However, there are limited studies regarding the role of important OPEC's policies for oil-production (oil supply). Especially, changes on oil production modify the prices and the volatility of energy commodities and stock markets indices. The present study reveals new insights about the impact of OPEC agreement 27/11/2014 on energy and stock markets, since this incident significantly decreased the values of energy commodities and created excess volatility. Therefore, investors, financial institutions may rebalance their portfolios and make alternative investments in order to hedge, speculate or protect their investments.

4. Dataset Analysis

The present research uses the logarithmic value (units) of five stock market indices (CAC-40, FTSE-100, NIKKEI225, S&P500 and DAX-30) in advanced economies and the logarithmic value (price) of two energy commodities (crude oil and natural gas). The variables are listed in table 1 (below).

Particularly, this study examines the impact of the 166th OPEC meeting in Vienna, Austria on 27th November 2014 (OPEC, 2014). Most of the market analysts had forecast that the OPEC would reduce the daily oil production (Reed, 2014). However, the official announcement of that day revealed that OPEC countries decided to leave the oil production levels unmodified. The reaction of the markets effectively decreased the oil and natural gas price in a month. In particular, the crude oil price reduced sharply by 55% (27/11/2014 to 31/12/2014). Also, the natural gas price collapsed from 4.09$ per Mmbtu (before OPEC announcement) to 2.64$ per Mmbtu[4] (a fall of 35%) during the same period.

The research uses intra-day data on stock markets indices and oil prices for the period data accounting for the timespan from 15:00 GMT 27 November 2014 (OPEC press release time) to 23:00 GMT 31 December 2019. The data frequency is equal to 5 minutes. This frequency is chosen because the literature has shown that 5 minutes intervals are most commonly used (Wang *et al*, 2006). At the same time, the dataset

[4]A standard unit of measurement used to denote both the amount of heat energy in fuels and the ability of appliances and air conditioning systems to produce heating or cooling. A BTU is the amount of heat required to increase the temperature of a pint of water (which weighs exactly 16 ounces) by one-degree Fahrenheit. MBTU is occasionally expressed as MMBTU, which is intended to represent a thousand BTUs.

does not include data for early 2020, due to the Covid-19 pandemic outbreak crisis and the excess volatility at the stock and energy markets.

Table 1: Variables Presentation

Country	Variable	Frequency (GMT)	Trading Measure
France	CAC-40	5 minutes	units
UK	FTSE-100	5 minutes	units
Japan	NIKKEI	5 minutes	units
US	S&P500	5 minutes	units
Germany	DAX-30	5 minutes	units
Global	Crude oil price	5 minutes	USD
Global	Natural gas price	5 minutes	USD

Source: Bloomberg®

The dataset covers a period of over five consecutive years and the number of the observations is equal to 1222 trading days. The examination of the dataset was generated under the realized dynamics and volatility. The realized variance is useful because it provides a relatively accurate measure of volatility which is useful for many purposes, including volatility forecasting and forecast evaluation. The data was extracted from the official database of Bloomberg®.

Important milestones for the construction of the intra-day time series are the following:

1) Non-trading hours: We excluded from the dataset any trading that took place from Friday 21:00:01 GMT until Sunday 20:59:59 GMT.
2) Holidays: We do not include any bank holidays in the dataset owing to the evident fact that the trading activity is extremely low. We also opted to remove the following bank holidays: Christmas, Boxing Day, New Years' Eve, Catholic Good Friday, Catholic Easter Monday, International Workers' Day and Thanksgiving Day.
3) Common sample: We selected the trading days where the Crude oil and natural gas are traded in order to have a common sample across each time series.
4) Time zone: We decided to use the Greenwich Mean Time (GMT) as our time-zone on purpose of constructing and weighting our dataset.

5) Calendar sampling: We selected the calendar sampling as it is most commonly used in the global literature and hence permits the comparability of the results.
6) Modified Sample: We adjusted the dataset to the trading hours where each stock market is opened (US: 14.30 GMT to 21.00 GMT, Japan: 00:00 GMT to 07.00 GMT, Europe (France, Germany, UK): 08.00 GMT to 16.30 GMT.

5. Methodology

5.1 Fractional Co-integration

A process is integrated of order d, denoted by I(d), if its k^{th} difference has a spectral density:

$$\boldsymbol{f(\lambda) \sim C|\lambda|^{-2(d-k)}, \lambda \to 0, (1)}$$

Where C >0, and k is a nonnegative integer such that d−k <1/2. Here, d is the memory parameter. An I(d) process without deterministic trends is weakly stationary if d <1/2 and nonstationary otherwise. We mention that {Xt}and{Yt} are fractionally co-integrated if both processes are I(d) and there exists a linear combination Ut=Yt−βXt such that{Ut} is I(dU), with d_U< d. Fractional cointegration is a generalization of standard cointegration, where d=1 and d_U= 0. Both fractional and standard cointegration were originally defined simultaneously in Engle and Granger (1987), but standard cointegration has been studied far more extensively. Standard cointegration allows only integer values for the memory parameter, and tests for the existence of cointegration rely on unit root theory. The fractional cointegration framework is more general since it allows the memory parameter to take fractional values and d−d_U to be any positive real number (Dolatabadi *et al.* 2015). Fractional cointegration analysis often focuses on the reduction of the memory parameter from d≥1/2 to d_U<1/2, since cointegration is commonly thought as a stationary relationship between non-stationary variables. But cases where d <1/2 comes into force, are also of great interest, particularly if one wishes to study fractional cointegration in volatility. A popular method for estimating the cointegration parameter β in standard cointegration analysis is the ordinary least squares (OLS) estimator. Robinson and Yajima (2002) noted that for 0<d<1/2, the OLS estimator will in general be inconsistent in the presence of correlation between {Xt},{Ut}, and he proposed a narrow-band least squares estimator (NBLSE) of β in the frequency domain.

5.2 Fractionally Co-integrated Vector Autoregression (FCVAR) or Fractionally Co-Integrated Error Correction Model (FCECM)

The Fractionally Co-integrated Vector Autoregression (FCVAR) model is proposed in Johansen (2008), and first applied in Johansen and Nielsen (2010; 2012; 2016); its advantages are highlighted by Caporin *et al.* (2013). The FCVAR model allows for long memory (fractional integration) in the equilibrium errors, and following Figuerola-Ferretti and Gonzalo (2010), it additionally allows for the existence of long-run backwardation[5] or contango[6] in the equilibrium as well, i.e. a non-unit cointegration coefficient. Similarly, FCVAR is based on the Cointegrating VAR (CVAR) model of Johansen (1995), where $\Pi = \alpha\beta'$, and using the lag operator differencing $Ly_t = y_{t-1}$ one obtains:

$$\Delta \boldsymbol{y_t} = \boldsymbol{\alpha\beta' L y_t} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\gamma_i} \Delta \boldsymbol{L^i y_t} + \boldsymbol{\varepsilon_t} \quad (\mathbf{2})$$

Where α and β are kxr matrices with rank r. By replacing the difference and lag operator Δ and L=1-Δ in (3) with their fractional counterparts Δ^b and $L_b = 1 - \Delta_b$, respectively, as in Johansen (2008):

$$\Delta \boldsymbol{y_t} = \boldsymbol{\alpha\beta' L_b y_t} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\gamma_i} \Delta^{\boldsymbol{b}} \boldsymbol{L_b^i y_t} + \boldsymbol{\varepsilon_t} \quad (\mathbf{3})$$

And with $y_t = \Delta^{d-b} x_t$, equation (4) becomes:

$$\Delta^{\boldsymbol{d}} \boldsymbol{x_t} = \boldsymbol{\alpha\beta'} \Delta^{\boldsymbol{d-b}} \boldsymbol{L_b x_t} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\gamma_i} \Delta^{\boldsymbol{d}} \boldsymbol{L_b^i x_t} + \boldsymbol{\varepsilon_t} \quad (\mathbf{4})$$

where Δ^d is the fractional operator, and L_b is the fractional lag operator defined as above. The elements of $\beta' x_t$ are the cointegrating relationships in the system, where r represents the number of long-run equilibrium relationships, i.e. the cointegration or co-fractional rank. $\gamma = \gamma_i, \ldots, \gamma_k$ govern the short-run dynamics. The coefficients in matrix α represent the speed of adjustment towards equilibrium for each of the variables in response to shocks. The fractional parameter d is the order of integration of the individual time series and d - b (with b < 0) is the degree of fractional cointegration, the fractional integration order of $\beta' x_t$which is lower

[5] A normal backwardation market—sometimes called simply backwardation—is confused with an inverted futures curve.

[6] A contango market is often confused with a normal futures curve.

compared to that of itself. In other words, fractional cointegration assumes the existence of a common stochastic trend which is integrated of order d, and the short-term departures from the long-run equilibrium being integrated of order d-b (Johansen and Nielsen 2012).

The model describes cointegration and adjustment towards equilibrium but it is more general, as it incorporates fractional integration and cointegration. X_t are integrated of d order, and b is the strength of the cointegrating relations (a higher means less persistence in the cointegrating relations; can also be called the cointegration gap).

5.3 Fractionally Co-Integrated Error Correction Model (FCECM)

The following formula represents the Fractionally Co-integrated Error Correction Model that it is implemented in this research.

$$\Delta^d index_t = \alpha\beta' L_b com_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta^d L_b^i index_{t-1} + \varepsilon_t \quad (5)$$

where $index_t$ is the dependent variable (natural logarithmic of stock market index), com_t represents the natural logarithmic price of energy commodities (crude oil price, natural gas price), γ is the coefficient of short-term dynamics, $\beta'$is the coefficient of long-term dynamics and α represent the speed of adjustment towards equilibrium for each of the variables in response to shocks.

5.4 Asymmetric Component GARCH model (AC-GARCH)

Engle and Lee (1999) suggested the asymmetric component GARCH (AC-GARCH) model in order to explore the long-term and short-term volatility and the existence of leverage effect. The asymmetric component GARCH model permits mean reversion to a time-varying level q_t and allows shocks to affect the volatility components asymmetrically. An AC-GARCH model is defined as:

$$\sigma_t^2 = q_t + \mu\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \rho\left(d(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 - 0.5q_{t-1}\right) + \lambda\left(\sigma_{t-1}^2 - q_{t-1}\right) \quad (6)$$

$$q_t = \omega + q_{t-1} + \psi\left(d(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 - 0.5\sigma_{t-1}^2\right) + \varphi\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right) \quad (7)$$

Where, $d(.)$ denotes the indicator function (i.e. $d(\varepsilon_{t-i} < 0) = 1$ if $\varepsilon_{t-i} < 0$ and $d(\varepsilon_{t-i} < 0) = 0$ otherwise). μ parameter presents the volatility clustering, ρ parameter shows the volatility asymmetry, λ displays the short-term component of conditional variance or transitory effect, ψ is the long-term component of conditional variance and φ parameter is related with the difference of ARCH and GARCH effect.

6. Results and Discussion

This section includes the empirical results of preliminary tests as well as the two advanced econometric procedures (FCECM, AC-GARCH). The preliminary tests are prerequisite in order to examine the non-stationarity and the co-integration of a group of variables. We discovered that the time series have a unit root and a co-integration condition exists. Therefore, we can implement the FCECM model and the AC-GARCH model. We used the FCECM as the mean equation and the AC-GARCH(1,1) as the conditional variance equation in order to examine possible realized dynamics, volatility persistence, volatility clustering and volatility asymmetry.

Table 2 provides evidence about the stationarity of the time series (first differences) by using the unit root breakpoint test of Perron (1997). Both examined variables are non-stationary at 5% level of significance. The Perron breakpoint unit root test is most suitable to empirically determine the cut point of the dataset. Figure 1 reinforces that the breakpoint date is 28/02/2017.

Table 2: Estimation Results of Perron breakpoint unit root test

Series – Values	**t-statistic**	**Probability**
Δ(CAC-40)	-5.02*	0.001*
Δ(FTSE-100)	-6.07*	0.000*
Δ(DAX-40)	-4.13*	0.005*
Δ(S&P500)	-3.43*	0.009*
Δ(NIKKEI)	-5.45*	0.000*
Δ(Crude oil)	-4.32*	0.011*
Δ(Natural Gas)	-3.02*	0.029*

**statistically significant at 0.05 level*

The breakpoint date is quite reasonable since it has been related with the stability on energy commodities prices. The decision of 166th OPEC meeting (on 27th November

2014) created a volatile period in the energy markets. Therefore, this cut point date is associated with the agreement of OPEC and non-OPEC allies in late-2016 to limit crude oil production and stabilize the prices. The agreement entails twenty-four of the world's leading oil producers committing to removing around 1.8 million barrels/day of crude oil from global supplies from the beginning of 2017.

Figure 1: Perron unit root test Breakpoint

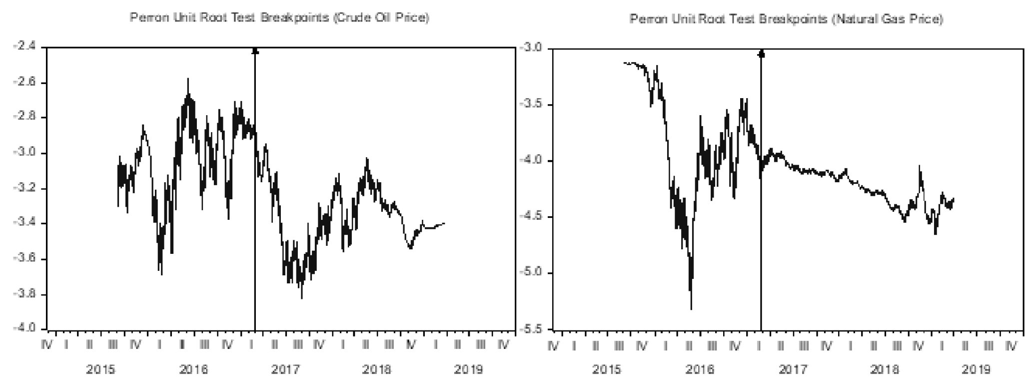


Table 3 presents the empirical evidence of fractional cointegration test. When RANK=0, the likelihood ratio (LR) statistic is significantly larger than the corresponding critical value signifying that the null hypothesis of zero cointegrating relations is rejected.

Table 3: Cointegration rank test by Johansen and Nielsen										
Variables	Rank=0				Rank=1				Rank=2	
	d	**b**	**LR**	**$CV_{5\%}$**	**d**	**b**	**LR**	**$CV_{5\%}$**	**d**	**b**
Ln(FTSE)	0.679	0.375	23.82	9.49	**0.999**	**0.301**	0.059	3.84	1.01	0.293
Ln(CAC)	0.712	0.323	24.50	9.49	**0.982**	**0.328**	1.68	3.84	1.02	0.228
Ln(DAX)	0.621	0.412	22.35	9.49	**0.971**	**0.352**	2.34	3.84	0.947	0.377
Ln(SP500)	0.511	0.512	19.82	9.36	**1.01**	**0.621**	0.01	3.59	1.00	0.622
Ln(NIKKEI)	0.712	0.365	17.66	9.49	**0.986**	**0.443**	1.09	3.84	0.979	0.542
Ln(Crude oil)	0.528	0.538	16.39	9.36	**1.02**	**0.471**	0.35	3.84	0.982	0.656
Ln(Gas)	0.478	0.491	22.60	9.49	**0.979**	**0.348**	2.37	3.84	0.968	0.422

Note: maximum k is set at 3 and this gives the order of the error correction mechanism in the FCVAR system. The LR is the Likelihood Ratio statistics, computed for rank r = 0 and 1. This is not available for rank 2 since we are not rejecting any more rank.

When RANK=1, the LR statistic is significantly smaller than the corresponding critical value and thus, the null of one cointegrating relation is accepted. The results, showing at table 3, indicate that there is one significant cointegration relationship for all the examined variables. Consequently, there are evident linkages in the long-run for each variable.

According to Johansen and Nielsen (2012), when there are cointegration relationships at the examined variables, we are able to proceed to the estimation of a fractional co-integrated error correction model so that the dynamic short- and long-term linkages and the adjustment speed back to equilibrium be discoverable (error correction term).

Table 4 and 5 demonstrate the empirical evidence of FCECM and AC-GARCH (1,1) model for each examined stock market index using the natural logarithmic value of crude oil or natural gas and their returns as the control variable. To be more precise, we utilized the FCECM as the mean equation and the Realized GARCH(1,1) as the conditional variance equation. The dataset is divided into two periods (breakpoint 28/02/2017) according to the results of the Perron (1997) breakpoint unit root test.

The adjustment speed back to equilibrium (ECT) is negative and statistically significant for every examined stock market index, indicating that there is a cointegration relationship and stability at the model. The negative sign of ECT reveals a convergence from short run to long run and manifests a causal relationship of the explanatory variables with the dependent variable. For instance, the ECT is equal to -0.00040 for CAC and then the -0.040% of a deviation from the error correction mechanism is corrected within 5 minutes due to the crude oil price movements during the 1st period. The short-term coefficient presents positive realized relationships for every stock index for both examined eras. However, the impact seems to be lower during the second period. Short-term positive relationship may occur due to portfolio allocation of investors (investment on stocks, oil and derivatives) and the investment strategies, such as hedging, speculation and diversification. The largest short-term impact of crude oil price happens on NIKKEI and DAX. An increase of crude oil price will lead to a rise on the Japanese and American stock market index and vice versa.

Table 4	FCECM with AC-GARCH estimation results Crude Oil									
Parameters	**Ln(SP500)**		**Ln(NIKKEI)**		**Ln(DAX)**		**Ln(FTSE)**		**Ln(CAC)**	
Periods	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**
Long-term dynamics (б)	-0.1981 (-2.28)*	-0.0959 (-2.12)*	-0.4409 (-3.08)*	-0.2189 (-2.02)*	-0.3058 (-3.11)*	-0.2178 (-3.12)*	-0.2306 (-2.65)*	-0.005 (-2.08)*	-0.2440 (-2.93)*	-0.0934 (-2.51)*
Short-term dynamics (γ)	0.1023 (66.50)*	0.0966 (61.79)*	0.1167 (50.12)*	0.0975 (47.70)*	0.1039 (45.64)*	0.0795 (43.66)*	0.1001 (57.05)*	0.0831 (54.50)*	0.1156 (50.24)*	0.0836 (48.19)*
ECT (α)	-0.00019 (-2.14)*	-0.00039 (-2.81)*	-0.00026 (-3.07)*	-0.00024 (-2.61)*	-0.00033 (-3.27)*	-0.00014 (-2.31)*	-0.00029 (-2.66)*	-0.00029 (-3.24)*	-0.00040 (-3.57)*	-0.00014 (-2.08)*
Constant (ω)	0.0014 (2.05)*	0.0003 (1.01)	0.0021 (2.74)*	0.0008 (2.73)*	0.0027 (3.14)*	0.0015 (2.52)*	0.0022 (2.65)*	0.0026 (3.29)*	0.0029 (3.44)*	0.0013 (2.27)*
Long-term volatility (ψ)	0.973 (87.87)*	0.999 (165.74)*	0.737 (177.25)*	0.999 (265.51)*	0.891 (81.09)*	0.932 (108.58)*	0.997 (70.90)*	0.938 (123.78)*	0.983 (90.86)*	0.986 (63.40)*
Persistence parameter (φ)	0.387 (26.58)*	0.014 (159.63)*	0.122 (43.41)*	0.009 (78.26)*	0.395 (237.36)*	0.190 (116.75)*	0.428 (236.21)*	0.157 (88.39)*	0.398 (237.01)*	0.222 (96.82)*
Volatility Clustering (μ)	0.092 (104.88)*	0.162 (193.90)*	0.055 (21.51)*	0.087 (42.38)*	0.142 (124.83)*	0.001 (2.05)*	0.179 (144.09)*	0.098 (29.09)*	0.185 (167.71)*	0.141 (49.46)*
Volatility Asymmetry (ρ)	-0.099 (-101.50)*	-0.012 (-19.91)*	-0.078 (-58.96)*	-0.108 (-72.32)*	-0.143 (-119.51)*	-0.025 (-30.56)*	-0.119 (-91.18)*	-0.009 (4.11)*	-0.123 (-102.27)*	-0.239 (-183.73)*
Transitory effect (λ)	0.562 (162.97)*	0.712 (436.45)*	0.464 (34.36)*	0.594 (100.17)*	0.519 (154.77)*	0.869 (385.33)*	0.459 (115.29)*	0.047 (1.56)	0.521 (154.28)*	0.012 (1.33)

statistically significant at 0.05 level

Moreover, the long-term dynamics are negative for every examined stock market index for both periods. The negative effect between crude oil price and the stock markets seems to be lower during the second period. This may occur because of the agreement of OPEC and non-OPEC countries to reduce the daily oil production at the end of 2016.

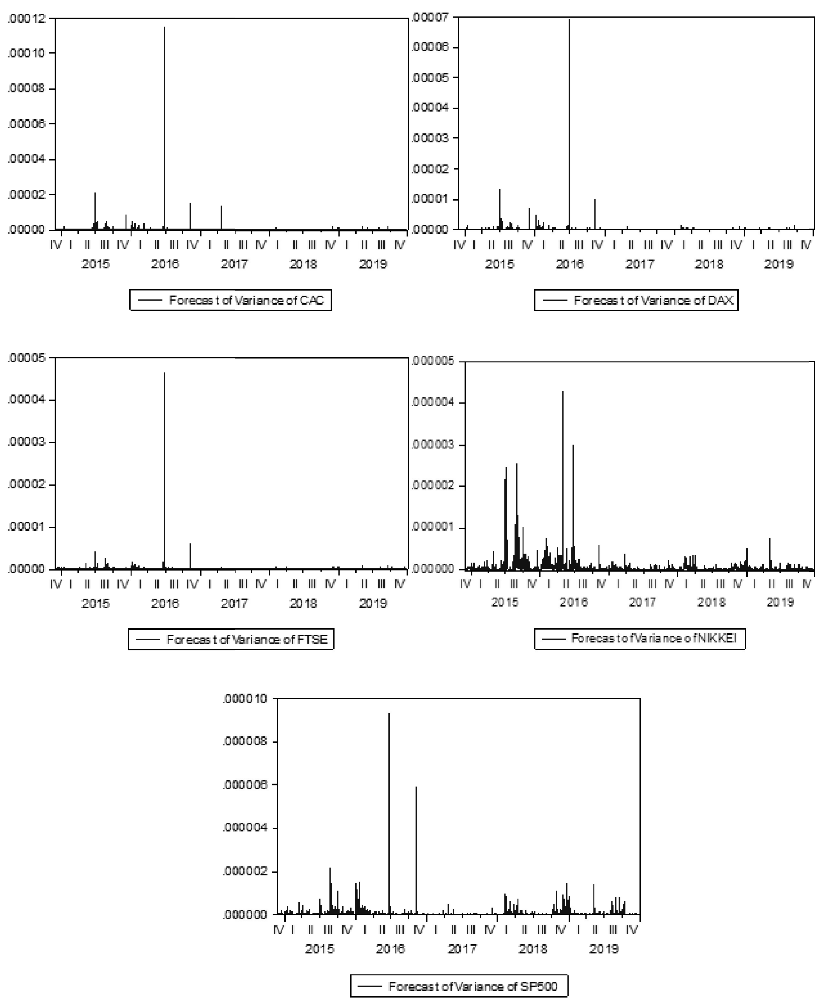
This agreement led to stabilization and an increase (afterwards) of oil prices in the energy markets in comparison with the previous volatile period. Higher oil prices increase the operational cost and margin profits of manufacturing industry. The stocks become less attractive to investors and their price falls. The long-term coefficient is strongly negative for NIKKEI and DAX index. In specific, an increase of crude oil price will lead to a decrease of stock market index and vice versa. This may occur due to the high exposure of the Japanese and German index on companies which broadly consume oil for their operational activity (e.g. car industry). On the other hand, the impact of crude oil is less strong but negative regarding the French, British and American stock market index during the second period.

The use of the AC-GARCH allows us to capture the volatility clustering, the volatility asymmetry, the short-term component of conditional variance or transitory effect as well as the long-term component of conditional variance. The current model expresses the process of conditional variance and allows mean reversion to time-varying. Also, it describes conditional variance to react asymmetrically to return shocks. Particularly, the research utilizes a AC-GARCH(1,1) including the threshold term (ρ). The z-statistic values can be found in the parenthesis at the tables.

The ψ parameter shows the time-varying long-term volatility. The value of this component is approximately equal to the unity for the majority of the stock indices. The long-term volatility memory of the stock markets is highly persistent against the shocks of crude oil price. However, the volatility persistence is lower for the Japanese and German stock market index during the first period. The μ coefficient is positive and shows the ARCH effect (volatility clustering), which presents the volatility sensitiveness of stock markets against the shocks of oil price. Thus, we expect that the volatility of the stock markets be more sensitive to large shocks of crude oil price. For instance, the French stock market index is more sensitive than the rest stock markets indices. Additionally, the ρ parameter is the threshold term which expresses the leverage effect. The leverage effect is negative for every advanced stock market for both periods. This indicates that the good news for the crude oil price demonstrates a larger impact on the volatility of the stock market indices price than what the bad news can accomplish. The volatility asymmetry seems to be higher for NIKKEI and CAC-40 revealing that crude oil price positive signals influence the volatility of these stock indices on a larger scale. Finally, the λ parameter suggests that the short-term volatility of the majority of stock market indices is medium persistent to the shocks of the crude oil price.

Figure 2 presents the conditional variance forecast asymptotes of AC-GARCH model for the stock market indices due to the volatility of crude oil price. The model forecasts a general increase in conditional variance before the processes converge to the theoretical unconditional variances. In addition, figure 2 offers that the first order AC-GARCH process forecasts converge fast to the unconditional variance implying that the latter process has a high forecast memory.

Figure 2: Forecast of variance of stock market indices due to volatility of crude oil price



At this part of the research, we introduce the findings between natural gas market and each developed stock market index. Table 5 demonstrates the empirical evidence of FCECM and AC-GARCH (1,1) models for natural gas price.

Table 5	FCECM with AC-GARCH estimation results Natural Gas									
Parameters	**Ln(SP500)**		**Ln(NIKKEI)**		**Ln(DAX)**		**Ln(FTSE)**		**Ln(CAC)**	
Periods	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**	**1st Period**	**2nd Period**
Long-term dynamics (б)	-0.1171 (-0.98)	0.6269 (2.55)*	-0.2914 (-1.54)	0.2605 (2.40)*	-0.2307 (-1.62)	0.3002 (2.12)*	-0.2526 (-1.67)	0.1289 (2.08)*	-0.1385 (-1.15)	0.3201 (3.91)*
Short-term dynamics (γ)	0.0096 (7.27)*	0.0014 (1.18)	0.0097 (4.67)*	0.0022 (1.52)	0.0101 (4.98)*	0.0002 (1.20)	0.0099 (6.27)*	0.0017 (1.53)	0.0103 (4.98)*	0.0003 (0.25)
ECT (α)	-0.00018 (-2.83)*	-0.00011 (-2.30)*	-0.00019 (-2.45)*	-0.00016 (-2.56)*	-0.00024 (-2.61)*	-0.00017 (-2.58)*	-0.00030 (-2.84)*	-0.00032 (-3.51)*	-0.00028 (-2.88)*	-0.00031 (-3.76)*
Constant (ω)	0.0013 (1.84)	0.0011 (2.54)*	0.0017 (2.28)*	0.0017 (2.69)*	0.0020 (2.52)*	0.0018 (2.74)*	0.0024 (2.81)*	0.0030 (3.60)*	0.0023 (2.78)*	0.0030 (3.91)*
Long-term volatility (ψ)	0.869 (112.40)*	0.999 (202.29)*	0.761 (156.79)*	0.998 (42.52)*	0.892 (48.09)*	0.936 (109.98)*	0.704 (135.88)*	0.938 (116.25)*	0.999 (69.02)*	0.876 (71.59)*
Persistence parameter (φ)	0.140 (124.29)*	0.015 (154.94)*	0.113 (29.39)*	0.008 (309.59)*	0.051 (81.40)*	0.188 (106.01)*	0.077 (79.10)*	0.165 (88.07)*	0.007 (264.81)*	0.184 (89.40)*
Volatility Clustering (μ)	0.343 (283.12)*	0.153 (147.65)*	0.128 (30.71)*	0.168 (67.54)*	0.355 (100.09)*	0.071 (21.98)*	0.381 (81.24)*	0.112 (33.41)*	0.392 (334.15)*	0.049 (14.32)*
Volatility Asymmetry (ρ)	-0.349 (-164.59)*	-0.044 (-52.89)*	-0.157 (-111.38)*	-0.048 (-43.96)*	-0.252 (-128.71)*	-0.074 (-37.47)*	-0.294 (-116.66)*	-0.042 (-18.99)*	-0.285 (-325.34)*	-0.115 (-55.83)*
Transitory effect (λ)	0.556 (353.38)*	0.685 (339.58)*	0.011 (1.15)	0.506 (73.66)*	0.633 (172.94)*	0.169 (6.99)*	0.611 (132.51)*	0.015 (0.57)	0.461 (242.18)*	-0.006 (-0.38)

statistically significant at 0.05 level

The negative sign of ECT reveals a convergence from short run to long run and shows a causal relationship of the explanatory variables with the dependent variable. For instance, the ECT is equal to -0.00032 for FTSE-100 and then the -0.032% of a deviation stemming from the error correction mechanism is corrected within 5 minutes due to the natural gas price movements during the second period.

In general, the short-term coefficient presents slightly positive dynamics for every stock market during the first period. More accurately, an increase of natural gas price will lead to an anemic rise of these indices and vice versa. On the other hand, stock market indices are not influenced by the fluctuations of the natural gas price in the short-run (zero effect) during the second period. This may occur because natural gas is a regional product instead of the oil which constitutes a global commodity as a matter of fact. This means that the impact of natural gas price is not so strong on the economy and businesses. Natural gas is used as a substitute to oil and an alternative investment product for hedging, speculation or diversification purposes.

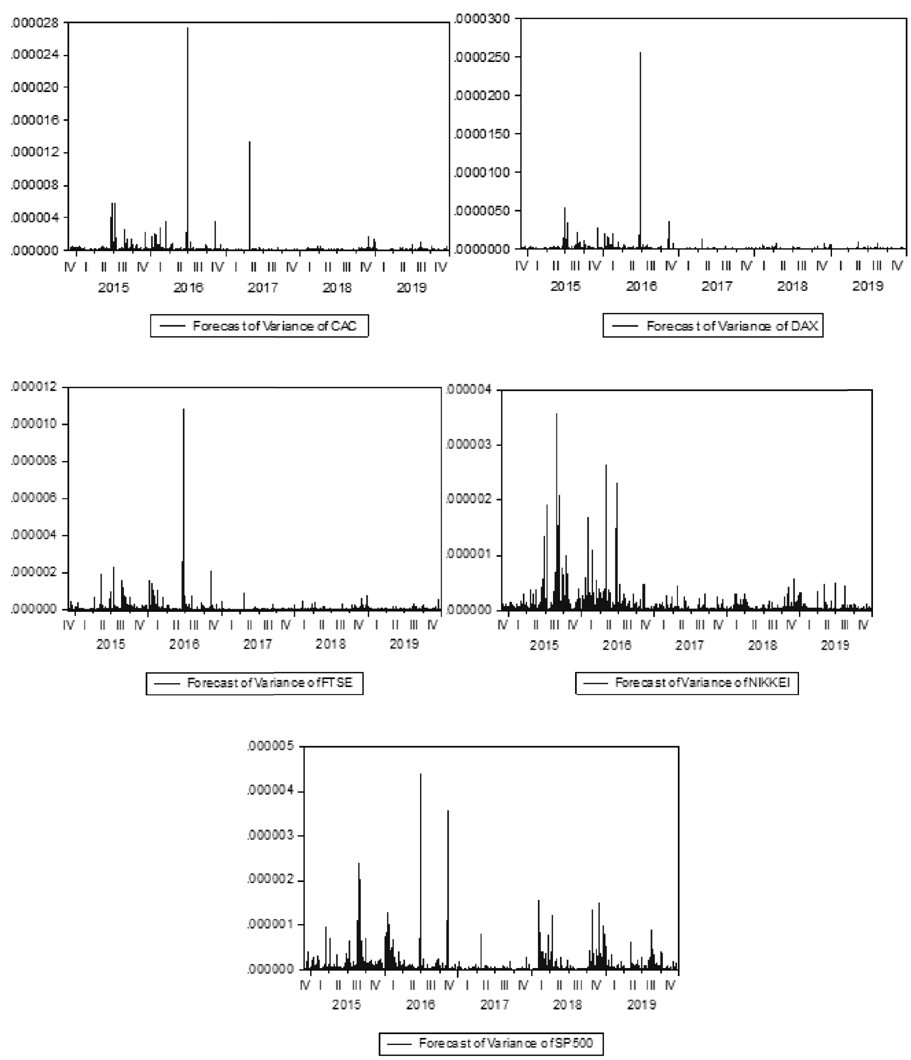
Furthermore, the long-term dynamics are statistically significant and positive for every stock market with regard to the second period but neutral for the first period. Thus, a positive relationship is established between advanced stock markets and the natural gas price. The impact of natural gas price on the American stock market index is larger than any other stock market index. This specifies that we expect a greater rise when the value of natural gas increases in the long-run. This may happen due to the substitution that exists between oil and natural gas. Inevitably, the agreement between OPEC and non-OPEC countries at the end of 2016 led to a reduction of global oil production. This condition increased the price of oil beyond this period. Therefore, manufacturing and utilities industry may differentiate their exposure to the oil with natural gas. Simultaneously, the cash flows of natural gas-producer companies increased due to this substitution. As a result, increased cash-flows lead to higher earnings for investors and the stocks of natural gas-producers companies rise. It constitutes a given reality that the natural gas-consumer companies decreased their operational cost since natural gas had been less expensive than oil. Lower operational costs lead to higher profit margin and total earnings by doing their stocks more attractive to investors.

Concerning the findings of AC-GARCH, the value of long-term volatility is approximately equal to the unity for all indices. The long-term volatility memory of the most stock market indices is highly persistent against the shocks of the natural gas price, except for NIKKEI and FTSE (1st period). A basic feature of long-term component is that it changes relatively slowly over time. The α coefficient shows the ARCH effect which presents the volatility sensitiveness of stock markets against the shocks of natural gas price. The value of μ parameter is positive for all the countries.

We expect that the volatility of FTSE and CAC be more sensitive to large shocks of natural gas price instead of the rest of the stock market indices during the first period. On the other hand, it is estimated that the volatility of S&P500 and NIKKEI be more sensitive to large shocks of natural gas price during the second period.

Figure 3 presents the conditional variance forecast asymptotes of AC-GARCH model for the stock market indices due to the volatility of natural gas price. The model forecasts a general increase in conditional variance before the processes converge to the theoretical unconditional variances. Figure 3 also, points out that the first order AC-GARCH process forecasts converge fast to the unconditional variance implying that the latter process has a high forecast memory.

Figure 3: Forecast of variance of stock market indices due to volatility of natural gas price



In summary, the empirical evidence confirms that crude oil and natural gas prices positively affect the stock market indices in the short-run. Crude oil prices negatively influence the stock market indices in the long-run. On the other hand, a positive impact exists between natural gas prices and stock market indices in the long-run during the second period. Moreover, high volatility persistence of stock market indices against the shocks of energy commodities prices characterize the 2008 post-crisis era. It has been revealed that the good news (positive announcements) of energy commodities influence the reaction of stock market indices more. The European and Japanese stock markets seem to be more vulnerable to the fluctuations of energy commodities price instead of those of American ones. By using the information that the results have provided, the short-term positive relationship and the long-term negative relationship between stock market indices and oil prices may occur owing to the conventional wisdom and stock valuation channel theory. This holds that an increase in oil prices will raise input costs for most businesses and force consumers to spend more money on oil products, thereby reducing the corporate earnings and dividends of other businesses (except for oil industry). Natural gas price positively influences the stock markets due to the substitution mechanism between the oil and natural gas. Oil prices rose during the second period due to a reduction on the global oil production (2016 OPEC-nonOPEC countries agreement). A change on the oil prices highly affects the stock market indices instead of the natural gas prices. The effect of crude oil prices is closely related with the micro-finance framework especially in the long-run. In particular, this may occur because it takes time for this effect to become apparent at the financial statements. Therefore, possible reduced earnings or losses will negatively affect the stock prices solely in the long-run. In this case, the investors and shareholders will start to sell their stocks in order to rebalance their portfolio and invest their money on alternative investments, such as bonds, financial derivatives or precious metals. Also, the oil and natural gas markets can provide hedging or speculation opportunities for stock markets. The involvement of hedge funds is primary at these markets (energy and stock). For this reason, short-term linkages among these markets could be entrenched especially after the end of 2008 global financial crisis. Nevertheless, more evidence needs to be accumulated on whether these findings come into force at the firm-level and whether the reverse hedging opportunities still apply (i.e. whether stock markets function as a hedging tool for oil price fluctuations). In addition, the European and Japanese stock markets are highly affected by the energy commodities prices due to their composition. Japanese stock market index returns are affected by crude oil and natural gas price shocks through changes to the expected real cash flows rather than to the changes in expected returns, despite the attempts of Japanese government policy to reduce the dependence of Japanese economy on the oil/natural gas consumption.

7.Conlusions and Policy Implications

The transmission channel between the stock markets and the energy commodities markets is direct due to the impact of oil/gas on the steam of modern global economy. The fluctuations of energy commodities prices influence oil/gas-consumer and oil/gas-producer economies by affecting differently every business sector. Investors' choices are also oriented by the changes and the volatility of oil/gas values. Researchers claimed that the relationship between these two markets are negative due to the stock valuation channel theory (Ghouri, 2006; Park Ratti, 2008; Ding *et al.*,2016). Additionally, other researchers support that the investors' choices are influenced by micro-finance factors or the financialization of the markets (Degiannakis *et al.* 2018b; Gatfaoui, 2019; Rehman *et al.*, 2019).

The motivation of this research was the OPEC announcement on 27/11/2014 which generated excess volatility on the crude oil and natural gas prices for at least 2 years. The energy commodities prices stabilized after the agreement of OPEC-nonOPEC countries at the end of 2016. The empirical evidence indicates that the advanced stock markets are more influenced by the oil prices changes instead of the natural gas fluctuations. Moreover, the volatility persistence of developed stock market indices is more vulnerable to the short-term volatility shocks from energy commodities.

Ultimately, the relationship between stock markets indices and oil/gas values is relied on the theory of conventional wisdom and the transmission mechanism of stock valuation channel. Therefore, investors could rebalance their portfolios in order to hedge and eliminate the systematic and market risk or even speculate by exploiting the momentum at the financial markets.

The findings of this paper are aligned with the research implications of Basta and Molnar (2018), as well as that of Antonakakis *et al.* (2017) and Nadal *et al.* (2017). Similar evidence was also found by Zhang *et al*. (2017) and Arouri and Nguyen (2010).

We consider that, from an academic point of view, it would be interesting to explore the dynamics and volatility responses between the energy commodities and stock market indices in the emerging economies.

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