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Return and volatility transmission between oil prices and Oil-exporting and Oil-importing Countries

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This paper provides further evidence of the comovements and dynamic volatility spillovers between stock markets and oil prices for a sample of five oil-importing countries (USA, Italy, Germany, Netherland and France) and four oil-exporting countries (United Arab Emirates, Kuwait, Saudi Arabia and Venezuela). We make use of a multivariate GJR-DCC-GARCH approach developed by Glosten et *al.* (1993). The results show that: *i)* dynamic correlations do not differ for oil-importing and oil-exporting economies; *ii)* cross-market comovements as measured by conditional correlation coefficients increase positively in response to significant aggregate demand (precautionary demand) and oil price shocks due to global business cycle fluctuations or world turmoil; *iii)* oil prices exhibit positive correlation with stock markets; and *iv)* oil assets are not a good 'safe haven' for protection against stock market losses during periods of turmoil.

Keywords: oil prices, stock markets, conditional correlations, DCC-GJR-GARCH model.

JEL Classification: Q43, E44, G15, C1.

1. Introduction

Our paper explores models that provide evidence of volatility transmission between crude oil prices and stock markets. Our objective is to complement this line of research by addressing the dynamics of volatility transmission using multivariate GJR-GARCH-class models which can detect the volatility asymmetry and spillover.

There have already been a few attempts to address the aforementioned topic, but none of the existing papers has approached the issue within a multivariate framework. The recent literature on volatility transmission and measurement has been developed through models that link the oil and stock market by investigating their comovements.[1] Hammoudeh et *al.* (2004) investigated spillover effects and dynamic relationships of five daily S&P oil sector stock indices and five daily oil prices for the US oil markets using cointegration techniques as well as ARCH-type models. They show evidence of some volatility spillover from the oil futures market and the stock returns of some oil sectors.

Accioly and Aiube (2008) analyze the dependence of extreme events in energy markets. They estimate and model both the over- all and the tail dependence of crude oil and natural gas returns. After adjusting auto regressive GARCH models to filter the linear and the nonlinear time dependence in the series of returns, the authors fit various copulas to the residuals of GARCH models. They results show srtong dependence between oil and gasoline prices.

Chiou and Lee (2009) examined the asymmetric effects of daily WTI oil prices on S&P 500 stock returns. Using the Autoregressive Conditional Jump Intensity model with expected, unexpected and negative unexpected oil price fluctuations, they found that high fluctuations in oil prices have unexpected asymmetric effects on stock returns. Malik and Ewing (2009) relied on bivariate GARCH models to estimate the volatility transmission between weekly WTI oil prices and equity sector returns and found evidence of spillover mechanisms.

Choi and Hammoudeh (2010) extended the time-varying correlations analysis by considering the commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index.

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[1] Most of this literature offers substantial evidence of the impact of oil on stock prices, suggesting a negative relationship between oil price and stock market returns. For instance, Jones and Kaul (1996) used a standard cash-flow dividend valuation model and found a significant negative impact of oil price shocks on US and Canadian quarterly stock prices in the post-war period. Models relying on some variants of Vector Autoregressive Analysis show similar findings (Park and Ratti 2008, Sadorsky 1999, Papapetrou, 2001).

They showed that commodity correlations have increased since 2003, limiting hedging substitutability in portfolios. More recently, Arouri et *al.* (2010) examined the relationship between oil prices and 12 stock sectors in European countries. The authors showed that the reaction of sector returns to changes in oil prices differs considerably across sectors and that the inclusion of oil assets in a portfolio of sector stocks helps to improve the portfolio's risk-return characteristics. Choi and Hammoudeh (2010) extended the time-varying correlations analysis by considering the commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index. They showed that commodity correlations have increased since 2003, limiting hedging substitutability in portfolios.

Aloui et al. (2010) examines the extent of the current global crisis and the contagion effects it induces by conducting an empirical investigation of the extreme financial interdependences of some selected emerging markets with the US. They use copula process capturing the dynamic patterns of fat tail as well as linear and nonlinear interdependences. Using daily return data from Brazil, Russia, India, China (BRIC) and the US, their empirical results show strong evidence of time-varying dependence between each of the BRIC markets and the US markets, but the dependency is stronger for commodity-price dependent markets than for finished-product export-oriented markets.

Filis et *al.* (2011) investigated time-varying correlations between Brent oil prices and stock markets on both oil-importing and oil-exporting countries. Using a multivariate asymmetric DCC-GARCH approach, they found that the conditional variance of oil and stock prices remains the same for oil-importing and oil-exporting economies. However, time-varying correlations depend on the origin of the oil shocks: the response from aggregate demand-related shocks is much greater than supply-related shocks originating from OPEC's production cuts.

Using weekly data from January 2, 1990 to December 28, 2009,Wu et al. (2012) examine the economic value of comovement between WTI oil price and U.S. dollar index futures. They use Copula-GARCH models and they conclude that dependence structure between oil and exchange-rate returns becomes negative and decreases continuously after 2003.

Awartani and Maghyereh (2013) investigated return and volatility spillover effects between the oil market and the Gulf Cooperation Countries (GCC) stock markets using indices proposed by Diebold and Yilmaz (2009, 2012), and revealed transmission in both directions between 2004 and 2012. They identified a significant flow of information from oil returns and volatilities to the GCC stock exchanges, while the flow in the opposite direction was found to be marginal.

Moreover, the oil market appears to give other markets more than it receives in terms of both returns and volatilities. The empirical evidence from the sample is consistent with a system in which oil plays the dominant role in the information transmission mechanism between oil and equities in the GCC countries.

Our study also looks at models on volatility transmission and thus contagion among stock markets of oil-exporting and oil-importing countries. The first empirical paper on financial contagion was the simple comparative analysis of Pearson's correlation coefficients between stock markets in periods of calm and periods of crisis. Contagion is found when significant increases in correlations occur in crisis periods. King and Wadhwani (1990), and Lee and Kim (1993) used the correlation coefficient between stock returns to test for the impact of the 1987 US stock crash on the equity markets of several countries. The empirical findings show that the correlation coefficients between several markets increased significantly during the crash. Hamao et *al.* (1990) found statistically significant correlations across stock markets during the 1987 crisis by estimating conditional variance under a GARCH model. Using a switching ARCH model, Edwards and Susmel (2001) found that many Latin American equity markets are significantly correlated during times of high market volatility, which proves contagion effects. Forbes (2004) studied the impact of the Asian and Russian crises on stock returns for a sample of over 10,000 companies worldwide, arguing that trade linkages are a vector of volatility transmission.

However, evidence on financial contagion is not really conclusive. Bordo and Murshid (2001) found that after accounting for heteroscedasticity, there was no significant increase in correlation between asset returns in pairs of crisis-hit countries. They concluded that there was no contagion but only interdependence. This is somewhat in contrast with Corsetti et *al*. (2005) who tested for financial contagion on a single-factor model and found some contagion and some interdependence. Further, focusing on different transmission channels, Froot et *al*. (2001) confirmed the existence of the contagion effect. Guesmi et *al.* (2013) investigated the co-movements between monthly US stock markets and those of the other sixteen OECD countries over the period 2002-2009 in order to study the contagion effect in the case of the recent global financial crisis. Using a multivariate DCC-GARCH, their results show the presence of shift-contagion effects arising from the financial crisis to most of the OECD stock markets, apart from Germany, Italy, the UK and, to a certain extent, Japan, where only interdependencies were detected. The other OECD stock markets were significantly impacted by shift-contagion during the financial crisis (2007-2009).

Our current work extends the method used to measure volatility spillover between oil and stock markets by applying multivariate GJR-DCC-GARCH models. Our study thus differs from previous ones in at least two respects. First of all, it identifies two main findings. Oil price shocks in periods of global turmoil or during global business cycle fluctuations (downturn or expansion) appear 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 major events (like the 2008 oil price crisis). In the case of importing countries, the pattern of interaction is far smoother compared to exporting countries. Other oil price shocks originating from events such as OPEC's production cuts, hurricanes and so on, do not seem to have a significant impact on the correlation between oil and stock markets in importing countries.

The rest of the paper is organized as follows. Section 2 describes the data and methodology model. Section 3 reports the empirical results. Section 4 concludes.

2. Data and Methodology

2.1 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, Netherlands and France) and exporting countries (United Arab Emirates, Kuwait, Saudi Arabia and Venezuela). The following criteria had to be satisfied for inclusion in the sample: (i) the countries studied need to have a well-established stock market and (ii) the selected countries have to be in the top 20 oil-importing and exporting countries.

The Brent crude oil index was used as it accounts for 65% of the global daily oil production (IMF, 2010). The data range from 03/09/2000 to 03/12/2010 and were extracted from the Federal Reserve Bank of Saint Louis and Datastream International database. The study period is selected on the basis of data availability and intends to cover the major economic and political events over recent years such as the last global financial crisis, the September 11 terrorist attack in the US, the second Gulf war, the Russian economic crisis, and the different monetary and financial crises in the Asian, Latin American and Middle East regions. This choice thus enables us to come to robust conclusions regarding the link between oil price dynamics and the financial market returns. Figure 1 presents the Brent crude oil prices in dollars, from September 2000 to October 2010.

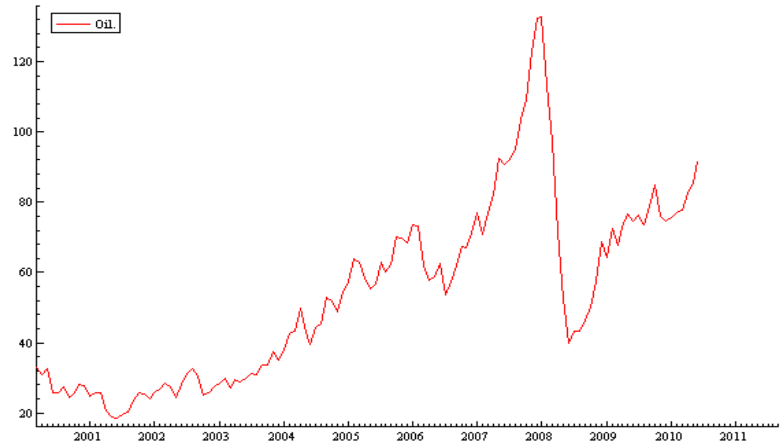

Fig 1. Brent crude oil price, in dollars, from 2000 to 2010

Oil price movements show some significant peaks and troughs during the study period. The main peaks are observed between 2007 and 2008. Another peak is observed in June 2009, when prices increased by more than 60% from their January 2009 price levels. All these changes are linked to aggregate demand-related oil price shocks. The first occurred during the Asian economic crisis, the second took place in 2000, when interest rates decreased significantly creating a bust in the housing market and construction industries. The third took place in the period 2006–2007, a result of the rising demand for oil in China, while the fourth demand-related oil price shock occurred during the global financial crisis of 2008.

Figures 2 and 3 describe stock market indices during the period under analysis respectively for oil-exporting and oil-importing countries. Taking into account the peaks and troughs of oil prices and the events that took place during our period of study, the relations between oil and stock market indexes exhibit some noteworthy aspects.

First, in exporting countries (Figure 2), we can observe the same oil price fluctuation movement in stock markets in the sub-period 2000-2005, with periods of increasing oil prices and stock market prices. However, for the sub-period 2005–2010, oil prices rose consistently. In addition, the period 2005 until mid-2007 is characterized by a continuous oil price increase, as well as increased stock market prices. During mid-2006 until early 2007, when we can observe an oil price trough, the stock markets also fell. Moreover, from 2007 until 2009, both oil prices and stock indexes were bullish. Finally, after the sub-period 2008-2009, both oil and stock market prices experienced a bearish performance. Venezuela exhibited a slightly different pattern, given the weaker development of its financial markets.

As a preliminary result, we can note that the visual inspection of the series does not provide a clear distinction between stock market performance and oil prices in oil-importing and oil-exporting countries. However, we may observe that the stock indices of importing countries (Figure 3) do not follow the same trend as 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 decreased while oil prices rose steadily.

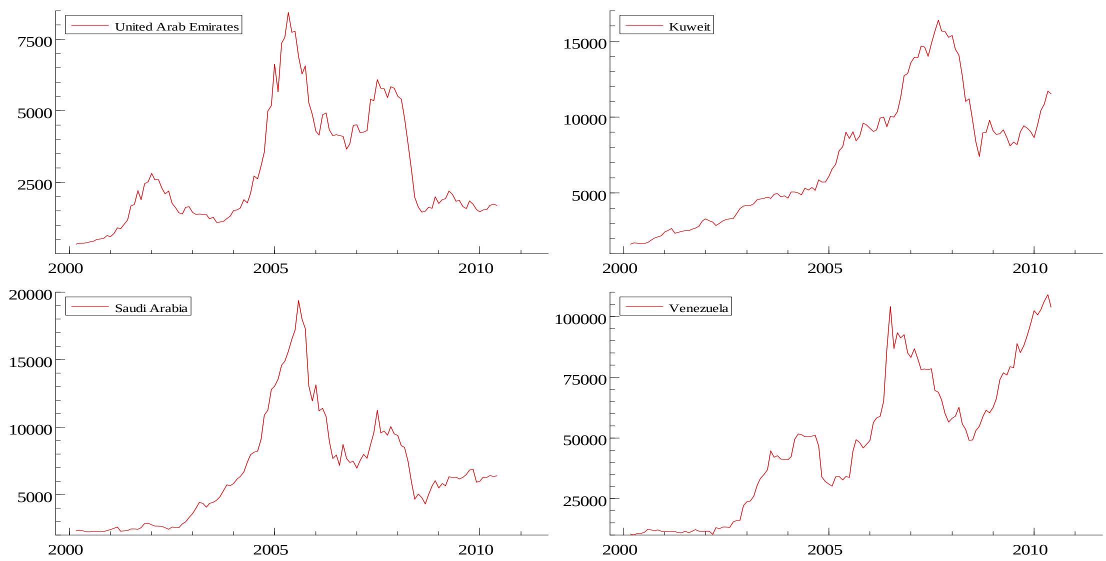

Fig 2. Stock Market Indices of Oil-Exporting Countries

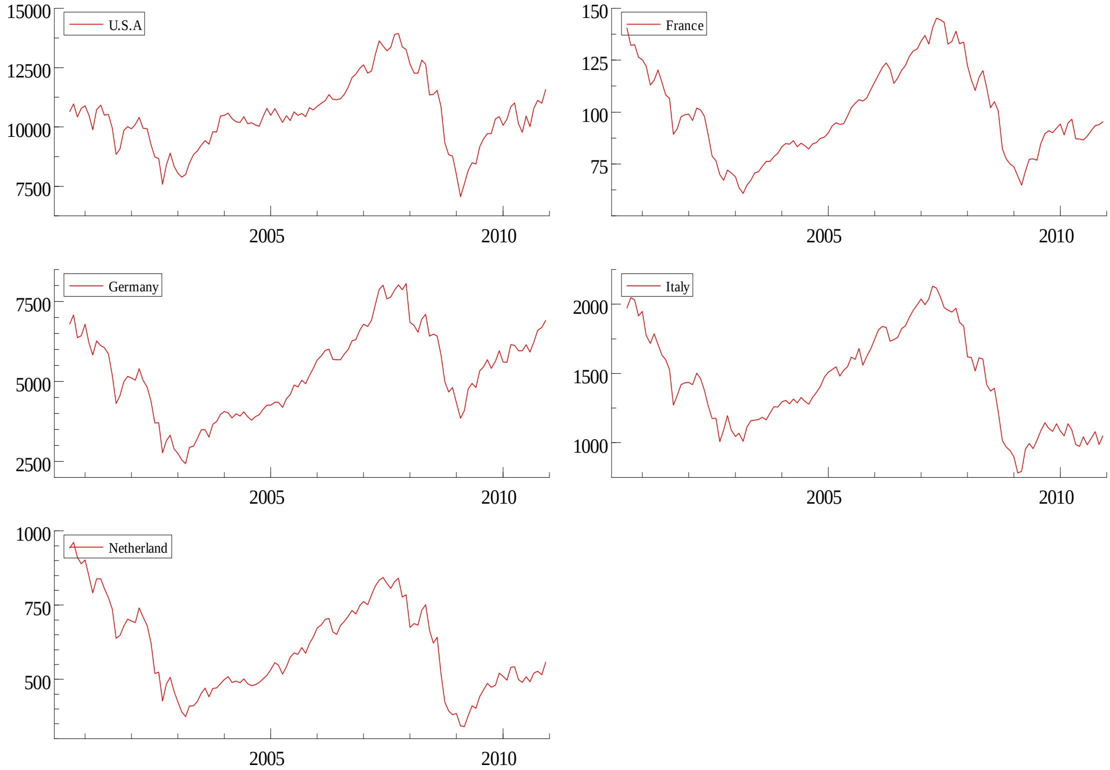

Fig 3. Stock Market Indices of Oil-Importing Countries

Table 1 reports the main statistics of return series for stock market, real exchange rate and Brent crude oil indices for the five stock markets considered.

Table 1. Descriptive statistics of return series

	Mean	*Std. dev.*	*Skewness*	*Kurtosis*	*ARCH (1)*
United Arab Emirates	0.013107	0.126709	0.118074	3.354331	17.145^{++}
Kuwait	0.015864	0.059667	-0.284409	3.587228	24.044^{+++}
Saudi Arabia	0.008233	0.083340	-0.822876	4.298505	23.696^{+++}
Venezuela	0.018655	0.083850	0.449107	6.660345	17.174^{+++}
USA	0.003945	0.061376	-0.867876	7.874304	20.294^{+++}
France	0.004031	0.005572	-0.998552	3.529250	28.966^{+++}
Germany	0.003945	0.005591	-0.695120	3.597867	27.126^{+++}
Italy	0.001543	0.064840	0.706611	3.592523	33.158^{+++}
Netherlands	0.003876	0.056325	-1.290798	6.326385	26.221^{+++}

Notes: ARCH(1) are the empirical statistics of the Engle (1982) test for the 1st order of ARCH effects. $^{+}$, $^{++}$, and $^{+++}$ indicate that the null hypothesis of no ARCH effects is rejected at the 10%, 5% and 1% levels respectively.

The average exchange rate returns range from -0.001% (Italy) to 0.18% (Venezuela). All of the series depart from normality conditions and conditional heteroscedasticity. The United Arab Emirates market was the most volatile during the period under study in terms of standard deviation (12.67%), while France was the least volatile (0.055%). The skewness coefficients are positive for the United Arab Emirates, Venezuela and Italy. They are significantly different from zero for almost all markets, indicating the presence of asymmetry in the return distribution. In addition, all the return series are characterized by a statistically significant and greater than 3 kurtosis coefficient, and thus have fatter tails than those of a normal distribution. Engle (1982)'s test for the 1st order of conditional heteroscedasticity is also performed and we cannot reject the hypothesis of no ARCH effects for all the return series considered. This result motivates our choice of a GARCH modelling approach for conditional variance processes.

2.2 Estimation of dynamic correlations

In this study, we apply the time-varying correlation coefficients estimated from a multivariate DCC-GARCH model intruded by Engle (2002). By allowing conditional correlations to vary over time, his specification is viewed as a generalization of the Constant Conditional Correlation GARCH model of Bollerslev (1990). To illustrate the dynamic conditional correlation model for our purposes, let x_t be a (11×1) vector (5 oil-exporting countries, 4 oil-importing countries, world market and oil market) containing the return, volume, and implied volatility series in a conditional mean equation as:

$$x_\mathbf{t} = \mu_\mathbf{t} + \varepsilon_\mathbf{t} \quad \text{with } \varepsilon_t \left| \psi_{t-1} \right. \sim N(0, H_t) \qquad (1)$$

where $\mu_\mathbf{t} = E\left[x_\mathbf{t} \| \Pi_{\mathbf{t-1}}\right]$ is the conditional expectation of $x_\mathbf{t}$ given the past information $\Pi_{\mathbf{t-1}}$, and $\varepsilon_\mathbf{t}$ is a vector of errors in autoregression AR(1). H_t is the variance-covariance matrix of returns at time *t*.

Under the assumption that the return, volume and implied volatility series x_t are determined by the information set available at time t-1, the model may be estimated using maximum likelihood methods, subject to the requirement that the conditional covariance matrix $H_\mathbf{t}$ be positive and definite for all values of $\boldsymbol{\varepsilon}_\mathbf{t}$ in the sample. We also assume that $\mu_\mathbf{t}$ is formed as follows:

$$\mu_{i,t} = \Phi_0 + \Phi_1 x_{i,t-1}, \forall \mathrm{i} \qquad (2)$$

Φ_1 measures the ARCH effect in the data series. In the traditional multivariate GARCH framework, the conditional variance-covariance matrix can be written as:

$$H_t = D_t R_t D_t' \qquad (3)$$

H_t is the variance-covariance matrix of returns at time *t*. R_t is the (11×11) symmetric matrix of dynamic conditional correlations. D_t is a diagonal matrix of conditional standard deviations for each of the return series, obtained from estimating a univariate GJR-GARCH[2] process developed by Glosten *et al.*, (1993) in the equation of variance expressed as:

$$h_{ii,t} = w_i + \alpha_i \varepsilon_{ii,t-1}^2 + \beta_i h_{ii,t-1} + \gamma_i I_{i,t} \varepsilon_{ii,t-1}^2 \tag{4}$$

where persistence is measured by the coefficients β_i, and the indicator variables $I_{i,t}$ capture asymmetry in the estimate of coefficients γ_i. A negative value of γ_i implies that negative residuals increase the variance more than positive residuals.

Therefore, for a pair of markets *i* and *j*, their conditional correlation at time *t* can be written as:

$$\rho_{ijt} = (1-\theta_1-\theta_2)\rho_{ij} + \theta_2 \rho_{ij,t-1} + \theta_1 \frac{\sum_{m=1}^{M} u_{i,t-m}, u_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} u_{i,t-m}^2\right)\left(\sum_{m=1}^{M} u_{j,t-m}^2\right)}}. \tag{5}$$

where $u_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{iit}}}$

The estimation of the vector of unknown parameters (θ) is carried out by the quasi-maximum likelihood estimation (QMLE) method that is robust to departures from normality of return series under regular conditions (see Bollerslev and Wooldridge, 1992). The log-likelihood function to be maximized is expressed as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log|D_t| + \log|R_t| + \mu'_t R_t^{-1}\mu_t), \tag{6}$$

where μ_t is the standardized residual derived from the first stage univariate GARCH estimation, which is assumed to be i.i.d with a mean zero and a variance of R_t.

3. Empirical Results

The graphs from the time-varying correlation coefficients as computed from equation (5) between each stock market index and the crude oil prices are presented in Fig.4 and Fig. 5.

In 2003, there was a relatively lower dynamic correlation in the case of exporting countries (Dubai, Kuwait and South Africa). This result is explained by the war in Iraq in March 2003

[2] This model gives a better statistical result than DCC-GARCH.

and the strike movement in Venezuela. We can observe a breakdown in dynamic correlation for all exporting countries in 2006. We explain this decrease in interdependence between oil prices and the stock market index by a military attack in Nigeria which caused the shut down of more than 600,000 billion barrels a day.

Another period of interest is that running from 2006 until mid 2008, characterized by high oil prices due to rising demand, mainly from China. The level of correlation shows an increasing and positive pattern for all countries. This aggregate demand-related oil price shock had a positive impact on stock markets (both in oil-importing and oil-exporting countries) as it signaled an increase in world trade. These findings are in line with Hamilton (2009) and Kilian and Park (2009), who suggest that aggregate demand-related oil price shocks, originating from world economic growth, have a positive impact on stock prices.

From mid-2006 to early 2009, the correlation rises sharply and reaches a higher value (except for Venezuela). The main event during this period is the global financial crisis triggered by the export of US mortgages to the rest of the world as asset-backed securities, which can be regarded as an aggregate demand-related oil price shock (International Energy Agency 2009). The greater interaction between oil and stock market prices can be explained by the fact that the resulting crisis caused stock markets to enter bearish territory and oil prices to decline heavily, as also documented by Creti et *al.* (2013).

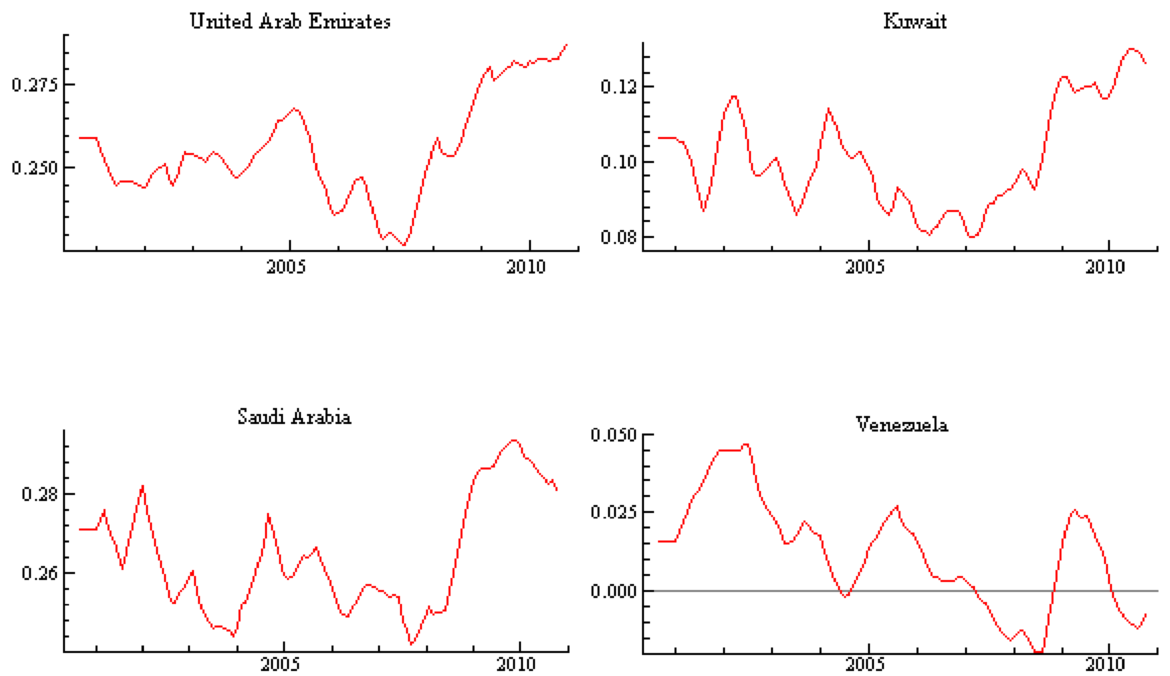

Fig 4. Correlations Between Oil Exporting Countries and Brent crude Oil

There are only three periods of noteworthy higher or lower correlation between oil prices and stock markets for exporting countries. These are early 2000 until 2001 (aggregate demand-oriented oil price shocks — higher correlation), 2003-2005 (aggregate demand-oriented oil price shocks — higher correlation), and 2007–2008 (aggregate demand-oriented oil price shock — positive correlation).

The years 2003-2005 (Figure 5) represent the sole period showing little difference between importing and exporting countries in terms of the correlation pattern of oil and stock market prices. The explanation for such findings may be due to the housing market boom in 2000, which created a positive environment for world markets and, at the same time, 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 led to significant uncertainty in all economies, causing similar stock market movements and thus similar correlation with oil prices. In addition, Chinese growth and its impact on world trade caused euphoria in all stock markets regardless of the country of origin. Likewise, the recent global financial crisis impacted on all stock markets in similar fashion and thus on their comovements.

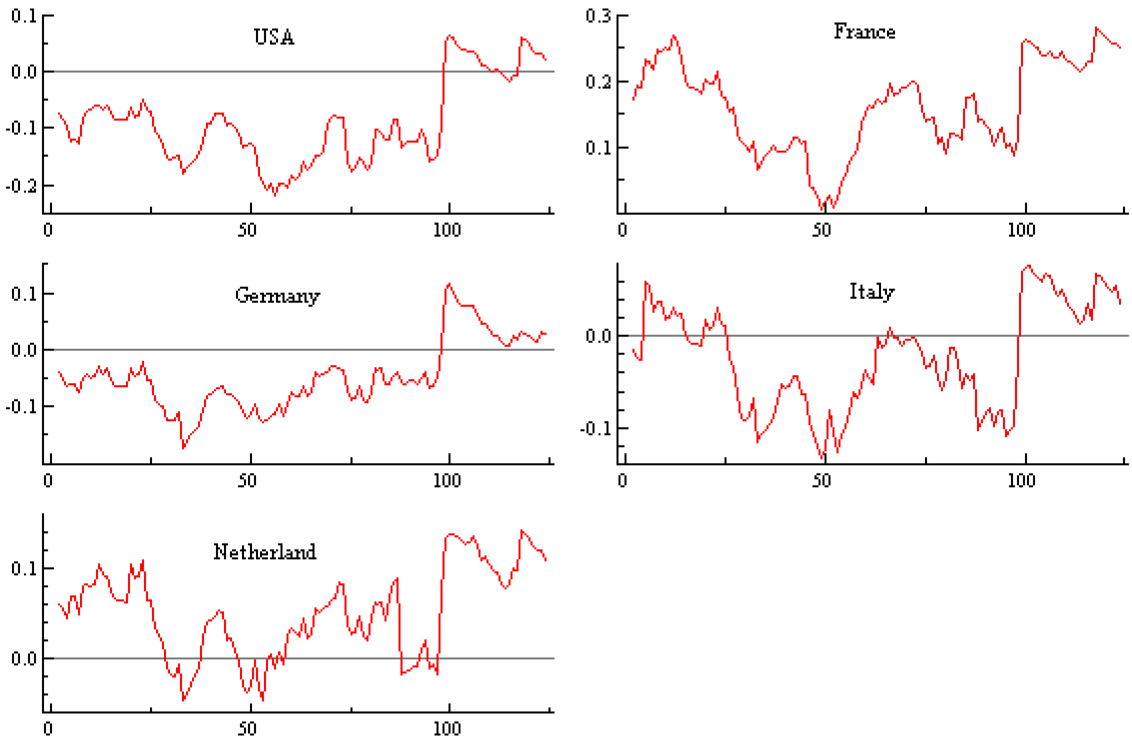

Fig 5. Correlations Between Oil Importing Countries and Brent crude Oil

Our analysis shows that aggregate demand-oriented oil price shocks (housing market boom, Chinese economic growth, and the recent global financial crisis) caused a significantly higher correlation between stock market prices and oil prices. Considerable precautionary demand-oriented oil price shocks (i.e. second war in Iraq, terrorist attacks) tended to cause higher correlation but of less magnitude compared to the aggregate demand-oriented oil price shocks. The origin of the shock seems to be an important determinant of the magnitude of correlation between oil prices and stock markets, as when the oil shocks originate from major world turmoil events, such as wars or changes in global business cycles.

Overall, the findings of the previous literature are confirmed concerning the impact of oil shocks on oil-importing and oil-exporting country stock markets, whereas in the case of supply shocks, our findings show some aspects that have been neglected to date. In particular, we highlight the role of crisis periods in oil prices as drivers of the comovements between oil and stock markets.

4. Conclusion

This paper investigates the issue of oil and stock market interdependence in oil exporting and importing countries by measuring the interaction between oil price and stock market indices using the asymmetric DCC-GARCH approach. This process is applied to the stock market indices of oil-exporting countries: the United Arab Emirates, Kuwait, Saudi Arabia and Venezuela, and oil-importing countries: the USA, Italy, Germany, the Netherlands and France.

Apart from the Venezuelan stock market, our analysis shows that high oil prices driven by demand-related shocks move in line with stock prices, especially in exporting countries. Supply shocks cause higher correlation only in exporting countries. Therefore, in terms of potential diversification, 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. On the other hand, if the shock originates from demand, oil prices and stock markets tend to move together with varying degrees of strength in both importing and exporting countries, depending on the origin of the shock.

References

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.

Awartani, B. and Maghyereh, A. (2013), Dynamic spillovers between oil and stock markets in the Gulf Cooperation Council Countries, *Energy Economics*, 36 (1), 28–42.

Bollerslev, T. and Wooldridge, J. M. (1992), Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, *Econometric Reviews*, 1, 143-173.

Bollerslev, T. (1990), Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model, *The Review of Economics and Statistics*, MIT Press, vol. 72(3): 498-50.

Bordo, M. D., and Murshid, A. P. (2001), Are Financial Crises Becoming Increasingly More Contagious? What Is the Historical Evidence on Contagion?, in S. Claessens and K. J. Forbes, International Financial Contagion, Boston: Kluwer Academic, chapter 14, pp. 367-403.

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.

Corsetti, G., Pericoli, M., Sbracia, M. (2005), Some contagion, some interdependence: More pitfalls in tests of financial contagion, *Journal of International Money and Finance*, 24, 1177-1199.

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

Diebold, F.X. and Yilmaz, K. (2009), Measuring Financial Asset Return and Volatility Spillovers, With Application to Global Equity Markets,"*Economic Journal*, 119, 158-171.

Diebold, F.X. and Yilmaz, K. (2012), "Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers," *International Journal of Forecasting*, 28, 57-66.

Engle, R. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation, *Econometrica*, 50, 987-1008.

Engle, R. (2002), Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models, *Journal of Business & Statistics*, 20 (3), 339-350.

Edwards, S. and Susmel, R. (2001), Volatility dependence and contagion in emerging equity markets, *Journal of Development Economics*, 66 (2), 505-532.

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.

Forbes, K. (2004), The Asian Flu and the Russian Virus: Firm -levelEvidence on How Crises are Transmitted Internationally, *Journal of International Economics,* 63, 59-92.

Froot, K.A., O'Connell, P.G.J., Seasholes, M.S. (2001), The portfolio flows of international investors, *Journal of Financial Economics,* 59, 151–194.

Glosten, L.R, Jagannathan, R. Runkle, D.E. (1993), On the Relation Between the Expected Value and the Volatility of the Nominal Excess Returns on Stocks, *Journal of Finance*, 48: 1791-1801.

Guesmi, K., Kaabia, O., Kazi I.A. (2013), Does Shift Contagion Exist Between OECD Stock Markets During The Financial Crisis, *Journal of Applied Business Research*, 29(2) : 469-484, 2013.

Hamao, Y.R., Masulis R.W. and Ng V.K. (1990), Correlations in Price Changes and Volatility Across International Stock Markets, *Review of Financial Studies*, 3, 281-307.

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

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.

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

King, M.A. and Wadhwani, S. (1990),Transmission of volatility between stock markets. *Review of Financial Studies*, 3, 5-33.

Jones, C.M., and Kaul, G. (1996), Oil and the Stock Markets, *The Journal of Finance*, 1996, 51 (2) : 463-491.

Lee, S.B. and Kim, K.J. (1993), Does the October 1987 crash strengthen the co-movements among national stocks markets?, *Review of Financial Economics*, 3, 89-102.

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

Papapetrou, E. (2001), Oil price shocks, stock market, economic activity and employment in Greece, *Energy Economics,* 23 (5) : 511-532.

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

Sadorsky, P. (1999), Oil price shocks and stock market activity, *Energy Economics* 2, 449-469.