Oil Price Shock and Effects on Stock Markets of Emerging Economies

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29 December 2016

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New Oil Price Shock and Stock Markets of Emerging Economies

Abstract

The present study investigates the effect of sharp continuous falling crude oil prices on stock market indices of emerging economies like Brazil, Russia, India, China, South Africa and South Korea and also the relationship between crude oil prices and stock indices of these countries. The period of the study spans from July 2009 to January 2016. Multivariate cointegration techniques along with vector error correction mechanism, impulse response functions and multivariate CCC-GARCH model have been employed in the study. The long-run relationship has been empirically established between the variables only in Brazil and Russia, but, no such relationship has been found in case of other emerging economies. Except South Africa, stock indices of the other emerging economies adjust to changes in crude oil prices to correct short-run disequilibrium although, with varied speed of adjustment. CCC-GARCH estimation reveals the existence of volatility spillovers between crude oil prices and stock indices and convergence have been achieved for all the emerging economies.

Keywords: emerging economies, new oil price shock; stock indices.

JEL code: M210

1 Motivation of the Study

Global crude oil prices have experienced a continuous and steady decline particularly over the last twelve months, leading to a noteworthy revenue deficit in many crude oil exporting nations, while for consumers in many crude oil importing countries lower crude oil price means paying less to heat their homes or drive their cars. But cheap oil, at its lowest price in over a decade, is also having far-reaching and unexpected geopolitical and economic consequences around the world.

Brazil, the second largest producer of crude oil in Latin America also suffered a setback. More than 50% of total oil production in Brazil comes from its pre-salt fields. Pre-salt refers to the oil reservoirs found under the thick layer of salt in Brazil's deepwater. These fields have proved to be highly productive, with production already at more than 700,000 barrels a day in May 2015. Lower crude oil prices added pressure to the Brazilian economy as because elevated crude oil prices are required to stimulate investment in the country's deep-water offshore oil fields that contribute to country's economic growth. According to the World Economic outlook published by the International Monetary Fund, Brazil's gross domestic product (GDP) has contracted by 1.5% in 2015 which simply reflects the dampening effect of lower crude oil prices and tighter external financial condition.

The economy of Russia depends heavily on energy revenues with oil and gas accounting for more than seventy per cent of export incomes.The growth rate of Russian economy shrinks by about 0.7% in 2015 and there is a forecast by World Bank that the Russian economy will sink into recession in 2016, if oil prices do not recover. Russian rouble (RUB) already suffers a heavy setback and Russia is compelled to hike its interest rate to 17% in support of its currency which simply shows that the Russian economy is hardly pressed by falling oil prices

On the other hand, falling crude oil price is just like a blessing for Indian economy, though there are many hitches. It helps to narrow down India's current account deficit - the amount India owes to the world in foreign currency. Again, the Indian rupee (INR) exchange rates also gets affected though, to a very few extent. The value of a free currency like rupee depends on its demand in the currency market. This is because it significantly depends on the current account deficit. A towering deficit means the country has to sell rupees and purchase dollars to disburse its bills. This diminishes the value of the rupee. A plunge in oil prices is, thus, good for the rupee. However, the disadvantage is that the dollar strengthens each and every time, whenever crude oil prices plunge down, which counteracts any benefits that have been derived from a fall in current account deficit.

Brent crude oil was recorded at a new low of $28.94 per barrel (as on January 10, 2016) and WTI (West Texas Intermediate) crude is down to below $29.44 per barrel (as on February 7, 2016). Simultaneously, demand for crude oil has plummeted throughout the globe and especially in Asia where the bigger economy and energy consumer, China, is undergoing the slowest economic growth in a decade. With the global economy looking shaky due to China's slowdown, traders said the outlook for oil remains for cheap prices for much 2016. According to the analysts, the reasons for this sharp decline in oil prices are two-fold - weak demand in many countries due to gloomy economic situation, coupled with surging US production. They are of the opinion that the enormous US storage project is the main cause for falling WTI crude. Keeping in tune with these decisions taken by the United States and OPEC, Russia, the second largest producer of crude oil only next to Saudi Arabia also decided not to cut production in order to shore up oil prices. But, the actual fact is that there is an apprehension amongst the oil producing nations that if these oil producing countries like Russia, United States, Brazil and member countries of OPEC cut their production they will lose their dominant niche in the market to their competitors.

A number of substantial finance researchers have concentrated on the issue of the relationship between oil prices, stock markets and macroeconomic variables like growth rate, employment, inflation, monetary policy, etc. Authors like, Loungani (1986), Brurbridge & Harrison (1984) and Mork (1989) shows that nonlinear relationship exists between economy and the oil prices. Barnanke, Gertler & Watson (1997), Sadorsky (1999), Papapetrou (2001), Barsky & Kilian (2001), Lee & Ni (2002), Hamilton & Herrera (2004), Yang & Bessler (2004), Anoruo & Mustafa (2007), McSweeney & Worthington (2007), Miller & Ratti (2009), and others investigate the impact of oil price shock on stock markets of developed countries. Basher et al. (2010), applies structural vector autoregression model for examining the dynamic relationship between oil prices, exchange rates and stock markets of emerging economies.

The objective of this paper is to examine the relationship between crude oil price and stock market indices of the emerging economies in the context of plunge in the crude oil price in recent times. It may be relevant to point out that the recent shock is different than the previous shocks. Major oil shocks after World War II include Suez Crisis of 1956-57, the OPEC oil embargo of 1973-1974, the Iranian revolution of 1978-1979, the Iran-Iraq War initiated in 1980, the first Persian Gulf War in 1990-91, and the oil price spike of 2007-2008. All these historical oil shocks are associated with increase in crude oil price and its negative effects on the economy. The recent decline in inflation may be a "supply side" effect associated with the declining price of oil, in the same respect that the surge in oil prices in the 1970's was responsible for soaring inflation. Falling oil prices are also an important part of the recent phenomenon of resurging economic growth in the U.S. Much like how the increase in the price of oil in the 1970's was "a negative supply shock" effectively creating unemployment and declining output, this recent decline in the price of oil is behind a “positive supply shock” in part responsible for the recent boost in economic activity and decline in unemployment in the US (ibid.).

Ono (2011), Ghorbel & Boujelbene (2013) and Morales & Gassie-Falzone (2014) have done something similar studies but have used different data periods and methods for analysis. There are also considerable number of research work like Gisser & Goodwin (1986); Hamilton (2003); Bittlingmayer (2005); Kilian (2008); Kilian & Park (2009) and Fang (2010) that study the effect of increasing oil prices or positive oil price shock on the stock markets and the country’s economic health. But, none of them or any other studies have been found to be conducted that evaluate the impact of declining oil prices or negative oil price shocks on the stock markets even during sharp continuous fall in crude oil price in the recent times.

From February 02, 2014 to January 31, 2016, i.e. over the last twenty four months WTI crude oil price has fallen by 103%. The massive supply of crude oil by the oil producing countries throughout the globe continued to pressure markets. The study of Basher et al. (2010), reveal that oil prices react positively to a surprising hike in demand for oil consumption, while it reacts negatively to sudden increase in oil supply. According to Goldman Sachs, volatility in oil price which is at its highest since the collapse of Lehman Brothers in 2008, could reach 100% as storage capacity comes under pressure. Moreover, China, which is the second largest importer of crude oil only next to United States is also experiencing economic slowdown and depressing stock markets, has reduced its import of crude oil. This entire situation and particularly falling crude oil prices has a substantial effect on the economy and stock markets of oil exporting countries like Brazil and Russia. In this backdrop, this paper entails a dataset up to January 31, 2016 so as to capture the volatility spillovers and also the latest effect of falling crude oil prices on the stock markets of the emerging economies like Brazil, Russia, India, China, South Africa and South Korea which can surely be considered a new contribution to the existing oil price literature.

2. Literature Review

Oil price shocks that originate from the energy markets are defined in various ways. According to Hamilton (2003), oil price shock is an increase in net oil price, i.e. the logarithm change in the nominal price of oil in the current year in relation to the previous years. He argues that oil price shocks may precisely affect short-run economic performance of a country due to its temporary ability to disrupt bulk purchases for consumption and investment goods. The findings of Hamilton are reflected in the earlier study conducted by Gisser and Goodwin (1986) and Darby (1982). Again the study results of Mork (1989) reveal an asymmetric affiliation between changes in oil price and output growth. On the other hand, Kilian (2008a) states that oil price shocks may be demand driven and the nominal oil price shocks measured by Hamilton (2003), does not sort out or wiped out the oil price changes caused by the exogenous political actions. Moreover, it cannot be implied that nominal oil shocks necessarily includes corresponding real oil price shocks. So, in order to overcome these problems, Kilian (2009) employs vector autoregression (VAR) by using real oil price, oil supply and a proxy variable for measuring global demand for industrial commodities as three variables.

Basher et al. (2010), applies six-variable SVAR model and impulse response functions to find out the affiliation between oil price shock, exchange rates and stock markets of the emerging countries. Their study results reveal that oil prices react positively to a surprising hike in demand for oil consumption, while it reacts negatively to sudden increase in oil supply. Bittlingmayer (2005) shows that increase in oil price is interrelated with decrease in stock prices. Hamilton (2009) are of the opinion that consistent rise in real oil price during the period of 2002 to 2008 are mainly because of strong and growing demand for crude oil from China, India and other emerging economies. The impact of oil price shock on the stock markets of three BRIC countries, i.e. Russia, India and China have been analyzed by Fang (2010). He uses the model proposed by Kilian and Park (2009) and the study results reveal that oil price shocks and oil specified demand shocks do not have any significant impact on Indian stock markets, whereas these shocks have positive impact on Russian stock markets. Again, in case of China, he finds that oil specified demand shocks alone positively affect the stock markets of China, while oil price shocks has mixed condition on the stock markets of China. Abdelaziz et al. (2008) investigates the linkages between oil prices, exchange rates and stock prices of four Middle East countries – Kuwait, Oman, Saudi Arabia and Egypt. VECM and FIML estimations suggest that there exists long-run positive impact of oil prices on the stock prices of these four oil exporting countries and long-run equilibrium readjustments in each stock market take place through changes in oil prices.

Ono (2011) investigates the effect of oil prices on real stock returns for BRIC countries for the period of 1999:1 to 2009:9. Using vector autoregression (VAR) model he found that real stock returns positively respond to some of the oil price indicators for China, India and Russia, but, in the case of Brazil no significant responses are found. Variance decomposition analysis shows that the contribution of oil price shocks to volatility in real stock returns is relatively large and statistically significant for China and Russia. Morales and Gassie-Falzone (2014) examines the volatility spillovers between oil prices and emerging economies like BRIC. The paper investigates the BRIC financial markets and their movements with regards to energy markets (oil, natural gas and electricity) and to US stock returns fluctuations.

Most of the studies on oil price shocks and stock markets concentrate on developed countries rather than putting their attention on emerging economies. Very few studies like Hammoudeh and Aleisa (2004); Hammoudeh and Huimin (2005) and Basher and Sadorsky (2006) examine the relationship between oil prices and stock markets of emerging economies. In general, they are of the opinion that oil price shocks affect stock indices of these emerging countries.

The scrutiny of the above literatures reveals mixed results and the empirical findings show both positive and negative impact of oil prices on stock market indices. Therefore, the present study seeks to find out the effect of declining oil prices which is also regarded as "new oil price shock" on the stock markets of emerging economies as well as volatility spillovers between crude oil prices and stock indices of emerging economies like Brazil, Russia, India, China, South Africa and South Korea.

3 Data Set and Methodology

For the present study, weekly data of the closing indices of Bovespa (stock index of Brazil), MICEX (stock index of Russia), BSE Sensex (stock index of India), Shanghai Composite (stock index of China), FTSE South Africa (stock index of South Africa) and KOSPI (stock index of South Korea) as well as the closing prices of the crude oil index represented by the WTI (West Texas Intermediate) crude oil prices have been considered. WTI crude oil index is used as a benchmark for world oil markets. Data on stock market indices are retrieved from Bloomberg database and the closing indices of all these countries are taken in terms of USD. Because of non-synchronous data we have taken weekly data and to avoid the weekend effect we have chosen Wednesday's closing prices. The total study period spans from 05 July, 2009 to 31 January, 2016. However, it needs to mention that this is the period of post global recession. To determine this period, we have consider reports of Business Cycle Dating Committee of U.S. National Bureau of Economic Research (NBER) as the standard benchmark. According to the Business Cycle Dating Committee of U.S. National Bureau of Economic Research, the global recession begin in December 2007 and ended in June 2009.For better analysis, all the data values are expressed in terms of logs. To analyze the data obtained from different sources as mentioned above, econometric tools like Elliott, Rothenberg and Stock point optimal (ERS) unit root test, Johansen Cointegration Test, Vector Error Correction Model (VECM), and Impulse Response Function have been used. Volatility spillovers between crude oil prices and stock markets are measured by using multivariate CCC-GARCH model.

4 Results and Discussion

4.1 Test of Stationarity: Unit Root Test

In our study we examine the presence of unit root by using Elliott, Rothenberg and Stock point optimal (ERS) unit root test (1996) to determine whether the time series is non-stationary. ERS test is a modified version of the Dickey-Fuller t test and it is substantially powerful than ordinary ADF unit root test. The results of ERS unit root test are given in table 1.

Lag lengths and model of the test are preferred according to the MAIC (Modified Akaike Info Criterion). The test is run taking first differences of all the series allowing intercept and deterministic time trend in the regression. The null hypothesis is rejected at 1 per cent level of significance indicating that all the series are stationary. This means that the selected series are integrated of order one, i.e. $I(1)$ and thus suitable for long memory test.

Table 1 here.

4.2 Johansen Cointegration Test

Johansen cointegration test provide a mean to determine whether a set of endogenous variables for each of the emerging economies (i.e. for Brazil - Bovespa and crude oil price; for Russia – MICEX and crude oil price; for India - BSE Sensex and crude oil price; for China - Shanghai Composite and crude oil price; for South Africa – FTSE SA and crude oil price and for South Korea – KOSPI and crude oil price) share a common long-run stochastic trend, while allowing for the possibility of short-run divergences. Table 2 reports the results for testing the number of cointegrating relations. The (nonstandard distribution) critical values are taken from MacKinnon-Haug-Michelis (1999) so they differ slightly from those reported in Johansen and Juselius (1990). To determine the number of cointegrating relations *r* conditional on the assumptions made on the trend, we can proceed sequentially from r = 0 to r = k – 1 until we fail to reject. The estimation for each group assumes the level data Z_t have no deterministic trends and the cointegrating equations have intercepts. Lags interval of 1 to 4 is used based on Akaike Information Criterion (AIC).

Table 2 here

For Brazil and Russia both trace statistic and maximum eigenvalue statistic indicates one cointegrating equation in each case which is significant at 5 per cent level. But, no cointegrating equations have been found in case of India, China, South Africa and South Korea. The results show that in only in Brazil and Russia the set of variables (crude oil price and stock market index) is cointegrated, as both the trace statistic and maximum eigenvalue statistic reject the null hypothesis of no cointegration and therefore there exists a stationary long-run relationship between the set of variables. This implies that there are common stochastic trends indicating a degree of economic integration between crude oil price and stock index for Brazil, and Russia. This may due to the fact that both Brazil and Russia are oil producing countries and thus their economy rely much on the demand and supply of crude oil and so it is quite natural to find out a stationary long-term relationship between stock markets and crude oil prices for these two countries.

4.3 Vector Error Correction Model (VECM)

The multivariate cointegration test results reveal that while allowing for the (linear) trend, the set of series for Brazil and Russia are cointegrated, that is, there is a long-run or equilibrium relationship between the set of series. But, of course, in the short-run there may be disequilibrium. On the other hand, although there is no long-term relationship between crude oil prices and stock markets in case of India, China, South Africa and South Korea, very short-term relationship may exist along with disequilibrium. Therefore, it is equally important to see whether any adjustments for short-run disequilibrium are made by VECM in case of India, China, South Africa and South Korea. Again, in case of Brazil and Russia causal relations should be examined with VECM that corrects for disequilibrium.

The VECM which is first used by Sargan and later popularized by Engle and Granger has cointegration relations built into the specifications so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term, since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. In this connection, VECM is applied in this study and corresponding VEC model is:

$$\Delta SI_t = \beta_0 + \sum_{i=1}^{q} \beta_{1i}\, \Delta SI_{t-i} + \sum_{i=1}^{q} \beta_{2i}\, \Delta COP_{t-i} + \alpha_1 Z_{t-1} + e_{1t} \qquad (1)$$

n n

$$\Delta COP_t = \delta_0 + \sum_{i=1} \delta_{1i} \Delta COP_{t-i} + \sum_{i=1} \delta_{2i} \Delta SI_{t-i} + \sigma_1 Z_{t-1} + e_{2t} \quad (2)$$

Where, SI_t and COP_t represent stock indices and crude oil price and Z_{t-1} is the error correction term which we get from the cointegration equation, so that changes in variables ΔSI_t, and ΔCOP_t are partially driven by past values of Z_t. The coefficient of error correction α_1 and σ_1 are expected to capture the long-run equilibrium adjustments of ΔSI_t and ΔCOP_t while the coefficients on ΔSI_{t-i}, and ΔCOP_{t-i} are expected to capture the short-run dynamics of the model. Table 3, 4, 5, 6, 7 and 8 displays the results of VECM for each emerging economies.

Table 3 here

Table 4 here

Table 5 here

Table 6 here

Table 7 here

Table 8 here

The responses of each selected series to correct the disequilibrium are captured by the significance and size of the estimated coefficients α_1 and σ_1 of the VECM equations 1 and 2. However, the VECM estimations give varied results. For Brazil α_1 is found to be statistically significant (at 10%) while σ_1 is not. This implies that with respect to Brazil, only stock indices follows and adjusts to disturbances to restore long-run equilibrium, but that the crude oil prices do not react significantly and about 2.02% of disequilibrium is corrected each week by changes in Bovespa. For Russia, both α_1 and σ_1 are significant at 1% and 5% level, i.e. both MICEX and crude oil price react significantly and about 5.58% and 0.18% of disequilibrium is corrected each week by changes in MICEX and crude oil prices. In case of India, σ_1 is found to be statistically significant at 1% level and only 0.02% of disequilibrium is corrected each week by changes in crude oil price. For China, only α_1 is found to be significant at 1% level and about 3.92% of short-run disequilibrium is corrected each week by changes in Shanghai Composite. In case of South Africa, only σ_1 is found to be statistically significant at 1% level and only 0.05% of disequilibrium is corrected each week by changes in crude oil price. Finally, for South Korea it is found that both α_1 and σ_1 are significant at 1% level, i.e. both KOSPI and crude oil price react significantly and about 5.15% and 0.28% of disequilibrium is corrected each week by changes in KOSPI and crude oil prices. In Russia and South Korea, stock indices series adjust more rapidly to crude oil price shocks. However, in China and Brazil the speed of the short-run disequilibrium adjustment is much slower than compared to Russia and South Korea.

The short-run interactions are shown by the coefficients of the lagged differenced terms of the respective stock indices and crude oil price series for each country. In tables 3 to 8 it has been found that few short-run adjustment coefficients of stock indices series are statistically significant. This implies that there is very little evidence of short-run dynamics among the variables of interest in all the emerging economies.

4.4 Impulse Response Analysis

According to Christopher Sims, the estimated lagged coefficients of unrestricted vector autoregression (VAR) fail to provide enough information about the dynamic affiliation between the variables in the system, but it is supportive in tracing out the responses of the system to random shocks.

Thus, to measure the impulse response functions, we applied structural VAR (SVAR) model as used by Kilian & Park (2009).

$$e_t = \begin{pmatrix} e_{1t}^{crude\ oil\ price} \\ \\ e_{2t}^{stock\ indices} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \epsilon_{1t} \\ \\ \epsilon_{2t} \end{pmatrix}$$

Here, ε_{1t}, and ε_{2t}, correspond to white noise error term and e_{1t} and e_{2t} represents the residuals from VECM equations. Any disturbance in ε_{1t} is quickly and directly transmitted to e_{1t} through the first equation and also to e_{2t} through the second equations respectively. Similar reactions occur in case of any disturbances in ε_{2t}. Therefore, it is found that a random shock in one innovation in SVAR model form a chain reaction with the other variables over time in the system. These chain reactions for each emerging economy are measured by impulse response functions which are displayed in figures 1, 2, 3, 4, 5 and 6.

Figure 1 here

Figure 2 here

Figure 3 here

Figure 4 here

Figure 5 here

Figure 6 here

For all the countries impulse response functions have been derived using lag intervals of 3 and 4. In the case of Brazil, it is found that crude oil price shocks have positive impact on Bovespa and crude oil price is directly related with it. This means that an increase in crude oil price also increases Bovespa and vice versa. Brazil being an oil exporting country, higher crude oil prices boosts up Brazilian stock markets. Similarly, in Russia too we observe direct relationship between crude oil prices and stock markets. This means when crude oil prices increases, MICEX also increases and vice versa. Thus, in oil exporting countries like Brazil and Russia, the effect of higher crude oil exports that brings in more foreign currencies helps to bump up domestic stock markets as well as country's economy. Moreover, both Bovespa and MICEX adjust to innovations in crude oil prices to correct short-run disequilibrium though, the adjustment speed of MICEX is much faster than that of Bovespa. On the other hand, when we measure response of crude oil price to Bovespa and MICEX, we find that crude oil price is responsive to changes in Bovespa but does not react to changes in MICEX.

In India , it is observed that BSE Sensex is also quite sensitive to changes in crude oil prices although, BSE Sensex does not adjust to innovations in crude oil prices. Next, in the case of China, the first figure that measures responses of Shanghai Composite to crude oil price, the graph of Shanghai Composite is almost flat even after taking higher lag intervals of 4 and 5, 5 and 6, 6 and 7, etc. Thus, Shanghai Composite is less susceptible to changes in crude oil prices but, of course in the short-run it adjusts to crude oil price innovations at a moderate speed to correct disequilibrium. Similarly, in case of South Africa also, the graph of FTSE SA index is flat even at higher lag intervals and thus, FTSE SA index does not react to changes in crude oil prices. Moreover, it does not even adjust to innovations in crude oil prices for correction of short-run disequilibrium. Finally, for South Korea it is found that KOSPI is responsive to changes in crude oil prices and furthermore, it also adjusts at a much higher speed to innovations in crude oil prices to correct short-run disequilibrium.

4.5 CCC-GARCH Model

Multivariate GARCH Model

In our study the volatility spillovers between crude oil prices and stock indices like Bovespa, MICEX, BSE Sensex, Shanghai Composite, FTSE SA and KOSPI are estimated by multivariate Constant Conditional Correlation (CCC)-GARCH model. As in the univariate case, we can define multivariate GARCH models by specifying their first two conditional moments. An R^m-valued GARCH process (ε_t), with $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{mt})$, must then satisfy, for all $t \in Z$, (Franq & Zakoian, 2010)

$$E(\varepsilon_t / \varepsilon_u, \ u < t) = 0, \ \mathrm{Var}(\varepsilon_t / \varepsilon_u, u < t) = E(\varepsilon_t \varepsilon'_t / \varepsilon_u, \ u < t) = H_t . \qquad (3)$$

The multivariate extension of the concept of the strong GARCH process is based on an equation of the form

$$\varepsilon_t = H_t^{1/2} \eta_t \qquad (4)$$

Where (η_t) is a sequence of iid R^m-valued variables with zero mean and identity covariance matrix. The matrix $H_t^{1/2}$ can be chosen to be symmetric and positive definite but it can also be chosen to be triangular, with positive diagonal elements (see, for instance, Harville, 1997, Theorem 14.5.11). The second alternative may be of consideration because if, for instance, $H_t^{1/2}$ is chosen to be lower triangular, the first component of ε_t only depends on the first component of η_t (Franq & Zakoian, 2010).

Specification selection for H_t is evidently further sensitive than that in the univariate framework as: (i) H_t should be (almost surely) symmetric, and positive definite for all t; (ii) the specification should be simple enough to be agreeable to probabilistic study (existence of solutions, stationarity, . . .), while being of sufficient generality; (iii) the specification should be prudent enough to facilitate reasonable and practical estimation. Nevertheless, the model should not be that easy to be capable to capture the – possibly complicated – dynamics in the covariance structure (Franq & Zakoian, 2010).

Moreover, it may be useful to have the so-called *stability by aggregation* property. If $\bar{\varepsilon}_t$ satisfies Eqn. 3, the process ($\bar{\varepsilon}_t$) defined by $\varepsilon_t = P\ \varepsilon_t$ where P is an invertible square matrix, is such that,

$$E(\bar{\varepsilon}_t / \bar{\varepsilon}_u,\ u < t) = 0,\ \mathrm{Var}(\bar{\varepsilon}_t / \bar{\varepsilon}_u,\ u < t) = \bar{H}_t = PH_tP' \tag{5}$$

The steadiness by aggregation of a class of specifications for H_t requires that the conditional variance matrices $\bar{H}_t$ fit in to the identical group for any choice of P. This property is mainly pertinent in finance because if the components of the vector ε_t are asset returns, $\bar{\varepsilon}_t$ is a vector of *portfolios* of the same assets, each of its components consisting of amounts (coefficients of the corresponding row of P) of the initial assets (Franq & Zakoian, 2010).

Constant Conditional Correlation Model

CCC-GARCH model is a model of conditional variances and correlations that is based on the on the decomposition of the conditional covariance matrix into conditional standard deviations and correlations. In this model, the conditional correlation matrix is time-invariant (Silvennoinen & Terasvirta, 2008). Suppose that, for a multivariate GARCH process of the form as given by eqn. 4, all the past information on ε_{kt} , involving all the variables $\varepsilon_{\ell\ t-i}$, is summarized in the variable

$h_{kk,t}$, with $E_{hkk,t} = E\,\varepsilon^2_{kt}$. Then, letting $\eta_{kt} = h^{-1/2}_{kkt}\,\varepsilon_{kt}$, we define for all k a sequence of iid variables with zero mean and unit variance. The variables η_{kt} are generally correlated, so let $R = Var(\eta_{kt}) = (\rho_{k\ell})$, where $\eta_t = (\eta_{1t}, \ldots, \eta_{mt})$`. The conditional variance of

$$\varepsilon_t = diag(h^{1/2}_{11,t}, \ldots, h^{1/2}_{mm,t})\,\overline{\eta_t} \tag{6}$$

is then written as

$$H_t = diag(h^{1/2}_{11,t}, \ldots, h^{1/2}_{mm,t})\,R\,diag(h^{1/2}_{11,t}, \ldots, h^{1/2}_{mm,t}). \tag{7}$$

To complete the specification, the dynamics of the conditional variances $h_{kk,t}$ has to be defined. The simplest constant conditional correlations (CCC) model relies on the following univariate GARCH specifications (Franq & Zakoian, 2010):

$$h_{kk,t} = \omega_k + \sum_{i=1}^{q} a_{k,i}\,\varepsilon^2_{k,\,t-I} + \sum_{j=1}^{p} b_{k,j}\,h_{kk,\,t-j}\,,\ k = 1,\ldots..,m \tag{8}$$

where, $\acute{\omega}_k > 0, a_{k,I} \geq 0, b_{k,j} \geq 0, \ -1 \leq \rho_{k\ell} \leq 1\,, \rho_{kk} = 1$ and R is symmetric and positive semi-definite. Observe that the conditional variances are specified as in the diagonal model. The conditional covariances clearly are not linear in the squares and cross products of the returns (Franq & Zakoian, 2010).

In a CCC-GARCH (p, q) process, let (η_t) be a sequence of iid variables with distribution η. A process (ε_t) is called CCC-GARCH (p, q) if it satisfies

$$\begin{cases} \varepsilon_t = H_t^{1/2} \eta_t , \\ H_t = D_t R D_t , \\ \underline{h}_t = \underline{\omega} + \sum_{i=1}^{q} A_i \underline{\varepsilon}_{t-i} + \sum_{j=1}^{p} B_j \underline{h}_{t-j} , \end{cases} \tag{9}$$

where, R is a correlation matrix, $\underline{\omega}$ is a m x 1 vector with positive coefficients, and the A_i and B_j are m x m matrices with nonnegative coefficients.

We have, $\varepsilon_t = D_t \bar{\eta}_t$, where $\bar{\eta}_t = R^{1/2} \eta_t$ is a centered vector with covariance matrix R. The components of ε_t thus have the usual expression $\varepsilon_{kt} = h_{kk,t}^{1/2} \bar{\eta}_{kt}$, but the conditional variance $h_{kk,t}$ depends on the past of all the components of ε_t (Franq & Zakoian, 2010).

One advantage of this specification is that a simple condition ensuring the positive definiteness of H_t is obtained through the positive coefficients for the matrices A_i and B_j and the choice of a positive definite matrix for R. We shall also see that the study of the stationarity is remarkably simple (Franq & Zakoian, 2010).

However, as stated by Franq & Zakoian (2010), CCC model suffers from some limitations like (i) the assumption of constant conditional correlation is arbitrary in nature and (ii) the non-stable nature of constant conditional correlation by aggregation.

The results of CCC-GARCH estimation that measures the volatility spillovers between Bovespa and crude oil; MICEX and crude oil; BSE Sensex and crude oil; Shanghai Composite and crude oil; FTSE SA and crude oil and finally between KOSPI and crude oil are given below in table 9. The graph of time varying volatilities of crude oil along with the stock indices of each emerging economies are displayed in figure 7.

Table 9 here

Figure 7 here

The results of CCC-GARCH estimation show that there are co- movements between the crude oil prices and the stock indices of the emerging economies. In Brazil convergence achieved after 133 iterations, in Russia convergence achieved after 130 iterations, in India convergence achieved after 201 iterations, in China convergence achieved after 144 iterations, in South Africa convergence achieved after 193 iterations and finally in case of South Korea convergence achieved after 108 iterations.

5. Conclusions

This study investigates the relationship between crude oil prices and stock indices of emerging economies. The results of Johansen cointegration analysis indicate a degree of economic integration between crude oil prices and stock indices only in case of Brazil and Russia. Therefore there exists a stationary long-run relationship between the set of variables in Brazil and Russia, but, no such relationship has been found in case of other emerging economies like India, China, South Africa and south Korea. VECM reveal that in Russia and South Korea, MICEX and KOSPI adjust more rapidly to crude oil price shocks. However, in China and Brazil the speed of the short-run disequilibrium adjustment is much slower than compared to Russia and South Korea.

For oil exporting countries like Brazil and Russia, crude oil price has significant effect on Bovespa and MICEX. In India, BSE Sensex is also somewhat sensitive to changes in crude oil prices although, BSE Sensex does not adjust to innovations in crude oil prices. Shanghai

Composite is less susceptible to changes in crude oil prices but, of course in the short-run it adjusts to crude oil price innovations at a moderate speed to correct disequilibrium. FTSE SA index does not react to changes in crude oil prices and it does not even adjust to innovations in crude oil prices for correction of short-run disequilibrium. KOSPI is responsive to changes in crude oil prices and it also adjusts at a much higher speed to innovations in crude oil prices to correct short-run disequilibrium. CCC-GARCH estimation shows the existence of volatility spillovers between crude oil prices and Bovespa, MICEX, BSE Sensex, Shanghai Composite, FTSE SA and KOSPI and convergence have been achieved for all the emerging economies.

As because the fall in oil prices is anticipated to have a huge enduring factor, oil exporters like Brazil and Russia will require financial adjustments, through their magnitude and speed that varies according to the size of buffers (fiscal vulnerability). Oil importers on the other hand, need to balance rebuilding room for policy along with managing and administering domestic cyclical risks. However, the countries with severe financial vulnerabilities should go for saving much of the windfall, while the countries that are facing large output gaps should spend it. In a nutshell, the oil importing countries should use this period as a chance to reinforce and fortify their monetary policy frameworks (IMF Discussion Note, 2015).

Lower crude oil prices offer an opportunity to commence and carry out serious fuel pricing and budgetary reforms in both oil-importing and oil-exporting countries. The resulting stronger fiscal balances would create room for rising priority expenditures and cutting distortionary taxes that speeds up economic growth.

For oil importing countries, the economic impact of plummeting oil prices depends on various geopolitical factors and also on the motive that are behind the fall in oil prices. If the oil prices plunge down due to increase in production and supply, consumers have more money in hand to spend on domestic products instead of imported oil, which in turn boosts up the domestic economy. On the other hand, if oil prices fall because of dilemma in the global economy, nevertheless, then the lower oil price is more an indication for problems than a reason to celebrate. Consequently, some modest stimulus can be expected from low oil prices for oil importing countries.

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TABLES

Table 1: ERS Point-Optimal unit root test results

Indices	Level		First difference	
	constant	Constant + trend	constant	Constant + trend
Bovespa	6.4799	21.7233	1.7874***	0.8887***
MICEX	25.9734	15.1775	0.4167***	0.8429***
BSE Sensex	53.8488	16.1975	1.5483***	1.6598***
Shanghai Composite	6.4340	15.3511	0.8196***	2.2585***
FTSE South Africa	13.2894	11.0313	0.4323***	0.8217***
KOSPI	24.7686	14.4043	0.1755***	0.6195***
Crude Oil	14.1021	42.7076	1.5653***	1.8842***

**** represent the statistical significance level of 1%; ** represent the statistical significance level of 5%;*

Table 2: Multivariate cointegration test results

Brazil			
Hypothesis		**Trace Test**	**Critical Values at 5%**
Null	**Alternative**		
r = 0	r = 1	25.8680* (0.0439)	20.2618
r ≤ 1	r = 2	1.9323 (0.9830)	9.1645
		Maximum Eigenvalue Test	**Critical Values at 5%**
r = 0	r = 1	18.2512* (0.0563)	15.8921
		0.6967 (0.9830)	9.1645
Russia			
Null	**Alternative**	**Trace Test**	**Critical Values at 5%**
r = 0	r = 1	22.0847* (0.0277)	20.2618
r ≤ 1	r = 2	1.4751 (0.8778)	9.1645
		Maximum Eigenvalue Test	**Critical Values at 5%**
r = 0	r = 1	20.6097* (0.0084)	15.8921
r ≤ 1	r = 2	1.4751 (0.8778)	9.1645
India			
Null	**Alternative**	**Trace Test**	**Critical Values at 5%**
r = 0	r = 1	13.3252 (0.3421)	20.2618
r ≤ 1	r = 2	3.0880 (0.5644)	9.1645
		Maximum Eigenvalue Test	**Critical Values at 5%**
r = 0	r = 1	10.2372 (0.3132)	15.8921
r ≤ 1	r = 2	3.0880 (0.5644)	9.1645
China			
Null	**Alternative**	**Trace Test**	**Critical Values at 5%**
r = 0	r = 1	10.1852 (0.6216)	20.2618
r ≤ 1	r = 2	0.6016 (0.9896)	9.1645
		Maximum Eigenvalue Test	**Critical Values at 5%**
r = 0	r = 1	9.5836 (0.3738)	15.8921
r ≤ 1	r = 2	0.6016 (0.9896)	9.1645

* Significant at 5% critical values. ( ) MacKinnon-Haug-Michelis (1999) p-values

Table 2: Multivariate cointegration test results (cond.)

South Africa			
Null	**Alternative**	**Trace Test**	**Critical Values at 5%**
r = 0	r = 1	12.9825 (0.3652)	20.2618
r ≤ 1	r = 2	4.2594 (0.3749)	9.1645
		Maximum Eigenvalue Test	**Critical Values at 5%**
r = 0	r = 1	8.7231 (0.4641)	15.8921
r ≤ 1	r = 2	4.2594 (0.3749)	9.1645
South Korea			
Null	**Alternative**	**Trace Test**	**Critical Values at 5%**
r = 0	r = 1	11.5256 (0.4922)	20.2618
r ≤ 1	r = 2	1.3113 (0.9058)	9.1645
		Maximum Eigenvalue Test	**Critical Values at 5%**
r = 0	r = 1	10.2125 (0.3457)	15.8921
r ≤ 1	r = 2	1.3113 (0.9058)	9.1645

Table 3: VECM estimations for Brazil

	Δ *Bovespa*	**Δ *Crude oil Price***
Z_{t-1}	-0.020184* [-1.52461]	1.63E-05 [0.64797]
Δ *Bovespa* $_{t-1}$	-0.072695 [-1.21009]	7.79E-05 [0.68146]
Δ *Bovespa* $_{t-2}$	0.007119 [0.11865]	4.65E-05 [0.40710]
Δ *Crude oil Price* $_{t-1}$	47.12779 [1.49762]	0.010069 [0.16810]
Δ *Crude oil Price* $_{t-2}$	20.43504 [0.64917]	-0.055587 [-0.92770]
Constant	-37.11609 [-0.41128]	-0.108413 [-0.63112]
R^2	0.016630	0.005971
Adj. R^2	0.001679	-0.000954
F-statistics	3.523910	0.008865

*, ** and *** denotes significance at 10%, 5% and 1% levels. [ ] t statistics.

Table 4: VECM estimations for Russia

	Δ *MICEX*	**Δ *Crude oil Price***
Z_{t-1}	-0.055827*** [-4.05945]	-0.001811** [-1.82458]
Δ *MICEX* $_{t-1}$	-0.071907 [-1.33899]	-0.002292 [-0.59110]
Δ *MICEX* $_{t-2}$	0.066687 [1.26727]	0.005016 [1.32043]
Δ *Crude oil Price* $_{t-1}$	3.269977*** [4.31248]	0.042855 [0.78293]
Δ *Crude oil Price* $_{t-2}$	1.472834** [1.90110]	-0.036260 [-0.64835]
Constant	2.808797 [1.18378]	-0.112921 [-0.65926]
R^2	0.104077	0.018205
Adj. R^2	0.090705	0.003552
F-statistics	7.783218	1.242378

*, ** and *** denotes significance at 10%, 5% and 1% levels. [ ] t statistics.

Table 5: VECM estimations for India

	Δ BSE Sensex	**Δ Crude oil Price**
Z_{t-1}	5.66E-05 [0.00794]	-0.000160*** [-3.22238]
Δ BSE Sensex $_{t-1}$	0.056465 [1.03579]	-0.000172 [-0.45324]
Δ BSE Sensex $_{t-2}$	-0.053217 [-1.03567]	0.000228 [0.63786]
Δ *Crude oil Price* $_{t-1}$	43.48208*** [5.61247]	0.024051 [0.44667]
Δ *Crude oil Price* $_{t-2}$	-1.869818 [-0.23101]	-0.036996 [-0.65765]
Constant	33.03923 [1.34995]	-0.110736 [-0.65101]
R^2	0.094963	0.034574
Adj. R^2	0.081455	0.020164
F-statistics	7.030150	2.399387

*, ** and *** denotes significance at 10%, 5% and 1% levels. [ ] t statistics.

Table 6: VECM estimations for China

	Δ Shanghai Composite	**Δ Crude oil Price**
Z_{t-1}	-0.039158*** [-2.70667]	-0.000378 [-0.82840]
Δ Shanghai Composite $_{t-1}$	0.058399 [1.06805]	0.000810 [0.47024]
Δ Shanghai Composite $_{t-2}$	0.027710 [0.50526]	0.001103 [0.63812]
Δ *Crude oil Price* $_{t-1}$	0.359843 [0.20567]	0.033203 [0.60205]
Δ *Crude oil Price* $_{t-2}$	1.184586 [0.67682]	-0.038073 [-0.69012]
Constant	-2.228188 [-0.40878]	-0.105967 [-0.61675]
R^2	0.023329	0.005814
Adj. R^2	0.008752	-0.009025
F-statistics	1.600385	0.391813

*, ** and *** denotes significance at 10%, 5% and 1% levels. [ ] t statistics.

Table 6: VECM estimations for South Africa

	Δ FTSE South Africa	**Δ Crude oil Price**
Z_{t-1}	-0.005584 [-1.08482]	-0.000473*** [-2.47173]
Δ FTSE South Africa $_{t-1}$	-0.015400 [-0.25723]	0.001118 [0.50203]
Δ FTSE South Africa $_{t-2}$	-0.063237 [-1.05626]	-0.001293 [-0.58015]
Δ *Crude oil Price* $_{t-1}$	0.061375 [0.03852]	0.015783 [0.26623]
Δ *Crude oil Price* $_{t-2}$	-0.059352 [-0.03732]	-0.030087 [-0.50844]
Constant	8.225897** [1.77422]	-0.108642 [-0.62969]
R^2	0.008300	0.022358
Adj. R^2	-0.006501	0.007766
F-statistics	0.560786	1.532249

*, ** and *** denotes significance at 10%, 5% and 1% levels. [ ] t statistics.

Table 6: VECM estimations for South Korea

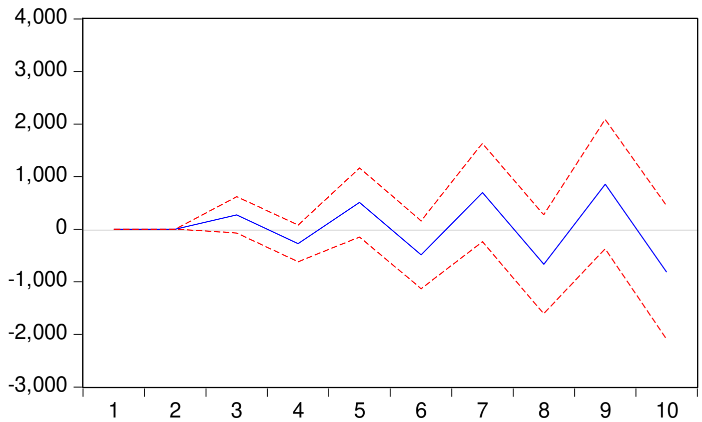
	Δ KOSPI	**Δ Crude oil Price**
Z_{t-1}	-0.051487*** [-3.37183]	-0.002820*** [-2.34418]
Δ KOSPI $_{t-1}$	-0.051764 [-0.89879]	0.004376 [0.96464]
Δ KOSPI $_{t-2}$	0.075218 [1.30900]	-0.000219 [-0.04836]
Δ *Crude oil Price* $_{t-1}$	0.877120 [1.18999]	0.006528 [0.11244]
Δ *Crude oil Price* $_{t-2}$	0.283889 [0.38563]	-0.045890 [-0.79135]
Constant	1.289871 [0.59440]	-0.117896 [-0.68969]
R^2	0.047042	0.020342
Adj. R^2	0.032818	0.005720
F-statistics	3.307371	1.391189

*, ** and *** denotes significance at 10%, 5% and 1% levels. [ ] t statistics.

Figure 1: Impulse response of Bovespa to crude oil prices.

Response to Cholesky one S.D. innovations ± 2 S.E.

Response of BOVESPA to CRUDE_OIL



Response of CRUDE_OIL to BOVESPA

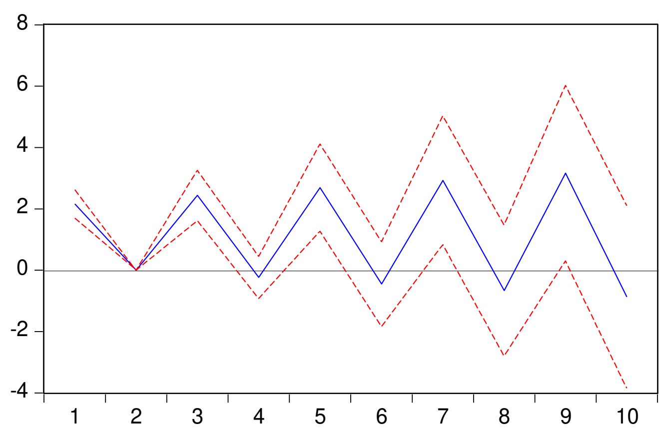
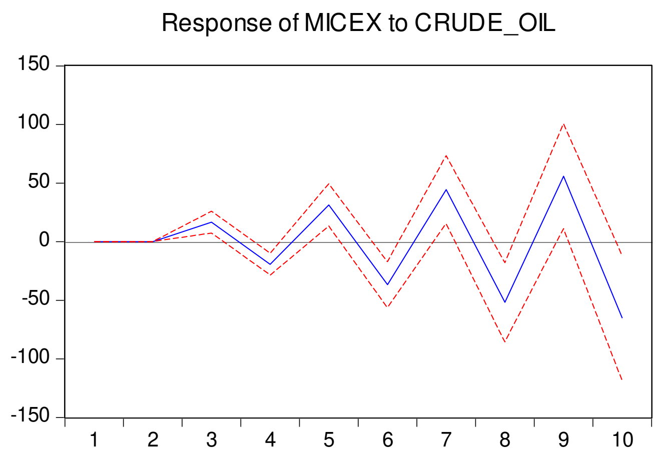


Figure 2: Impulse response of MICEX to crude oil price.

Response to Cholesky one S.D. innovations ± 2 S.E.



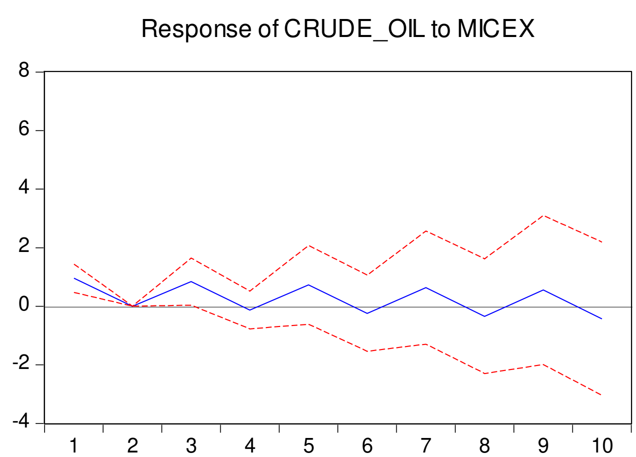
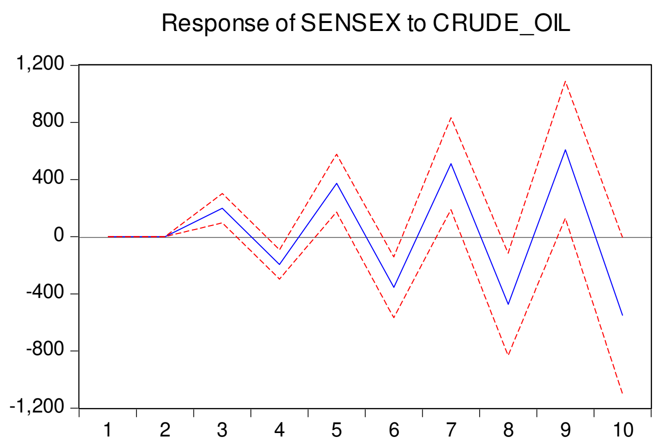


Figure 3: Impulse response of BSE Sensex to crude oil prices.

Response to Cholesky one S.D. innovations ± 2 S.E.



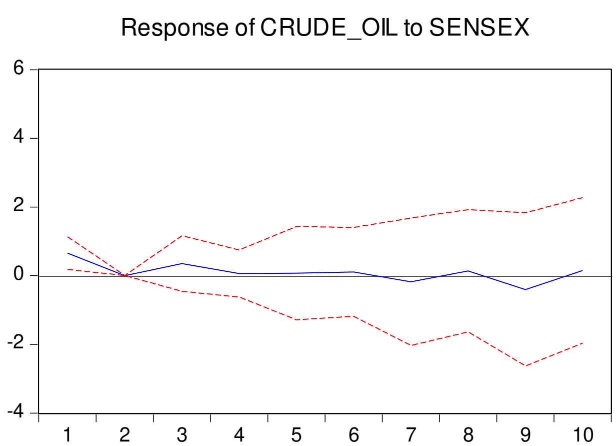
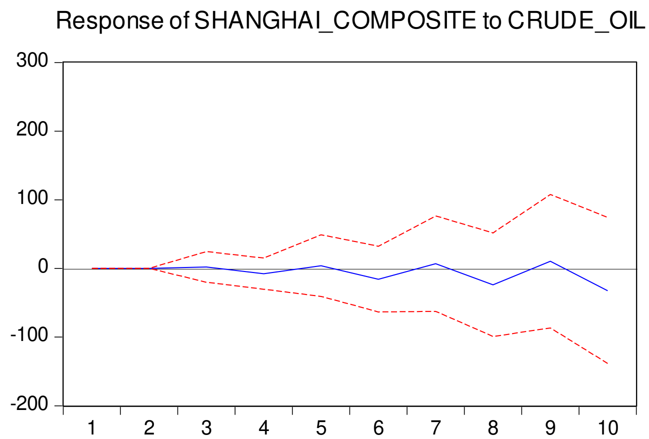


Figure 4: Impulse response of Shanghai Composite to crude oil prices.

Response to Cholesky one S.D. innovations ± 2 S.E.



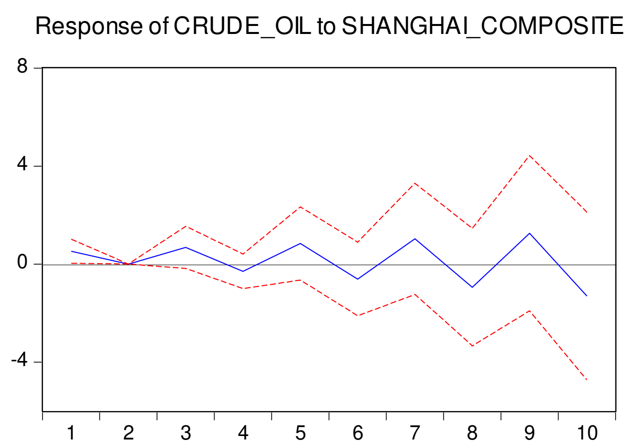
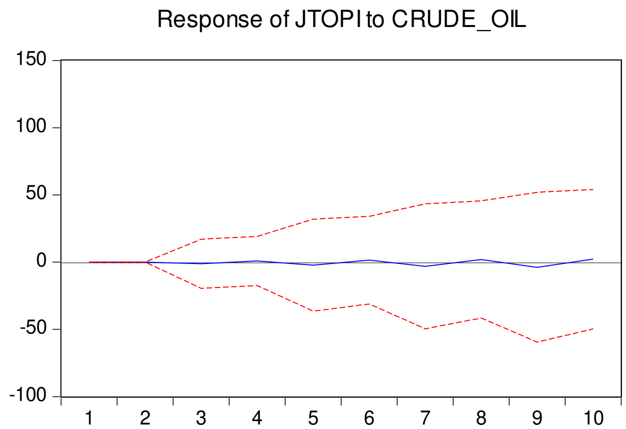


Figure 5: Impulse response of FTSE SA to crude oil prices.

Response to Cholesky one S.D. innovations ± 2 S.E.



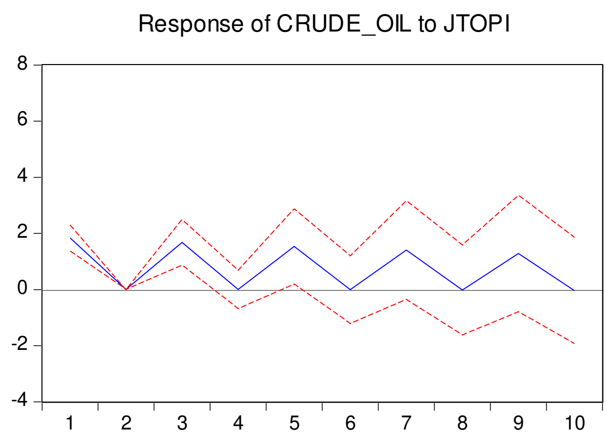
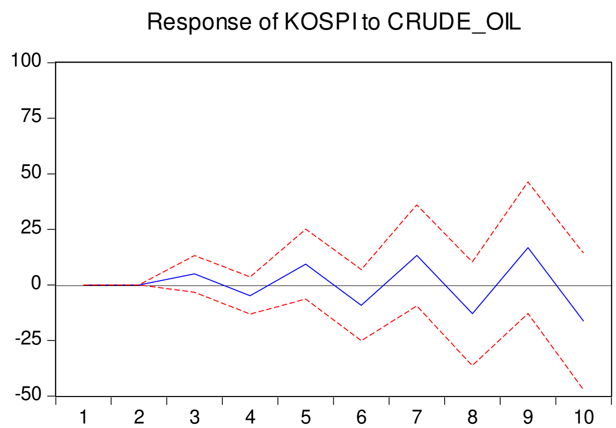


Figure 6: Impulse response of KOSPI to crude oil prices.

Response to Cholesky one S.D. innovations $\pm$ 2 S.E.



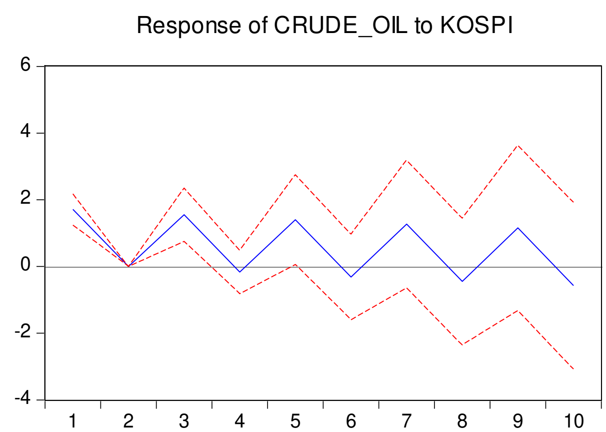
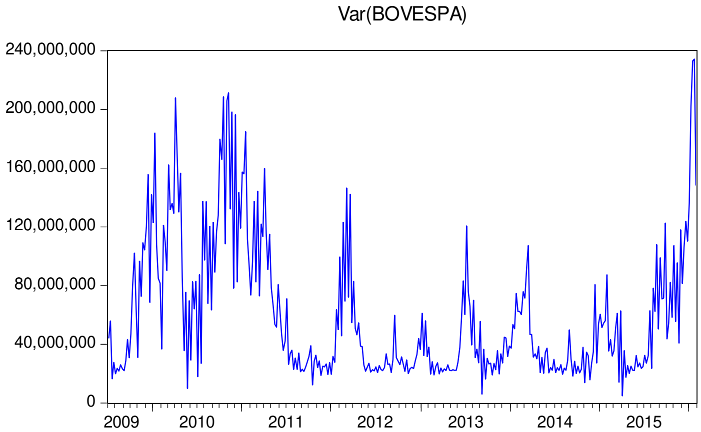
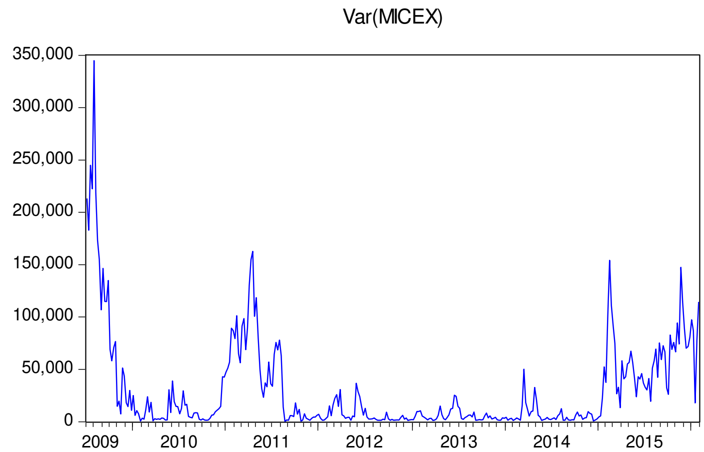


Table 9: Multivariate CCC-GARCH Estimation Results

Brazil				
	Coefficient	Std. Error	z-Statistic	Prob.
Bovespa	55851.12	450.0292	124.1055	0.0000
Crude Oil	94.37944	0.319013	295.8480	0.0000
Russia				
	Coefficient	Std. Error	z-Statistic	Prob.
MICEX	1451.465	3.812277	380.7345	0.0000
Crude Oil	94.33337	0.314193	300.2406	0.0000
India				
	Coefficient	Std. Error	z-Statistic	Prob.
BSE Sensex	18514.22	203.5039	90.97721	0.0000
Crude Oil	94.50119	0.325444	290.3764	0.0000
China				
	Coefficient	Std. Error	z-Statistic	Prob.
Shanghai Composite	2341.797	7.686751	304.6536	0.0000
Crude Oil	92.08316	0.390236	235.9677	0.0000
South Africa				
	Coefficient	Std. Error	z-Statistic	Prob.
FTSE SA	3278.724	9.653885	339.6274	0.0000
Crude Oil	93.84101	0.337621	277.9482	0.0000
South Korea				
	Coefficient	Std. Error	z-Statistic	Prob.
KOSPI	1966.111	5.589439	351.7547	0.0000
Crude Oil	95.09210	0.462898	205.4279	0.0000





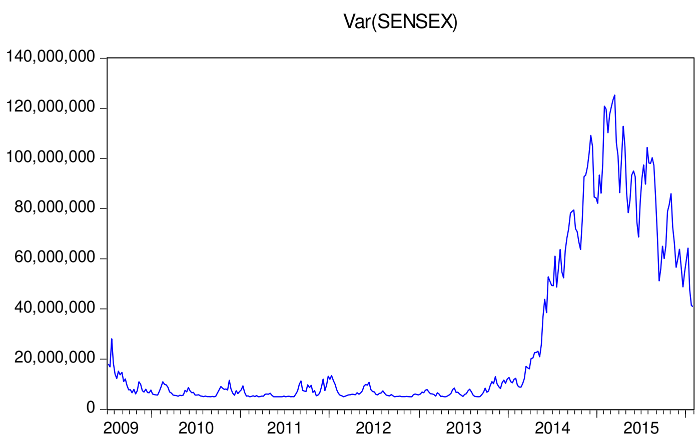
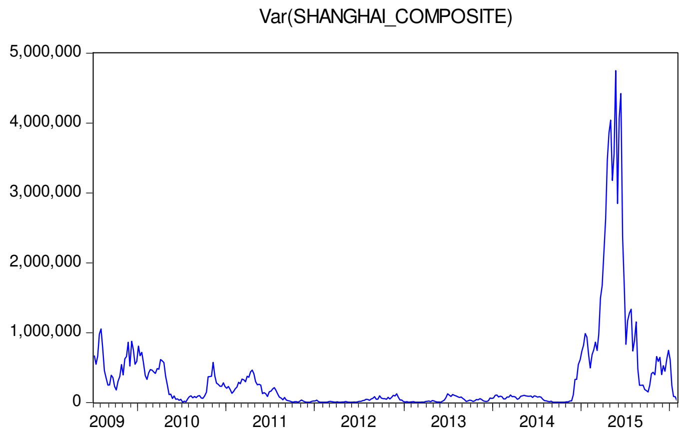
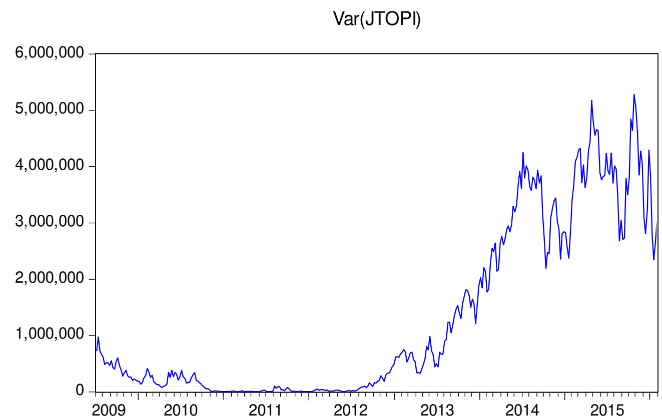


Fig. 7: Time varying volatilities of crude oil and stock indices of emerging economies





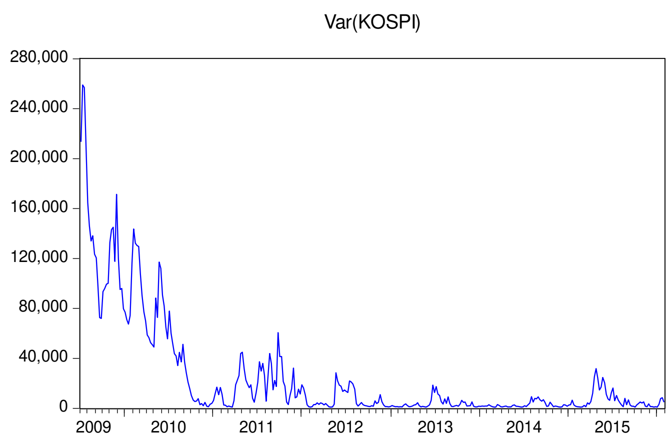
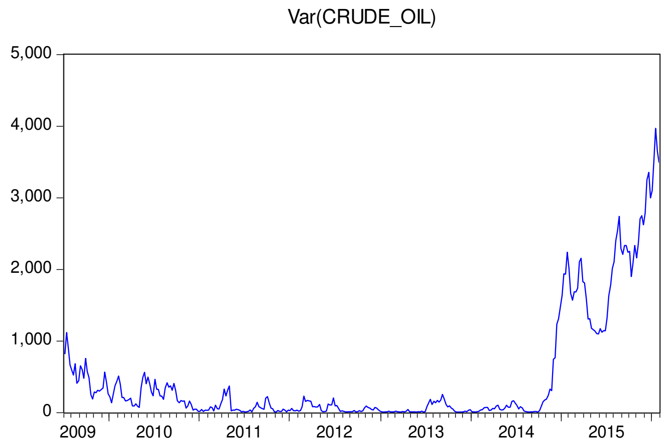


Fig. 7: Time varying volatilities of crude oil and stock indices of emerging economies (contd.)



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