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OIL PRICE SHOCK AND ITS EFFECT ON STOCK MARKETS OF INDIA

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Abstract

The present study makes an attempt to investigate the effect of sharp continuous surging crude oil price on stock market indices of India, and also the long-term and short term relationships between crude oil prices and stock indices. The 'period of the study' spans from July 2009 to December 2016. We have found surge in oil price has positive correlation with equity indices and negative correlation with the exchange rates. The result is suited with the existing economic theory. Multivariate cointegration techniques along with vector error correction mechanism have been applied in the study.

Keywords: *crude oil prices; emerging economy; exchange rates; oil price shock; stock indices.*

JEL code: *M210*

1. Motivation of the Study

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

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

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India's current account deficit - the amount India owes to the world in foreign currency. A fall in oil prices by $10 per barrel helps to reduce the current account deficit by $9.2 billion, according to a report by Livemint. This amounts to nearly 0.43% of the Gross Domestic Product - a measure of the size of the economy (www. kotaksecurities.com/ksweb/). Moreover, falling oil prices also help to curb down inflation. As per the report published by Moneycontrol, an Indian financial agency, every $10 per barrel fall in crude oil price helps reduce retail inflation by 0.2% and wholesale price inflation by 0.5% (www.moneycontrol.com/business/reports). 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 (www. kotaksecurities.com/ksweb/).

The objective of this paper is to examine the dynamic relationship between crude oil price and stock market indices of India in the context of continuous fall in the crude oil price in recent past. 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.

But, the fall in oil prices helps in the economic expansion along with falling inflation ("expansionary disinflation"); and this situation may persist if oil prices continue to fall bolstering what economists would call a "positive supply shock" (http://www.forbes.com/sites/jonhartley/2016/01/12/the-economic-impact-of-declining-oil-prices-expansionary-disinflation/2/). The recent decline in inflation may be a "supply side" effect associated with the declining price of oil; in the same respect, 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; the 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 somewhat similar studies but have used different data periods and methods for analysis. There are also considerable number of research works like 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, nor any other studies, has been found to have been conducted to evaluate the impact of declining oil prices or negative oil price shocks on the stock markets or measure the volatility spillovers between crude oil price and stock markets in the wake of sharp continuous fall in the crude oil price in the recent times. Again, most of these studies use IGARCH model to reveal the phenomenon of volatility clustering, but our Johansen Co-integration Test along with VECM and Structural VAR with Impulse Response Function estimation results prove that the phenomenon of long-run dynamics can be better estimated with these models.

From February 02, 2014 to December 31, 2016, crude oil price has fallen by 103%. The massive supplies of crude oil by the oil producing countries throughout the globe continue to pressure markets. The study of Basher et al. (2010) reveals 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. This entire situation, particularly falling crude oil prices, has a substantial effect on the economy of oil importing country like India, and hence, considering this backdrop, we have considered a dataset up to December 31, 2016 (because, after this period the global oil prices starts soaring high in a gradual pace) so as to capture only the effect of falling crude oil prices on the stock markets of India, 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 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 India.

3. Data and Methodology

For the present study, weekly data of the closing indices of BSE Sensex and NIFTY as well as the closing prices of the crude oil index represented by the Brent crude oil prices have been considered. Brent crude oil index is used as a benchmark for world oil markets. Data on stock market indices are retrieved from Bloomberg database. Because of non-synchronous data we have taken weekly data and to avoid the weekend effect we have chosen Wednesday's closing prices. According to Business Cycle Dating Committee of the National Bureau of Economics Research (NBER), USA, the global recession ended on June, 2009 and therefore to cover the period of post-global recession, we have decided to select a study period beginning from July, 2009 to December, 2016. 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, Vector Error Correction Model (VECM), and Impulse Response Function have been used.

4. Results and Discussion

Following charts reflect the nature of volatility noticed in National Stock Exchange and BSE Sensex

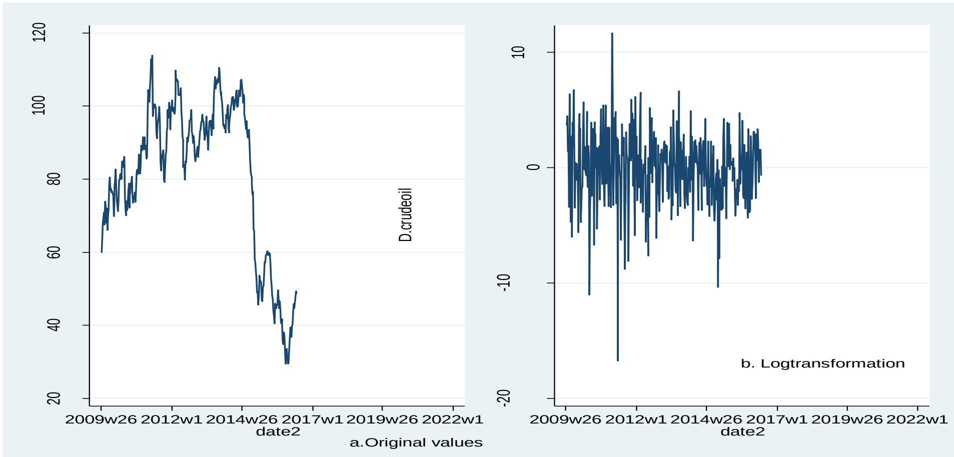


Figure 1

CRUDE OIL PRICE TREND

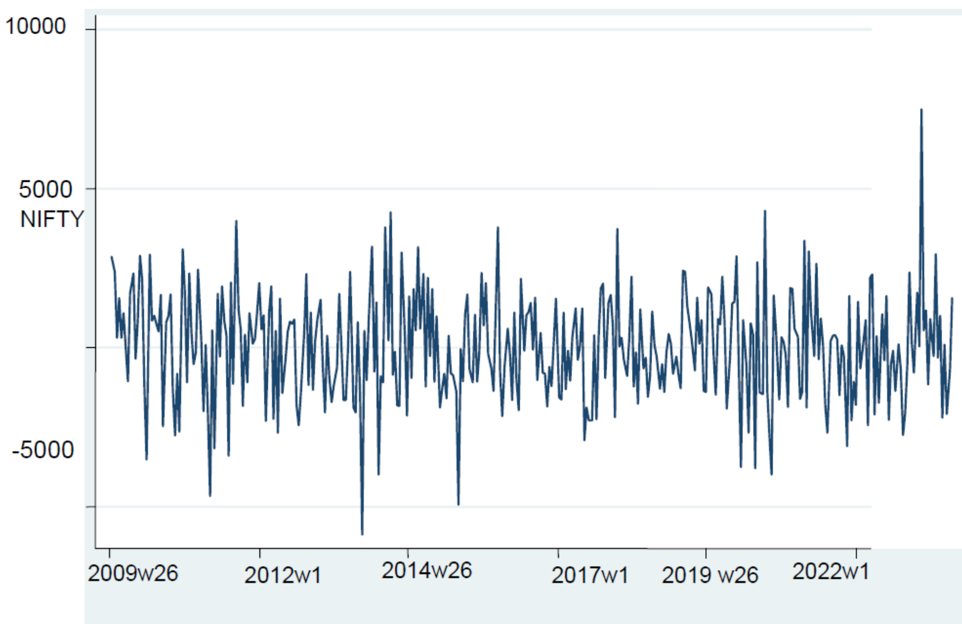


Figure 2A: Trend of NIFTY

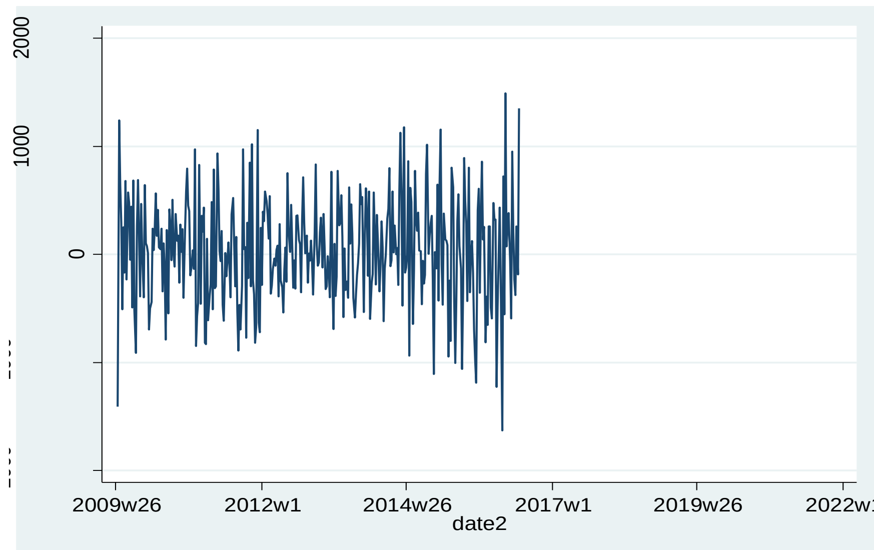


Figure 2B: Trend of BSE Sensex

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: ERS Point-Optimal unit root test results

Indices	Level		First difference	
	constant	Constant + trend	constant	Constant + trend
BSE Sensex	53.8488	16.1975	1.5483***	1.6598***
NIFTY	6.4340	15.3511	0.8196***	2.2585***
Crude Oil	14.1021	42.7076	1.5653***	1.8842***

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

4.2: Johansen Co-integration Test

Co-integration method has been developed by Granger as a novel technique in exploration of long-term equilibrium relationship between variables. Further, a joint study made by Engle-Granger has helped in further developing this theory and examining affiliations among long-term equilibrium relationships and short-term dynamic relationships. Engle & Granger (1987) show that if there are two or more non-stationary series, then their linear combination may be stationary. And, with the existence of such a stationary linear combination, the non-stationary time-series are said to be co-integrated. The stationary linear combination is called the co-integrating equation and may be interpreted as a long-run equilibrium relationship among the variables. To see whether non-stationary series in the level act together in the long-run, Johansen co-integration test developed by Johansen & Juselius (1990) is used.

The Johansen tests may be carried out applying a group object or an estimated Vector Auto Regression (VAR) object. Consider a VAR of order p:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + Bx_t + \varepsilon_t \qquad (1)$$

where, y_t is a k-vector of non-stationary $I(1)$ variables, x_t is a d-vector of deterministic variables, and ε_t is a vector of innovations. We may rewrite this VAR as,

$$\Delta y_t = \prod y_{t-1} + \sum_{i=1}^{p-1} r_i \Delta y_{t-i} + Bx_t + \varepsilon_t \qquad (2)$$

where:

$$\prod = \sum_{i=1}^{p} A_i - I \quad ,$$

$$r_i = -\sum_{j=i+1}^{p} A_j \qquad (3)$$

The hypothesis to be examined in this study with Johansen cointegration test is presented below:

H_o: there is no co-integration relationship between variables

H_1: there is co-integration relationship between variables

The number of distinct co-integrating vectors can be obtained by determining the significance of the characteristic roots of $\prod$. To identify the number of characteristic roots that are not different from unity, the trace test and maximum Eigen Value test are used. The result of Johansen co-integration test is given in table 2.

Table 2: Multivariate cointegration test results
Period: July 2009 – December 2016

Lags interval (in first differences): 1 to 2
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Trace Statistic	0.05 Critical Value	Prob.**
None *	141.8949	125.6154	0.0035
At most 1	93.10741	95.75366	0.0750

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	48.78748	46.23142	0.0261
At most 1	28.69769	40.07757	0.5125

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
*denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The results show that he set is cointegrated, as both the trace statistic and maximum Eigen Value statistic reject the null hypothesis of no co-integration and one co-integrating vector have been identified by the trace test and maximum Eigen Value test which are significant at 5% level. Moreover, one co-integrating vector has been identified by the trace test and maximum Eigen Value test which are significant at 5% level. This implies that there are common stochastic trends indicating a degree of economic integration between crude oil prices and stock indices during the whole study period. Therefore, there exists a stationary long-run relationship between the set of variables (crude oil prices, BSE Sensex and NIFTY).

4.3: Granger Causality Test (Wald Statistic)

The short-run dynamics between crude oil prices, exchange rates and stock indices can be examined by using bi-variate Granger causality tests (Stavarek, 2005). It also determines the direction of the relationships between the endogenous variables used in the study (Granger, 1969). In performing Granger causality test all data series concerned should be stationary, failing which the inference from the results might be spurious. Granger causality between crude oil prices and stock indices is examined by estimating the following pair of equations:

$$SI_t = \beta_0 + \sum_{i=1}^{kq}\beta_{1i} SI_{t-i} + \sum_{i=1}^{kq}\beta_{3i}\, COP_{t-i} + \mu_{1t} \qquad (4)$$

$$COP_t = \delta_0 + \sum_{i=1}^{kn}\delta_{1i}\, COP_{t-i} + \sum_{i=1}^{k\,n}\delta_{3i}\, SI_{t-i} + \mu_{2t} \qquad (5)$$

In the above equation, *k* shows the lag length and it is assumed that error terms are independent from each other (white noise) (Granger, 1969). SI_t and COP_t represent stock indices and crude oil prices. It is also assumed that the disturbances μ_{1t} and μ_{2t} are uncorrelated. Equation 4 postulates that SI_t is related to past values of itself as well as that of COP_t. Equation 5 postulates similar behavior for COP_t.

Table 3: VEC Granger Causality-Wald Test
Period: July 2009 – December 2016

Dependent variable	Independent variable	Wald statistic	Probability	Decision
BSE Sensex	Crude Oil	5.562541	0.0089	Reject
NIFTY	Crude Oil	4.658971	0.0125	Reject

Results of Granger causality-Wald test based on Vector Error Correction Model (VECM) with purpose of revealing causal relationships between variables in each model is shown in table 2. The null hypothesis in each case is that the variable under consideration does not 'Granger-cause' the other variable. In both the cases, the null hypothesis is rejected and thus crude oil 'Granger-cause' the stock indices. The estimation results reveal that there is no feedback causality between the series. Unidirectional causality runs from crude oil to BSE Sensex and crude oil to NIFTY.

4.4: Vector Error Correction Model (VECM)

The multivariate co-integration test results show that while allowing for the (linear) trend, the set of series seems to be co-integrated, 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. Therefore, to determine co-integration relationship (co-integration vector), which reveal the existence of long-run relationship amongst endogenous variables, causal relations should be examined with error correction mechanism (ECM) or vector error correction model (VECM). Our VECM analysis is two-fold. 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:

$$\Delta SI_t = \beta_0 + \sum_{i=1}^{q} \beta_{1i} \Delta SI_{t-i} + \sum_{i=1}^{q} \beta_{2i} \Delta COP_{t-i} + a_1 Z_{t-1} + e_{1t} \tag{6}$$

$$\Delta COP_t = \delta_0 + \sum_{i=1}^{n} \delta_{1i} \Delta COP_{t-i} + \sum_{i=1}^{n} \delta_{2i} \Delta SI_{t-i} + \sigma_1 Z_{t-1} + e_{2t} \tag{7}$$

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 a_1 and σ_1 are expected to capture thelong-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 4 and 5 displays the results of VECM for BSE Sensex and NIFTY. The optimum lag length is from 1 to 100.

Table 4: VECM estimations for BSE Sensex

	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 5: VECM estimations for NIFTY

	Δ NIFTY	**Δ Crude oil Price**
Z_{t-1}	-0.039158*** [-2.70667]	-0.000378 [-0.82840]
Δ NIFTY$_{t-1}$	0.058399 [1.06805]	0.000810 [0.47024]
Δ NIFTY$_{t-2}$	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.

The responses of each selected series to correct the disequilibrium are captured by the significance and size of the estimated coefficients a_1 and σ_1 of the VECM equations 1 and 2. However, the VECM estimations give varied results. In case of BSE Sensex, 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 NIFTY, only a_1 is found to be significant at 1% level and about 3.92% of short-run disequilibrium is corrected each week by changes in NIFTY.

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 4 and 5, 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.

4.5: Impulse Response Analysis

Impulse response function has been proposed and employed by Christopher Sims (1980), which states that, a shock to the i^{th} variable has a straightforward and direct impact on the i^{th} variable and at the same time it is also transmitted to the other endogenous variables in the system with the help of the dynamic lagged structure of the VAR. Impulse response functions are simply dynamic simulations that demonstrate the response of an endogenous variable to a one-time shock.

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

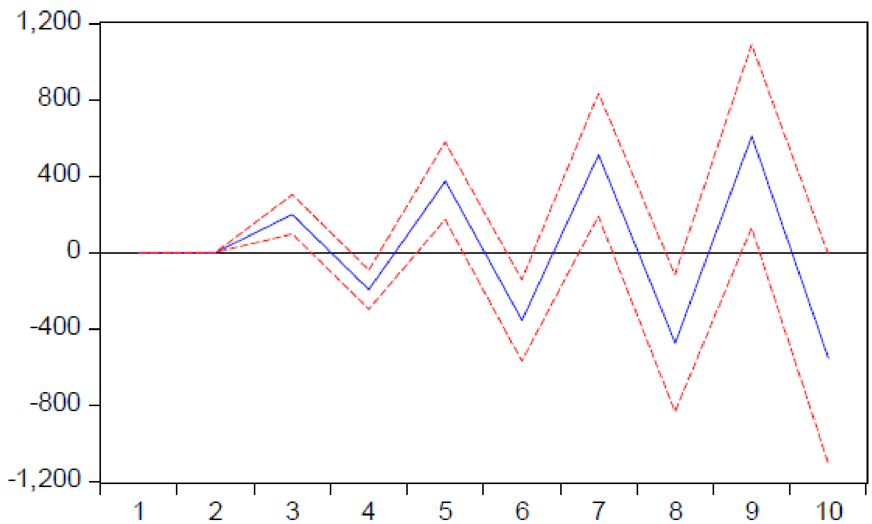
$$e_t = \begin{pmatrix} e_{1t}^{crude\ oil\ price} \\ e_{2t}^{stock\ indices} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix}$$

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 toe_{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 BSE Sensex and NIFTY are measured by impulse response functions whichg are displayed in figures 3 and 4.

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

Response to Cholesky one S.D. innovations (+,-) 2 S.E.

Response of SENSEX to CRUDE-OIL



Response of CRUDE-OIL to SENSEX

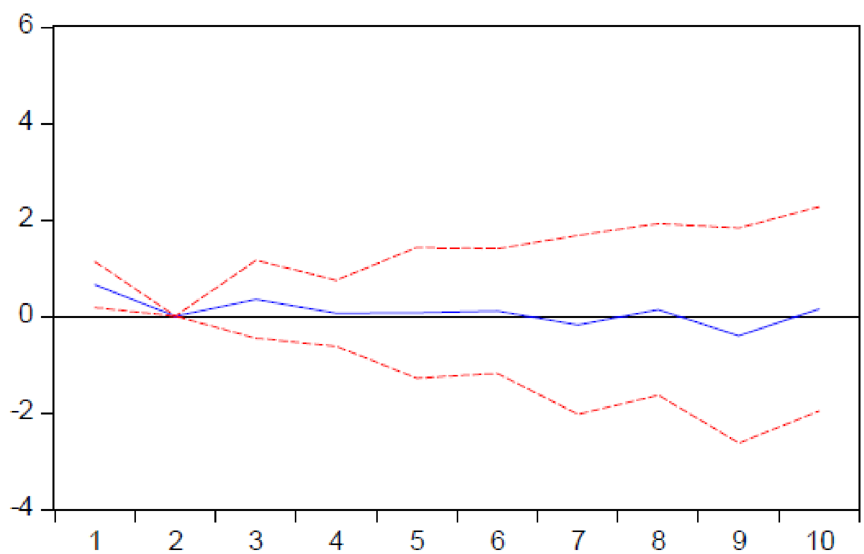
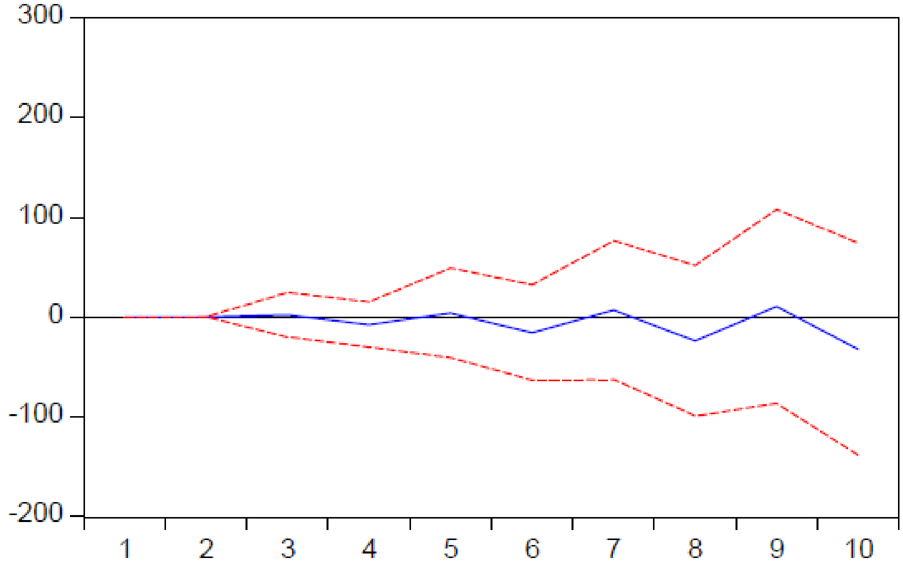


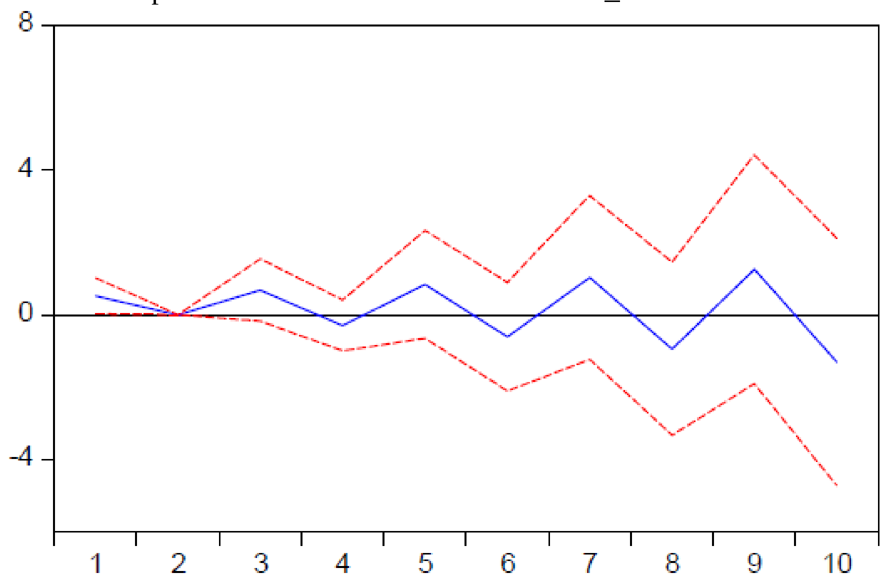
Figure 4: Impulse response of NIFTY to crude oil prices.

Response to Cholesky one S.D. innovations (+,-) 2 S.E.

Response of SHANGHAI_COMPOSITE to CRUDE OIL



Response of CRUDE OIL to SHANGHAI_COMPOSITE



Here impulse response functions have been derived using lag intervals of 3 and 4. In Indian context, 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 NIFTY, the first figure that measures responses of NIFTY to crude oil price, the graph of NIFTY is almost flat even after taking higher lag intervals of 4 and 5, 5 and 6, 6 and 7, etc. Thus, NIFTY 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.

India is the fourth-largest oil consumer in the world and relies on imports for more than three-fourths of its oil needs. About 30% of India's energy needs are met by petroleum and approximately 80% of this oil is imported by India, which stands to be the main reason behind the country's inflatable trade and current account deficits. In the fiscal year ending March 2013, India's net oil import was 2.6 million barrels per day (bpd) and in the fiscal year ending 2014, India imported 190 million tons or 3.8 million barrels per day of crude oil. Iraq accounted for about 13% of those imports, second only to Saudi Arabia which supplies about 20% of India's oil imports and in recent times the political turmoil in Iraq makes Indian markets a bit volatile due to heavy reliance of India on Iraqi oil. In the first and second week of June 2014, the stock prices of Indian oil and Reliance plunged heavily. These results are in line with the findings of Kilian & Park (2009) that an appreciation in crude oil price negatively affects stock indices for oil importing countries.

5. Conclusions

This study investigates the dynamic linkages between crude oil prices and BSE Sensex and NIFTY, the major stock indices of India. Our study results reveal that there does not exists any long-run relationship between crude oil prices and Indian stock indices like BSE Sensex and NIFTY. The results of VECM are further strengthened by the findings of Impulse Response Functions. BSE Sensex is also somewhat sensitive to changes in crude oil prices although, BSE Sensex does not adjust to innovations in crude oil prices. NIFTY 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.

Lower oil prices also underline the necessity for real and financial sector reforms in order to promote diversification of the economy of the oil exporting countries (IMF Discussion Note, 2015).Oil importers like India 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 thisperiod 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 taxation 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 boosts up economic growth. Moreover, in a number of low- and middle-income countries, energy sector reforms are being aimed at enlarging the access to reliable energy that has significant developmental advantages (IMF Discussion Note, 2015).

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. But low oil prices are also a reason to worry, as they are partly a symptom of slowing global growth.(www.bruegel.org/2016/01/the-oil-price-slump-crisis-symptom-or-fuel-for-growth/)

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