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Exploring Causal nexus between Crude Oil Price and Exchange Rate for India

Krishna Murthy Inumula[1] and Sandip Solanki[2]

[1] *Associate Professor, Symbiosis Institute of International Business [SIIB], Symbiosis International University, G. No. 174/1, Hinjewadi, Taluk - Mulshi, Dist. Pune – 411 057, E-mail: dr.krishna@siib.ac.in*
[2] *Associate Professor, Symbiosis Institute of International Business [SIIB], Symbiosis International University, G. No. 174/1, Hinjewadi, Taluk - Mulshi, Dist. Pune – 411 057, E-mail: sandip.solanki@siib.ac.in*

Abstract: The crude oil price and dollar exchange rate dynamics play an important role in developing economy like India as it imports nearly 80% of its total oil needs. The composition of Indian crude basket represents average of Oman & Dubai for sour grades and Brent (dated) for sweet grade in the ratio of 68.2:31.8 since August2016. Ceteris paribus the paper investigates the Co-integration or long term association between USD/INR Exchange rate and Indian crude oil price using VAR-VECM framework, direction of causality and impulse responses from deviation or shock to crude oil price and exchange rate.

The results show that Exchange rate and Indian crude oil price are co-integrated and there exists a uni-directional causality running from exchange rate to oil price meaning that oil price do not granger cause the exchange rate which implies that crude oil price variations are attributed to exchange rate fluctuations. This gives an important policy implication for the apex bank to monitor and strengthen Indian currency by bringing more economic reforms rather than put a caution on increase or decrease of crude oil price as it is evident from the recent data that reduction in crude oil price might have strengthen dollar but not Indian currency.

Key Words: Exchange Rate, Crude Oil Price, VAR-VECM, Causality

1. INTRODUCTION

This paper attempts to investigate empirically the casual linkage between USD/INR Exchange rate and Indian crude oil price using VAR-VECM framework, direction of causality and impulse responses from deviation or shock to crude oil price and exchange rate. Crude oil is one of the most important commodities in Indian economy as it imports nearly 80% of its total oil needs. A fall in crude oil price would drive down the value of its imports. This helps narrow India's current account deficit. The value of Indian currency depends on its demand in the international currency market play a vital role in the current account deficit.

A high deficit means the country has to sell rupees as it reduces the value of the rupee. In recent times the steady increase in oil imports pushing the demand for US dollar in international markets that in turns decays the purchasing power of Indian currency in the international market.

A fall in crude oil price is good for India; however, the downside is that the dollar strengthens every time the price of crude oil falls. This contradicts any benefits from a fall in current account deficit. The composition of Indian crude basket represents average of Oman & Dubai for sour grades and Brent (dated) for sweet grade in the ratio of 68.2:31.8 since August2016.In the recent past the inverse relationship between crude oil price and dollar currency is very much clear denoting higher crude oil price resulted in depreciation in dollar value and vice versa. But when the crude oil price decreases it results in appreciation of dollar value and not in Indian rupee because the decrease in international crude oil price has a very meagre impact of price reduction in petroleum price. According to livemint.com over the last 18 months, while the Indian crude basket has fallen around 23% in dollar terms, local petrol prices have come down only by 4%. Part of this wide discrepancy is, of course explained by the exchange rate. When the Indian crude basket is converted into rupees, the fall in prices is smaller. But it is still around 19%.

2. BRIEF REVIEW OF LITERATURE

For India one of the study done by Ghosh (2011) titled "Examining crude oil price – Exchange rate nexus for India during the period of extreme oil price volatility" examinedcrude oil price – exchange rate nexus for India using daily data for the time span July 2, 2007–November 28, 2008. Generalized autoregressive conditional heteroscedasticity (GARCH) and exponential GARCH (EGARCH) models have been employed to examine the impact of oil price shocks on nominal exchange rate. The study reveals that an increase in the oil price return leads to the depreciation of Indian currency vis-à-vis US dollar. The study also establishes that positive and negative oil price shocks have similar effects, in terms of magnitude, on exchange rate volatility and oil price shocks have permanent effect on exchange rate volatility.

Brahmasrene, T., *et al.* (2014) studied the short-run and long-run dynamic relationship between the U.S. imported crude oil prices and exchange rates. The monthly data of the U.S. crude oil imports from five source countries during January 1996 and December 2009 are examined. Empirical results indicate that the exchange rates Granger-caused crude oil prices in the short run while the crude oil prices Granger-caused the exchange rates in the long run.

Pershin, V., *et al.* (2016) investigated the relationship between oil prices and exchange rates in three African countries using a Vector Auto Regressive (VAR) model. We use daily data on nominal exchange rates, oil prices and short term interbank interest rates from 01/12/2003 to 02/07/2014. The results suggest that the exchange rate of the three selected countries behavior is different in the event of an oil price shock, not only before and after the oil peak of July of 2008, but also between each other. Therefore, no general rule can be made for net oil importing sub-Saharan countries, such as Botswana, Kenya and Tanzania.

Mensah, E. K., *et al.* (2016) study examined the role of global crude oil price on the exchange rate (EXR) and gross domestic product (GDP) of Ghana using the Johansen modelling technique for the period, 1980-2013. The short-term analysis points to Granger causality from oil price and GDP to energy consumption. It further reveals causality from oil price and EXR to GDP, which indicates that development in the global oil price as well as the performance of the currency can impact economic growth. No significant evidence of the oil price role in EXR volatility was found.

Haque, M. A., *et al.* (2015) examined the Granger causality through a vector error correction model (VECM) and a vector auto regression (VAR) test, respectively. From the Granger causality test, it is apparent that there is a one-directional causality between iron ore prices and the AUD/USD exchange rate, implying that iron ore prices generate Granger causes to the AUD/USD exchange rates whereas, conversely, the exchange rate does not have significant Granger causes on iron ore prices. However, while the structural vector auto regression (SVAR) is considered, interestingly, the impulse-response functions (IRFs) analysis revealed that owing to the shocks on AUD/USD exchange rates, iron ore prices have significant responses too, and vice versa.

Fowowe, B. (2014) model the volatility and jumps in exchange rate returns by using the GARCH autoregressive conditional jump intensity model of Chan and Maheu which models the effects of extreme news events (jumps) in returns. The empirical results show that oil price increases lead to a depreciation of the South African rand relative to the US dollar.

Bouoiyour, J. and R. Selmi (2015) employed wavelet decomposition and nonlinear causality test to investigate the nexus between the real oil price and the real effective exchange rate in three GCC countries: Qatar, Saudi Arabia and UAE. The study found strong evidence in favor of a feedback hypothesis in Qatar and UAE and of a neutrality hypothesis in Saudi Arabia. The first observation outcome means that Qatar and UAE should reinforce the downward effect of oil price on real exchange rate by improving diversification policy. The second one implies that the behavior of Saudi Arabia as a price taker may allow it to maintain a quick recovery under oil shocks.

Tiwari, A. K. (2015) analyzed the Granger-causal relationship in the time-frequency framework between return series of real oil price (ROP) and real effective exchange rate (REER) for Malaysia. Results found that the causal and reverse causal relations between oil price and real exchange rate vary across the scale for the period of 8-10 months during late in 1989. ROP was leading both variables during that phase as well as for 12-16 months in 1990-1991, for 10-16 months in 1997-1998, for 9-15 months in 2001-2003, and for 2-7 months in 2005 through early 2006. Further, evidence shows that during the 32-48 month scales of 1989-1998 the ROP was lagging throughout the study period while on a 60-64 month scale the ROP was leading. Hence, our evidence shows that there is evidence of both a cyclical and anti-cyclical relationship between ROP and REER while at shorter time periods a higher REER was lagging while receiving cyclical effects of ROP shocks.

Narayan, P. K., *et al.* (2008) examined the relationship between oil price and the Fiji-US exchange rate using daily data for the period 2000-2006 using generalized autoregressive conditional heteroscedasticity (GARCH) and exponential GARCH (EGARCH) models to estimate the impact of oil price on the nominal exchange rate. Results found that a rise in oil prices leads to an appreciation of the Fijian dollar vis-a-vis the US dollar.

Muhammad, Z., *et al.* (2012) studied about the oil price-exchange rate nexus for Nigeria using daily data over the period 2 January 2007-31 December 2010. The generalised autoregressive conditional heteroscedasticity (GARCH) and exponential GARCH models are employed to examine the impact of oil price changes on nominal exchange rate. The outcome of this research indicates that a rise in oil prices leads to a depreciation of the Nigerian Naira vis-a-vis the US dollar over the study period.

Coleman, S., *et al.* (2016) gave insights into the importance of the real oil price as a determinant of real exchange rates, for a pool of African countries. Using co-integration techniques and nonlinear dynamics they found that, for some of these countries, shocks in the real price of oil are particularly important in determining the real exchange rates, even in the long run.

Ahmed, R., *et al.* (2016) analyzed the impact of Real Oil Price Volatility on Real Exchange Rate Volatility in Pakistan over 1983-Q1 to 2014-Q2. Various econometric techniques like Johansen Cointegration and Vector Error Correction Model have been used for short run and long run analysis respectively. Findings suggest that productivity differential, real foreign exchange reserves, interest rate differential, real exports and oil prices are the determinants of exchange rate. While, Real Foreign exchange reserves volatility, CPI volatility and Real Oil Price Volatility have positive and NEWS has a negative effect on Real Exchange Rate Volatility. Volatility results through EGARCH (1,1) shows the presence of leverage effect in Real Oil Price Volatility and Real Exchange Rate Volatility.

Sahbaz, A., *et al.* (2014) study investigated the causality between crude oil prices and exchange rates in Romania employing monthly data from the beginning of floating exchange regime for November 2004 to December 2011. According to nonlinear causality test results there is no causality between the variables. Results show that frequency domain causality results slightly differentiate from the nonlinear causality analysis and imply that there is a causality running from real exchange rate to real oil price on the medium and long run.

3. DATA & MODELS

3.1. Econometric Modeling

Two or more variables in the study are said to be co-integrated if each of the series are themselves non-stationary, buta linear combination of them is stationary (Engle and Granger, 1987). The stationary linear combination is called the co-integratinge quation and may be regarded as a long- run equilibrium relationship among the variables. The purpose of the cointegration test is to determine whethera set of non-stationary seriesis co-integrated or not. In addition to the Engle-Granger causality technique, Johansen (1988, 1991) procedure of co-integration is also employed. Johansen's approach begins with unrestricted VAR involving non-stationary variables, which allows to deal with models having several endogenous variables. A key aspect of Johansen's co-integration approac his isolating and identifying the "r" co-integrating combinations among a set of "k"integrated variables and incorporate them into an empirical model. The co-integration rank divides the data into r relations, towards which the process is adjusting (equilibrium errors), and k - r (k, number of non-stationary I(1) variables) relations, which are pushing the process (common driving trends).

The vector autoregressive (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for conventional structural modeling by treating every variable as endogenous in the system as a function of the lagged values of all the other endogenous variables in the system. The following VAR framework at lag length k=2 is used in this study.

$$\text{INREXH}_t = C_1 + \sum_{i=1}^{k} a_{1i}\text{INREXH}_{t-i} + \sum_{i=1}^{k} b_{1i}\text{CrudeOil}_{t-1} + e_{1t}$$

$$\text{CrudeOil}_t = C_2 + \sum_{i=1}^{k} a_{2i}\,\text{INREXH}_{t-i} + \sum_{i=1}^{k} b_{2i}\,\text{CrudeOil}_{t-1} + e_{2t}$$

Where e_{1t}, e_{2t} are the stochastic error terms called as "Impulses or Innovations".

Vector Auto Regression (VAR) model is used to determine the direction of causality running in between the variables. The presence of a co-integrating relation forms the basis of the vector error correction model (VECM) specification. We estimate the following system of equations formulated in a VECM.

$$\Delta Xt = \Gamma_1 \Delta Xt\text{-}1 + \ldots + \Gamma k\text{-}1\ \Delta Xt\text{-}k\text{-}1 + \Pi X_{t-1} + \mu + \varepsilon t; \qquad t = 1, \ldots, N$$

Where,

Δ is the first difference operator, X denotes vector of variables in logarithmic form, ε_t error term is a normal, independent and identically distributed random variable with mean zero and standard deviation Σ,μ is a drift parameter, and Π is a (pxp) long run matrixoftheform $\Pi = \alpha \times \beta$.

3.2. Data Source

This time series study covers the monthlyperiod 2007:11-2016:10, the data variables are USD/INR Exchange rate;Indian crude oil price represents average of Oman & Dubai for sour grades and Brent in Indian Rupee per barrel. This secondary data has been taken from the source of Indexmundi data statistics.

This time series data is analyzed by using the econometric techniques namely Johansen's rank procedure a popular co-integration test and a useful method to determine long-run relationship between nonstationary variables. VECM-Error correction mechanism used to see the short run behavior of crude oil price,

3.3. Analysis and Discussion

All the data variables in log level form and first difference of the log level variables are tested for stationary by using ADF (Unit Root Hypothesis) statistics. All the data variables are converted into their log form to eliminate the scale effects and for the possible reduction of heteroscedasticity impact. The non-stationary acts as a pre-condition for the co-integration; therefore the dataset is tested for co-integration for possible long-run relationships.

Tests for Non-Stationary

The data variables in the log level form tested for non-stationary. The time series graphs clearly show an upward trend with some fluctuations (recession is clearly evident);however after testing for non-stationary using ADF statistics it is found that USD/INR Exchange rate; Indian crude oil price(in levels) are non-stationary in log form. The first difference of the level variables is checked for stationarythrough time series graphs and ADF test statistics. The time series graphs show more or less stability indicating the stationary of differenced variables and the same is confirmed by applying the ADF test for the unit root (non-stationary). All the *p*-values of ADF statistics are significant and imply that unit root hypothesis is rejected; thus the variables are integrated of order one (stationary). The results of ADF *p*-values and time series graphs in levels and difference are showed through Figures 1-2 and Table 1.

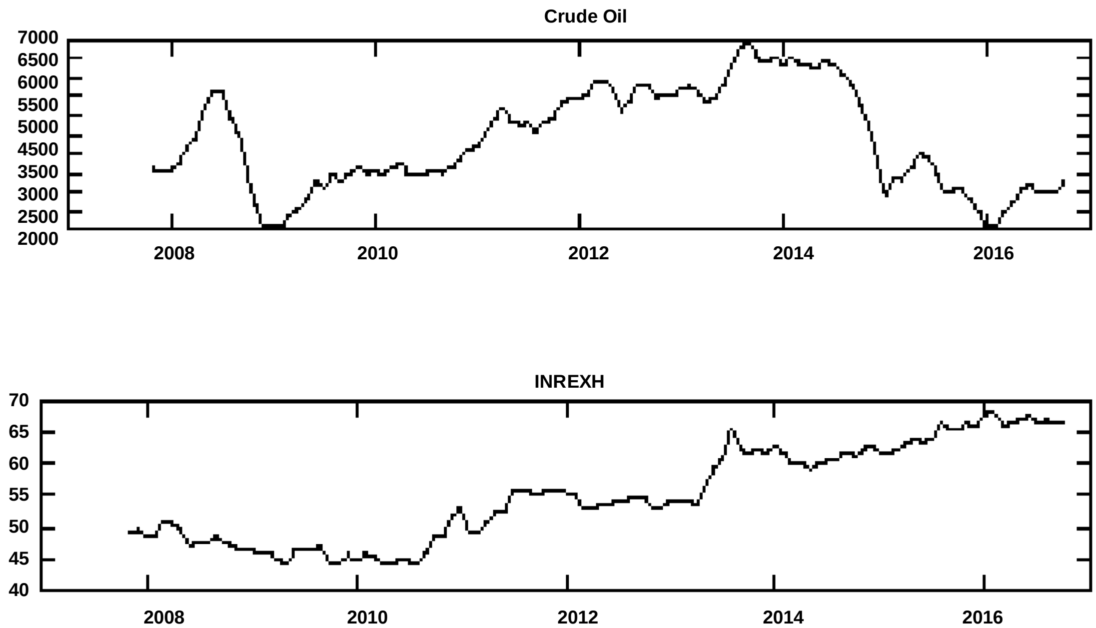

Figure 1: Time series graphs of non-stationary

Source: Eviews's Output

Table 1
Non-Stationary of levels and stationary of differenced time series

Variables	*Test*	*ADF test– p-Values*	*Variables*	*Test*	*ADF test– p-values*
l_INREXH	Without constant With constant With constant and trend	0.9747 0.9488 0.7125	d_l_INREXH	Without constant With constant With constant and trend	5.248e-050 4.485e-014 6.872e-013
l_CrudeOil	Without constant With constant With constant and trend	0.8577 0.5682 0.4998	d_l_CrudeOil	Without constant With constant With constant and trend	5.935e-011 2.046e-007 2.294e-006

Source: Eviews's Output

Tests for Co-integration

Havingfoundthatallthevariablesin the study haveunitroots, thatis,theyare integrated of order one, the next step is to determine whether or not there exists at least one linear combination of the non-stationary variables (in the level form).Thus thenext step is to see whether the variables USD/INR Exchange rate; Indian crude oil priceare co-integrated or not, that is, whether they have long-term or equilibrium relationship between them or not. Figure-3 time series graph of differenced variables shows an expected co-integration between the variables.

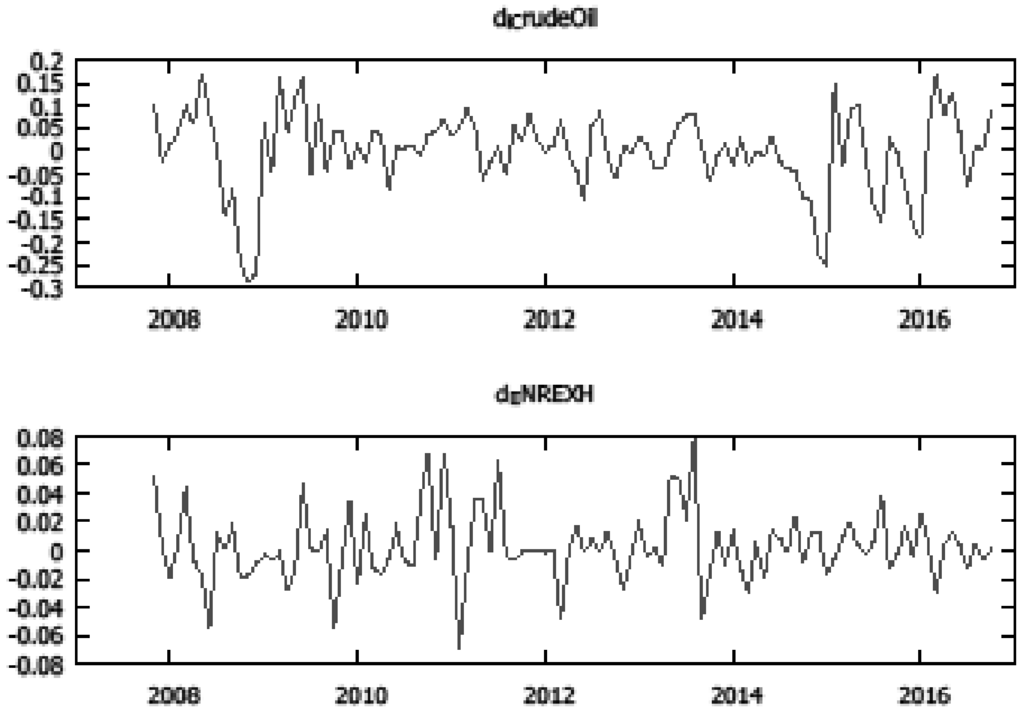

Figure 2: Time series graph showing differenced variables

Source: Eviews's Output

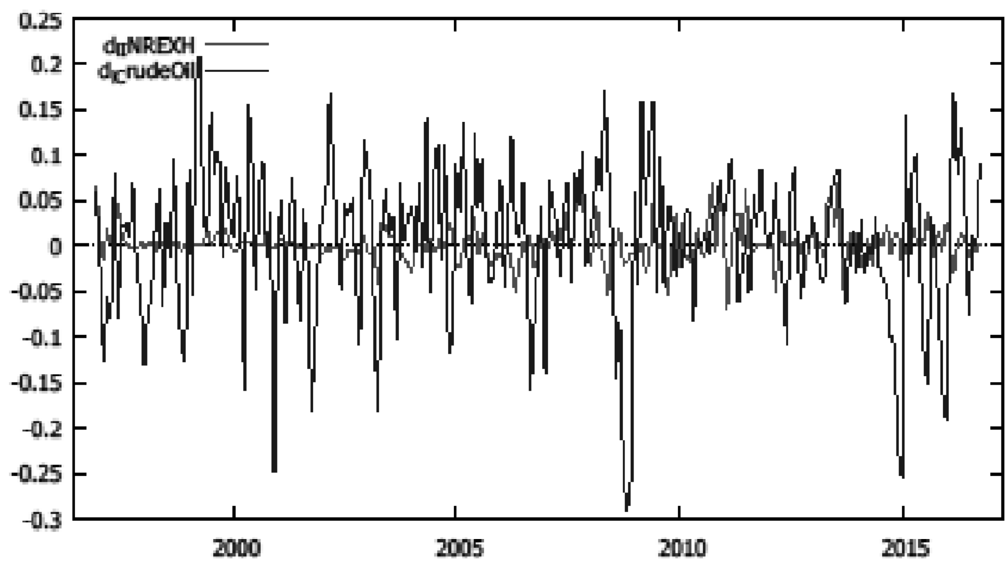

Figure 3: Time series graph of differenced variables

The purpose of the co-integration test is to determine whether as set of non-stationary seriesis co-integratedor not. In addition to the Engle–Granger causality technique, Johansen (1988, 1991) procedure of co-integration is also employed. Johansen's approach begins with anunrestricted VAR involving potentially non-stationary variables, which allows us to deal with models having several endogenous variables. A keyaspect of Johansen's approach is isolating and identifying the '*r*' co-integrating combinations amongaset of '*k*'-integrated variables and incorporate them into an empirical model. The co-integration rank divides the data into *r* relations, towards which the process is adjusting (equilibrium errors), and *k*–*r*(*k*, number of non-stationary I(1) variables) relations, which are pushing the process.

Selection of Lag Length

Johansen'sprocedureofmultivariateco-integrationrequirestheexistenceofasufficient numberoftimelags. To determine the lag length we used the standardinformation criteria, AIC = Akaike criterion, BIC = Schwartz Bayesian criterion and HQC = Hannan–Quinn criterion. All the three criterions are giving lag order two. The selection of lag lengthand stabilisation of VAR through inverse roots results are given in Table 2 and Figure 4.

Table 2
Selection of Lag Length

lags	*loglik*	*p(LR)*	*AIC*	*BIC*	*HQC*
1	372.83110		-6.348724	-5.603688	-6.046639
2	383.11383	0.00039	-6.465071*	-5.620696*	-6.122708*
3	385.52071	0.30695	-6.435569	-5.491856	-6.052927
4	387.63101	0.37698	-6.400574	-5.357523	-5.977655
5	389.19315	0.53725	-6.355429	-5.213039	-5.892231
6	391.97641	0.23394	-6.332897	-5.091169	-5.829421
7	399.46971	0.00473	-6.397587	-5.056522	-5.853834
8	403.25634	0.10852	-6.393636	-4.953232	-5.809605
9	403.80740	0.89394	-6.329767	-4.790025	-5.705457
10	406.36922	0.27484	-6.303134	-4.664054	-5.638546
11	414.10949	0.00380	-6.372398	-4.633980	-5.667532
12	415.37839	0.63788	-6.321822	-4.484065	-5.576678

The asterisks below indicate the best (that is, minimized) valuesof the respective information criteria, AIC = Akaikecriterion,BIC= Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

Source: Eviews's Output

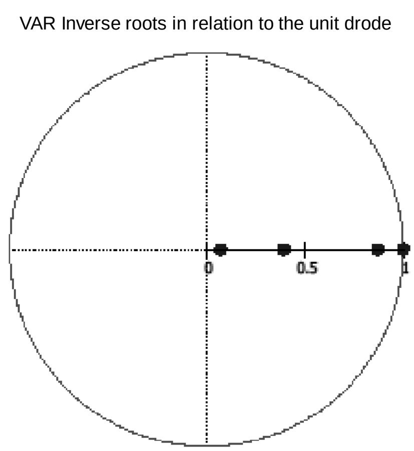

Figure 4: Time series graph showing VAR Inverse Roots

Source: Eviews's Output

4. RESULTS AND DISCUSSIONS

Table 3
Johansen's Co-integration Test

A. Co-integration rank Tests

Unrestricted co-integration rank tests, Trace & Maximum Eigen (Lmax) value

No. of co integrating Equations or Rank	*Eigen values (λ_i)*	*Trace Test*	*P-value*	*Lmax Test*	*P-value*
0	0.234223.14	[0.0092]	20.361	[0.0071]	
1	0.0367	2.6804	[0.1016]	2.6804	[0.1016]

*Both the Trace test and Lmax test indicates one co-integrating equation at both 5% and 1% levels

B. Normalized co-integrating β and adjustment α coefficients (standard errors in parenthesis)

l_INREXHl_Crude Oil Constant

β Coefficients: 1.00 (0.0000) 3.7432 (2.9188) -35.24 (12.003)

d_ l_INREXHd_l_CrudeOi

α Coefficients: -0.00060011-0.012730

P-values: 0.7732 0.035

Source: Eviews's Output

Table 3 gives the results of Johansen's co-integration test for determination of co-integration rank based on trace test and Maximum Eigen (Lmax) value. The trace statistics test the null hypothesis that there are at most "r" cointegrating relations against the alternative of "m" cointegrating relations where r = 0, 1, 2….m-1. Whereas the maximum Eigen value test the null hypothesis of "r" cointegrating relations against the alternative of "r+1" cointegrating relations.

Both the Johansen trace test and maximum Eigen values support the rejection of the null hypothesis that there are no co-integrating relations in the system. From the results of the co-integration rank tests, it can be concluded that the trace and max eigenvalue tests both indicate one co-integrating equation. Indeed, it could find support from the economic theory for long-run relationship between USD/INR Exchange rate and Indian crude oil price.

From the economic theory, the hypothesis is that crude oil prices directly related withUSD/INR Exchange rate. This relationship is important in explaining the deviation in the short run for USD/INR Exchange rate. The vector á is the vector of adjustment coefficients and vector â represents long term or co-integrating coefficients.

The co-integrating relation may be interpreted as expressing the variable USD/INR Exchange rate as the function ofIndian crude oil price. According to these results it appears that the long run USD/INR Exchange ratecould be measured in an equation with 3.74 percentcrude oil price, and an intercept equal to -35.24. The signs on the coefficients in the table are expressed in the form of the condition that the error correction relation, a linear function of I (1), series is stationary and centred on zero. The zero line indicates that error correction mechanism is equal to zero and variations denotes the deviations between the actualExchange rateand that predicted by the effect of the crude oil price and intercept (constant).The adjustments coefficients á is negative for both the exchange rate and crude oil price. The crude oil price fluctuations are significant at 5% level implies that in the short run crude oil price fluctuations is much significant in explaining the exchange rate.

The above results are consistent with a co-integrating relation, which can be considered as an error correction mechanism (ECM) expressed as:

ECM = -35.24+l_INREXH+3.7432*l_CrudeOil

The error correction mechanism at each observation interpreted as the departures from a long run relationships or equilibrium. The ECM centred at zero assuming its long run value, the exchange rate in the long term in VAR-VEC model can be expressed along with "t" ratios (enclosed in brackets) as:

l_INREXH= 35.24 –3.7432l_CrudeOil
(4.25) (3.89)

The coefficient for crude oil price is highly significantly affecting the exchange rate in the long run; a 10% increase in crude oil price would decrease exchange rate as much as37.43% which clearly indicates the role of crude oil price in studying the fluctuations in exchange rate.

VAR results showing direction of causality at different lags: (Null Hypothesis: Per capita GDP does not (Granger) cause per capita energy consumption and per capita co_2 emissions & vice versa)

Table 4
Direction of Causality

Direction of Causality	*Number of lags*	*F value [p value]*	*Decision*
l_INREXH→l_CrudeOil	2	9.3116 [0.0002]	Reject
l_CrudeOil→l_INREXH		0.32736 [0.7217]	Accept

Source: Eviews output

Decomposition of variance for l_INREXH

Table 5
Decomposition of variance among data variables

period	*std. error*	*l_INREXH*	*l_CrudeOil*
1	0.0230614	100.0000	0.0000
2	0.0318984	99.8343	0.1657
3	0.0374817	99.5330	0.4670
4	0.0413873	99.1391	0.8609
5	0.0442721	98.6675	1.3325
6	0.0464817	98.1251	1.8749
7	0.0482235	97.5168	2.4832
8	0.0496313	96.8482	3.1518
9	0.050796	96.1251	3.8749

10	0.0517812	95.3541	4.6459
11	0.0526322	94.5418	5.4582
12	0.0533821	93.6949	6.3051
13	0.0540551	92.8200	7.1800
14	0.0546692	91.9230	8.0770
15	0.0552378	91.0096	8.9904
16	0.0557709	90.0849	9.9151
17	0.0562762	89.1534	10.8466
18	0.0567595	88.2191	11.7809
19	0.0572251	87.2854	12.7146
20	0.0576765	86.3553	13.6447
21	0.0581161	85.4312	14.5688
22	0.0585459	84.5154	15.4846
23	0.0589676	83.6094	16.3906
24	0.0593824	82.7148	17.2852

Decomposition of variance for l_CrudeOil

period	*std. error*	*l_INREXH*	*l_CrudeOil*
1	0.0750921	1.3491	98.6509
2	0.128536	1.6360	98.3640
3	0.172899	1.9430	98.0570
4	0.210455	2.2606	97.7394
5	0.243082	2.5808	97.4192
6	0.2721	2.8975	97.1025
7	0.298406	3.2065	96.7935
8	0.322612	3.5049	96.4951
9	0.345141	3.7910	96.2090
10	0.366299	4.0637	95.9363
11	0.38631	4.3224	95.6776
12	0.405343	4.5671	95.4329
13	0.423532	4.7979	95.2021
14	0.440979	5.0153	94.9847
15	0.45777	5.2198	94.7802
16	0.473974	5.4119	94.5881
17	0.489648	5.5923	94.4077
18	0.504842	5.7617	94.2383
19	0.519596	5.9207	94.0793
20	0.533948	6.0699	93.9301
21	0.547928	6.2101	93.7899
22	0.561563	6.3417	93.6583
23	0.574879	6.4655	93.5345
24	0.587895	6.5818	93.4182

Source: Eviews output

The VAR calculation results are showed in the Table 4 indicating the directional causality running between crude oil price and the exchange rate. Results concluded that at lag 2 there exists a uni-directional causality running from exchange rate to crude oil price, which means that crude oil price does not granger cause exchange rate.

Table 5 gives the results of variance decomposition of data variables, results indicate that in the short run innovation or shock to crude oil price account for about 93% variation of the fluctuation in crude oil price(own shock), innovation or shock to exchange rate can cause 6% fluctuation in crude oil price, In the long run innovations in crude oil price contribute to about 20% variations in crude oil pricewhereas innovation in exchange rate contribute to 80% variations in crude oil price.

5. CONCLUSION AND POLICY IMPLICATIONS

Exchange rate and Indian crude oil price are co-integrated and there exists a uni-directional causality running from exchange rate to oil price meaning that oil price do not granger cause the exchange rate, which implies that crude oil price variations are attributed to exchange rate fluctuations. Crude oil price is highly significantly affecting the exchange rate in the long run; a 10% increase in crude oil price would decrease exchange rate as much as 37.43% which clearly indicates the role of crude oil price in studying the fluctuations in exchange rate.This gives an important policy implication for the apex bank to monitor and strengthen Indian currency by bringing more economic reforms rather than put a caution on increase or decrease of crude oil price as it is evident from the recent data that reduction in crude oil price might have strengthen dollar but not Indian currency.

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