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Nexus between Exchange Rate Volatility and Oil Price Fluctuations: Evidence from India

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Abstract

The price of crude oil has fluctuated in India over the past few decades which has drawn significant attention because of it impact on all economic sectors. The present study aims to identify how oil price volatility affects the real exchange rate in India from 1st July 2009 to 2nd January 2020. For short-run and long-run analysis, various econometric methods have been applied, including Granger Causality, ARDL Bound test, FEVD, and IRF. The study divided the entire sample into sub-samples based on Breakpoint analysis and then performed the ARDL Bound testing procedure in each sub-sample. Causality results revealed that most samples exhibited strong unidirectional causality from oil prices to exchange rates. However, the long-run and short-run results from the ARDL model failed to detect any cointegration among the underlying variables for the entire sample. The calculated F-statistics is 4.35, which is less than the lower and upper critical bound values provided by Pesaran, Shin, and Smith (2001). The GIRF has been used to calculate the dynamic marginal effect of a one-standard-deviation shock in oil prices on the current and future values of the Rupee-Dollar exchange rate. The exchange rate fell in the first three samples due to one standard deviation shock in oil prices. However, the contribution of oil prices to the exchange rate is positive in the fourth sample period.

Keywords: Oil Price, Exchange Rate, ARDL, GIRF, IRF, India.

1. INTRODUCTION

Among the key macroeconomic variables, the exchange rate and oil prices hold an important place. One of the major significance that these variables maintain is that it acts as a parameter in global competition. Even on the inflation front, there is some serious role, these variables perform. The Exchange rate is recognized as an effective measure in trimming down price rise. Regarding the adverse effects of the exchange rate on the economy, it has been found by some studies that it may impact the balance of payments and international flows of a country (Abrams, 1980; Hilton, 1984). Now for a developing country like India whether these two important macroeconomic variables are correlated is the main objective of the study. So, this chapter deals with the analysis, interpretation, and essential steps in achieving the objective.

This paper provides a brief analysis of the causality between the INR-USD bilateral exchange rate and oil prices. Further, the paper provides a detailed discussion of econometric investigation, which includes summary statistics of the variables, unit root testing, Engle and Granger causality test, Bai and Perron (2003) test, ARDL Bound testing approach respectively. Finally, to understand the reaction of the innovations in exogenous variables to endogenous variables, IRF and FEVD statistics were utilized.

The oil-exchange relationship has gained popularity, especially after the great financial crisis in the year 2008. After the end of the 2008 financial crisis, the global price of Brent crude oil rose steadily up to 115$ per barrel in mid-2014, thereafter falling deep down to a low of 26$ per barrel in January 2016. Over the same period, US dollar increased excessively against major oil importers and exporters currencies. This plunge motivates the researcher to revisit the link between oil and currency in a new global scenario (see Reboredo, 2012; Reboredo and Rivera-Castro, 2013; Beckmann, Berger, and Czudaj, 2016; Dreger, Kholodilin, Ulbricht, and Fidrmuc, 2016; Fedoseeva, 2018).

Figure 1, displays 365 days rolling window between nominal oil prices and INR-USD exchange rate. In Figure 1, it is observed that the correlation between the two series seems to be changing over time, i.e., showing negative and positive values. Before September 2013, the negative values predominate with an average correlation of -0.51 percent. The period is characterized by oil supply disruption from Middle-East especially due to Arab Spring and civil war in Libya in the year 2010 and 2011, followed by European Debt crises in 2010-11, the US sanction on Iran in June 2012, the Syrian crisis, North-Sea problem, and Tropical Storm Ernesto leads to jump in world oil prices by almost 20 percent.

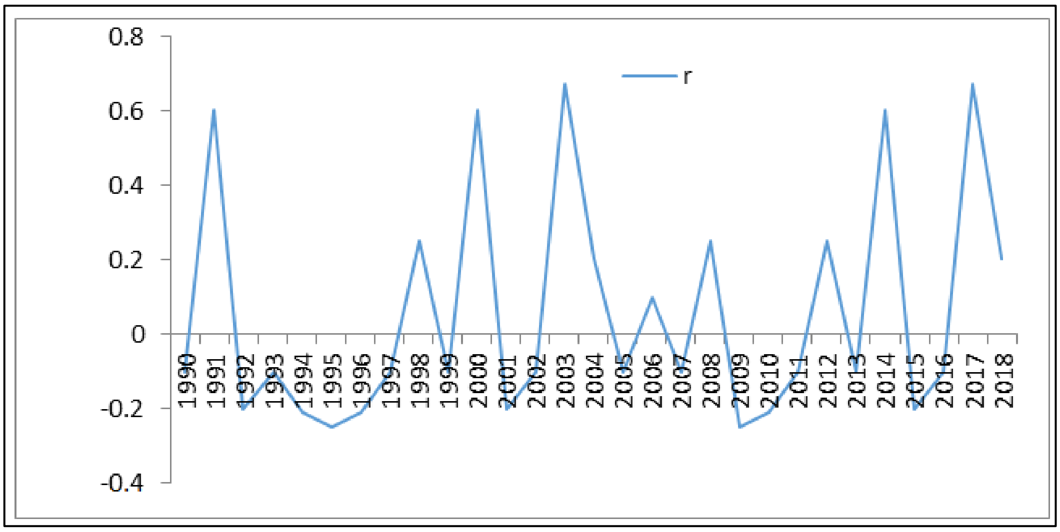


Figure 1: Rolling Correlation between Brent Oil and USD-INR Exchange Rate
Source: Author(s)

The correlation between September 2013 and December 2014 turns positive, with an average value of 0.20. During this period, the rupee appreciated against USD by 5.5 percent, whereas, in the same period, oil prices drastically reduced from 115$ per barrel to 55$ per barrel, almost 52 percent. This oil collapse was the result of various structural factors and geopolitical decisions, which includes an unprecedented resurgence of shale oil production in the United States and Canadian fields (Alquist and Guénette, 2014), weak global demand for oil (Hamilton, 2015), increased supply by Saudis and other Gulf countries (Holodny, 2016), investment in renewable energy (khan, 2017). The correlation is negative, with an average value of -0.48 percent, between December 2014 and May 2018. This episode was triggered by weak global demand, booming shale oil production, and changes in OPEC policies, which further reduces the oil prices to 12 years low of 26$ per barrel in January 2016. Finally, the correlation is positive from May 2018 onwards, with an average value of 0.56. In addition to increasing global oil demand, this period is characterized by a steady increase in oil prices thereafter a significantly drop in the 2018 year-end. The Venezuela crisis, the US sanction on Iran followed by an oversupply of oil from Saudi-Arabia after US sanctions on Iran, and the subsequent relaxation to Iran for exporting oil to its major importers were the major reasons for this roller coaster ride. Therefore, it can be seen that the relationship seems to be changing over time and should be considered while modeling such a relationship.

There are mainly three convincing reasons justifying the need for this empirical research. First, the majority of the studies conducted earlier are limited to European and oil-exporting countries, especially countries like Canada and Nigeria. However, less attention has been paid to the oil-currency nexus for an emerging and oil-importing country like India (see Ghosh, 2011; Singhal and Ghosh, 2016; Yiew, Yip, Tan, Habibullah, and Alih Khadijah, 2019). Second, In the global oil market, India is ranked at third position lagging just behind China and USA. Owing to high dependence on oil imports, the country has high exposure to fluctuating oil prices as compared to other developed countries that have better oil reserves. Third, since India has limited domestic oil production and reserves and imports take 84 percent of the country‘s oil consumption, any increase in oil prices is expected to huge dollar outflow, which in turn adversely affects its CD and FD. Such oil price fluctuations have some set of consequences for the Indian economy that must be dealt with by the competent authority. It is therefore important to conduct an empirical investigation into the connection between oil price and the INR-USD exchange rate, which will enable policymakers to provide useful insights into an efficient policy formulation.

The work adds many aspects to the existing literature. Firstly, the researcher took post-global financial crisis data, i.e., after 2008, that is long enough to explain the dynamic interaction between oil prices and Rupee-Dollar exchange rates. The dataset not only consists the period of exchange rate fluctuation in the year 2011 and in mid-2013 but also includes the period of dramatic oil price collapse in mid-2014 and early 2016. Secondly, the study used Breakpoint regression along with Bai- Perron (1998, 2003) statistics to determine the number of potential breaks in the oil price-exchange rate relationship. Based on Breakpoint regression, the researcher divided the entire sample into different sub-samples and then conducted the Bound testing procedure of Pesaran, Shin, and Smith (2001) in each individual sub-samples. This approach allows us to evaluate the exposure of oil prices to exchange rates across different time intervals.

The rest of the paper is organised as follows. Section 2 deals with a brief review of theoretical and empirical literature. Section 3 deals with data source and empirical findings. The last two sections examine the results and the outcomes followed by the conclusion.

2. REVIEW OF LITERATURE

The association between oil price and exchange rate holds an important place in contemporary macroeconomic research. Over the years there have been a lot of studies that were attempted to examine these relationships. The idea of the interrelationship between exchange rate and oil price can be traced back to the first oil shocks following the 1973 "Yom Kippur War. Among the different scholars, "Krugman and Golub (1983) were the main thinkers who provide a theoretical framework for this complex relationship. They were mainly of the idea that any increase in crude oil prices transfers resources away from oil importers and thus toward oil exporters. As a result, oil exporters' currencies would appreciate, while oil-consuming countries' currencies would depreciate.

Chaudhuri and Daniel (1998) investigated the relationship between US REER and ROP in 16 OECD countries after Bretton Woods. The Engle and Granger cointegration procedure was used in the study, which used monthly data from 1973:01 to 1996:02. The study discovered a cointegration relationship between REER and ROP after Bretton Woods. Furthermore, the findings were significant for the majority of the industrialized economies.

In their study, Habib and Kalamova (2007) investigated whether oil prices have any impact on the real exchange rates of three crosssections: Saudi Arabia, Norway, and Russia. The study found a positive relationship between the oil price and the Rubble exchange rate in the long run in Russia, but no such effect of oil price on the exchange rate was found in Norway or Saudi Arabia. While using a monthly time series ranging from February 1972 to January 1993 to investigate the relationship between actual crude oil prices and US REER. The study used the most popular and robust Johansen cointegration technique and discovered that both variables move together in the long run.

Huang and Feng (2007) investigated how fluctuations in oil prices affect China's actual exchange rate movements. Their findings indicated that oil price fluctuations contribute to a small appreciation of China's exchange rate owing to the country's lower reliance on oil inflows compared with other trading associates. Furthermore, the economy experiences depreciation when there are positive real oil supply shocks, and appreciation is the contribution of positive real demand shocks.

While using monthly data Chen and Chen (2007) worked on the panel of G7 countries. They utilized the data from January 1972 to October 2005. Their objective was to examining the long-run relationship between real crude oil prices and real exchange rates. Using panel FMOLS, Panel DOLS, and PMGE, they discovered that actual oil prices is expected to be the primary source of fluctuations in the long-term real exchange rate.

Lizardo and Mollick (2010) investigated the nexus between crude oil prices and exchange rates. For the panel of major oil-exporting and importing countries, they discovered that changes in the price of crude oil significantly affect the exchange rate in the long run. A surge in accurate crude oil prices causes the USD to appreciate significantly compared to oil-exporting countries such as Mexico, Canada, and Russia. In contrast, when actual oil prices rise, the currencies of oil-importing countries, such as Japan, weaken in comparison to the USD.

A study by Quere *et al.*, (2007) investigated the nexus between the actual oil price and the accurate dollar price for the period of 30 years. According to their findings, a ten percent increase in crude oil price corresponds to a four-and-a-half percent increase in dollar value in the long-term. Likewise, a study put forward by Nikbakht (2010), found that the main force behind real exchange rate fluctuations is changing oil prices. The study thus hints at a strong association between the real exchange rate and oil prices. The study also found that such a relationship holds true both in the long run and short run. While checking for robustness the study uses alternative measures for the exchange rate. However, there wasn't a significant effect on the results. The study thus concludes that the relationship holds true in different conditions. The research findings generally revealed a long-term positive relationship between actual crude oil prices and accurate exchange rates.

Reboredo (2012) examined the oil-exchange co-movements of European Union currencies using daily data from the 4th of January 2000 to the 15th of June 2010. According to the study, the nexus between increased oil prices and resulting depreciation alongside the US dollar have less significant relationship with two different modes of causality for other currencies. However, the nexus appears more robust for countries that are net oil exporters than the countries which are oil importers.

Using a novel wavelet methodology and scale-by-scale Granger causality tests, Tiwari *et al*., (2013) investigated the extent to which crude oil prices affect Romania's REER. According to their findings, crude oil prices significantly influence the effective exchange in real terms both in the short run and long run. By constructing the classical Granger linear framework, they discovered that crude oil prices do not affect the REER. Furthermore, they found that positive shocks associated with rising oil prices affect REER movements in both the short and long run. In their study Tiwari *et al*., (2013) investigated the linear and non-linear causalities between oil price movements and India's REER. Using the standard time-domain approach, they discovered no linear or nonlinear causal relationship amid the oil price and REER. Despite this, their findings indicated reasons between the two series because they used the Wavelets technique in decomposing a series into frequency bands. However, no causality was discovered at lower time scales, but as they moved to higher time scales, they found unidirectional causality from the exchange rate to oil prices.

Uddin *et al*., (2013) used a wavelet methodology within a time-frequency space to determine the cohesion between the exchange rate and oil price in the case of Japan. Using monthly time series data from 1983M06 to 2013M05, their findings indicated that the strength of co-movement between the two series varies and deviates over time. The short- and medium-month cycles have a strong relationship (time horizon less than 34 months). On the other hand, long-month processes revealed a weak relationship (time horizon of more than 34 months). Brahmasrene *et al*., (2014) used the Granger causality test, IRF, and VDF to investigate the relationship if any between the exchange rate and US oil prices. From January 1996 to December 2009, they used monthly data. In the short run, the results suggested unidirectional causality runs between the exchange rate and oil price, while in the long run, a reverse cause was discovered. Furthermore, the IRF function of the variable representing the exchange rate to a crude oil price shock is insignificant.

A study by Benhabib *et al*., (2014) examined the long-term cointegration of the oil price and the Dinar-Dollar exchange rate. According to the study, a one percent rise in oil prices brings about 0.35 percent depreciation in Algerian Dinar against the US dollar. Bal and Rath (2015) investigated the non-linear causality pattern between changes in oil prices and the exchange rates for two countries, China and India, respectively. They used monthly time series data from January 1994 to March 2013 to apply Hiemstra and Jones's (1994) non-linear Granger causality test to the VAR residuals. Using REER and WTI spot prices as oil price benchmarks, their findings show bi-directional non-linear Granger causality in the case of India and a unidirectional causal relationship between the exchange rate and oil price in the case of China.

Basher *et al*., (2016) employed Markov-switching models on the way to examine the effect of oil price shocks on currency exchange rates for various countries that deal with oil-exporting and importing crude oil. The study found that the currencies of oil-exporting countries had significantly strengthened in response to fluctuations in oil demand. However, the study found little confirmation that oil supply shocks influenced exchange rates, according to the study. Finally, the study discovered that international aggregate demand shocks impacts the exchange rates in both oil-exporting and oil-importing countries, despite the absence of a systematic pattern of genuine exchange rate appreciation and depreciation.

While tracking the movement of crude oil prices and currency exchange rates across time and frequency domains, Yang *et al*., (2017) used a continuous wavelet coherence framework from January 1, 1999, to December 31, 2014. Furthermore, they discovered strong but not uniform links around 2008 for all of the countries studied and from 2005 onwards for the oil-exporting countries. However, the oil-importing countries' strong interdependence is limited. Furthermore, the authors discovered a negative relationship between crude oil price returns and the currencies of oil exporters, while an uncertain relationship was found for oil-related currencies.

3. DATA AND EMPIRICAL FINDINGS

3.1. Data and Variable Construction

To carry out the objectives of this study daily data, spanning from 1st July 2009 to 2nd January 2020 is employed. Daily data provides sufficient data points that help to capture the relationship between variables and lag structure properly. The data pertaining to model variables i.e. Exchange Rate (lexc), Oil price (loil), are taken from the Reserve Bank of India, *handbook of statistics for Indian economy*. As the data available on RBI is on different bases, the study follows standard statistical procedures to link the different series in the same format.

3.2. Stationarity Tests

To ascertain the possible unit root, the study employed the conventional ADF and PP test on levels and the first difference of the series. Table 1 illustrated the results of ADF and PP test. The null hypothesis of no unit root against the presence of a unit root is tested for both ADF and PP tests. The study includes three models, one that includes only intercept, second that includes both intercept and trend, and the last without intercept and trend. The Schwarz Information Criteria with a maximum of 32 lags were chosen for the ADF test, whereas the Bartlett Kernal with Newey-West Bandwidth method was chosen for the PP test.

Table 1: Unit Root Test Results

	ADF			**PP**		
Variables	**Constant**	**Constant &Trend**	**None**	**Constant**	**Constant& Trend**	**None**
Lexc	-1.722	-3.194	2.879	-1.561	-5.147	2.822
*Δ*lexc	-17.872***	-17.624***	-17.32***	-26.832***	-26.624***	-26.32***
Loil	-2.121	-3.212	-1.883	-3.212	-3.090	-1.662
*Δ*loil	-34.412***	-34.263***	-34.26***	-34.342***	-34.221***	-34.32***

Note: *** indicates significant at 1percent level. Source: Author(s) calculation

From Table 1 it is revealed that both series are not stationary at level; however, after transforming into the first difference, it becomes stationary.

3.3. Breakpoint Regression Results

The researcher adopted Bai and Perron (1998, 2003) procedure to detect the infrequent structural shocks in the oil-exchange dynamics. The superiority of the BP test is well documented as it accounts for multiple structural breaks (see Wakamatsu & Miyata, 2015; Aruga, 2016; Vujić, Commandeur & Koopman, 2016; Groothuis, Rotthoff & Strazicich, 2017). Further, it assumes the breakpoints are unknown and determine endogenously as one would not know the timing of the break dates beforehand (see Noguera, 2013; Tamakoshi & Hamori, 2014; Kellard, Jiang & Wohar, 2015; Bekiros, Gupta & Kyei, 2016).

The BP estimation results through Breakpoint Regression in Eviews 10 are presented in Table 2 The study has chosen L+1 vs. L globally criteria as our break type and sequential evaluation as our break selection. Further, the study allowed a maximum number of breaks up to 6 with 12 percent as trimming percentage.

Table 2: Breakpoint regression results

Sample Period	**Particulars**	**Daily Data**
Sample 1 (1992-2000= 2590 obs)	Constant	2.079***
	Standard Error	0.013
	Loil	-0.041***
	Standard Error	0.003
Sample 2 (2000-2008= 2590 obs)	Constant	2.817***
	Standard Error	0.049
	Loil	-0.180***
	Standard Error	0.010
Sample 3 (2008-2016= 2590 obs)	Constant	2.208***
	Standard Error	0.005
	Loil	-0.037***
	Standard Error	0.001
Sample 4 (2016- 2021= 826 obs)	Constant	1.934***
	Standard Error	0.011
	Loil	0.036***
	Standard Error	0.002
R^2		0.962
Adj R^2		0.926

Notes: *** indicates significant at 1percent level respectively; Maximum breaks allowed 5; Significance level 0.05; Break dates suggested by the Bai-Perron test: 1992, 2008, and 2016

The results shown in Table 2 revealed the existence of structural breaks on 06/08/1992, 16/11/2008, and 14/05/2016, respectively. Further, the researcher observed that the respective breaks are well explained by exchange rate crises and oil price crisis. The structural break identifies in the year 1992 are in line with the depreciation of INR against USD in the liberalized era. The second break identified in the year 2008 was probably because of the 2008 global crises. Finally, the researcher verified the existence of a structural break in April 2016, which was probably because of the oil price crash in the beginning of the year 2016.

The summary statistics of the underlined variables for each sub-sample is shown in Table 3.

Table 3: Summary Statistics of the Variables

	Particulars	Exc	Oil
Sample 1	Mean	36.62	59.54
	Median	36.44	54.27
	Maximum	39.44	85.08
	Minimum	3.91	39.14
	Std. Dev.	1.04	12.13
	Skewness	0.56	0.39
	Kurtosis	2.21	1.28
	Jarque-Bera	40.45***	42.50***
Sample 2	Mean	42.51	74.21
	Median	43.03	74.03
	Maximum	45.54	86.09
	Minimum	38.77	59.59
	Std. Dev.	1.74	4.80
	Skewness	-0.51	-0.03
	Kurtosis	1.83	2.32
	Jarque-Bera	31.03***	2.73***
Sample 3	Mean	50.10	52.57
	Median	49.60	55.16
	Maximum	54.88	78.71
	Minimum	45.10	17.48
	Std. Dev.	1.98	19.80
	Skewness	0.38	-0.10
	Kurtosis	1.92	0.91
	Jarque-Bera	31.73***	58.08***
Sample 4	Mean	53.35	39.30
	Median	53.20	36.93
	Maximum	59.26	57.83
	Minimum	50.53	26.87
	Std. Dev.	2.04	7.62
	Skewness	0.73	0.33
	Kurtosis	2.57	1.37
	Jarque-Bera	82.17***	38.11***

Notes: *** indicates significant at 1percent level. Source: Author(s) calculation

In the first sample period, the average daily future crude oil price was about 88$ per barrel. This was increased to 110$ per barrel in the second sample period. After that, oil prices have shown the decreasing trend and was traded on a daily average of 78.25$ per barrel and 58.50$ per barrel in the third and fourth sample period. However, the exchange rate has shown the increasing trend and reached maximum to 67 per USD in the fourth sample, depicting continuous depreciation of INR against USD. Overall, crude oil prices are more volatile than the exchange rate, as depicted by the standard deviation. Unlike in the first sample period, the distributions of both variables are positively skewed; it turns out to be negative in the second sample. The oil price continues with a negatively skewed distribution in the third sample; however, exchange rate distribution turns out to be positive in the third sample. Further, the variables show platykurtic distribution in most of the sample, since the value of kurtosis is less than 3. At last, the Jarque-Bera test statistics rejects the null hypothesis of normal distribution in most of the samples, except for oil price series in sample 2.

4. RESULTS AND DISCUSSIONS

4.1. Engle and Granger Test Results

Over the past decade, extensive empirical literature has emerged exploring the causal linkage between the oil-exchange relationship in both developed and developing economies, but the results are inconclusive and contradictory. On one hand, studies like Amano and Van Norden (1998), Chaudhuri and Daniel (1998), Chen and Chen (2007), Zhang *et al*., (2008), Lizardo and Mollick (2010), Benhmad (2012), Tiwari *et al*., (2013) and Bouoiyour *et al*., (2015) have shown that the movements in oil prices may Granger cause of exchange rate fluctuations; while the others like Sadorsky (2000), Yousefi and Wirjanto (2004), H2quang and Guo (2007), Breitenfellner and Cuaresma (2008), Zhang *et al*., (2008), Akram (2009), Chen *et al*.,, (2010), Zhang and Wei (2010), Reboredo (2012), Beckmann and Czudaj (2013), and Coudert and Mignon (2016) has anticipated the reverse direction of causation from exchange rate to oil prices. Moreover, there are few authors who find the causality in both the direction (see Wang and Wu, 2012; Fratzscher *et al*., 2014).

Further, Ferraro, Rogoff, and Rossi (2015), Kaplan and Aktas (2016) and Beckmann, Berger, and Czudaj (2016) identifies the difference in the direction of the causality primarily because of two key reasons: i) choices of the data frequency (the prediction power appears to be more strong in case of daily data as compared to monthly data and quarterly data); ii) oil dependence of a country (i.e., the inverse relationship appears to be more strong for oil-dependent economies, i.e., oil-importing and oil-exporting countries as compared to countries which have a diversified portfolio)

Studies related to India include Tiwari *et al*., (2013), Bal and Rath (2015), Tiwari and Albulescu (2016), De Vita and Trachanas (2016) and Kumar (2019). Using a monthly time interval from 1993-2010, Tiwari *et al*., (2013) find unidirectional causality running from oil price to exchange rate only at high interval scales. Further, Tiwari and Albulescu (2016) identify unidirectional causality from oil price to exchange rate in the short run while reverse causality is found in the long run. By deploying structural breaks and non-linear causality, Bal and Rath (2015) have found the bi-directional causality between oil prices and INR-USD exchange rate. However, De Vita and Trachanas (2016) replicated the results of Bal and Rath (2015) and found no causality between oil prices and the exchange rate. In the recent scenario, Kumar (2019) explores the causal link between oil price and exchange rate and provides strong evidence of bi-directional causality between oil price and exchange rate.

Table 4: Granger Causality Test Results in a Multi-Time Horizon

	Null Hypothesis	**Chi-square (χ^2)**	**Df**	**Prob.**
Sample 1	loil does not Granger cause lexc	9.81	3	0.001***
	lexc does not Granger cause loil	4.28	3	0.022**
Sample 2	loil does not Granger cause lexc	1.21	4	0.819
	lexc does not Granger cause loil	7.24	4	0.021**
Sample 3	loil does not Granger cause lexc	18.8	2	0.016***
	lexc does not Granger cause loil	2.65	2	0.842
Sample 4	loil does not Granger cause lexc	40.342	5	0.000***
	lexc does not Granger cause loil	6.21	5	0.782
Full Sample	loil does not Granger cause lexc	18.21	7	0.000***
	lexc does not Granger cause loil	3.14	7	0.838

Notes: ***’** indicates significant at 1 percent and 5 percent level. Source: Author(s) calculation

Despite being several studies in India, the directional of causality is not clear and defined. Thus, the present study revisits the pattern of causality between Brent crude prices and the INR-USD bilateral exchange rate, which, by analyzing the relationship in different periods, adds to the current literature. In order to access this relationship, the study used the most common and robust Engle and Granger (1987) procedure, which measures the possible direction of causality among the variables. Table 4 summarizes the results of the same. The study estimate five VAR systems to estimate the causality pattern, four for each sub-sample, and one for the whole sample. According to the results presented in Table 4.4, most of the samples have shown a strong causality pattern running from oil prices to exchange rate; however, reverse causality is found only in sample 2. Besides this, the study also found weak bi-directional causality between the oil prices and the exchange rate in sample 1.

4.2. Co-integration and ARDL Bound test.

Selecting the correct lag length for the ARDL model is an arduous and ponderous task as sometimes it creates under fitting and over fitting issues, which may lead to spurious results. To deal with this problem, one can choose the different information criteria such as AIC, SBC, HQ, LR statistics provided in the economic literature. Based on the argument of Liew (1994) and Gutierrez, Souza & Guillen (2009), the AIC criteria is chosen over other information criteria as it produces better and more consistent results.

Starting with the whole sample, the ARDL bound testing approach failed to detect any Co-integration among the underlined variables. The calculated F-statistics is 4.35, which is below than the lower and upper bound values of Pesaran *et al*., (2001) critical value table. The diagnostic test, such as serial correlation, normality, and Heteroskedasticity failed, suggesting that the assumption of parameter constancy over the entire period might not be a decent choice

After confirming the time-varying relationship, the researcher adopted an alternate methodology and divided the entire sample into different sub-samples based on Breakpoint analysis and then conduct the Bound testing procedure in each individual sub-samples. The appropriate lag length was chosen as AIC as it produces the robust results stated earlier (see Figure A.1 in the appendix). Given that the bound testing procedure relatively performs better in small and finite sample sizes (see Tang, 2001; Narayan and Smyth, 2003; Ziramba, 2007), it is well suited for my study. Further, the method does not restrict the variables to be I(0) or I(1) or a mix of them. However, Ottarara (2004) explicitly mentioned that the procedure might produce spurious results in case of I(2) variables. The ARDL Bound test results for each sub-sample are stated in Table 5.

Table 5: ARDL Bound Testing Results

Variables	**Sample 1 ARDL (2,2)**	**Sample 2 ARDL (1,1)**	**Sample 3 ARDL (5,2)**	**Sample 4 ARDL (3,2)**	**Whole Sample ARDL(6,1)**
Constant	1.212	0.262**	0.124***	0.141***	0.002**
Trend	-	8.242	-	-7.332***	7.240***
$lexc_{t-1}$	-0.013	-0.081**	-0.052***	-0.036***	-0.014**
$loil_{t-1}$	-0.0001	-0.002	-0.002***	0.007**	0.000
$\Delta lexc_{t-1}$	-0.182***		0.141	0.163*	0.008
$\Delta lexc_{t-2}$	-		-0.232***	-0.128***	-0.009***
$\Delta lexc_{t-3}$	-		-0.015		0.024
$\Delta lexc_{t-4}$	-		0.224***		0.018**
$\Delta lexc_{t-5}$	-		-		0.067***
$\Delta loil$	-0.161***	-0.141***	-0.302***	-0.006	-0.126***
$\Delta loil_{t-1}$	-0.602***		0.201	0.064***	
			Diagnostic Results		
F_{PSS}	1.237	3.291	8.579***	8.973***	4.354
LM_{AUTO}	1.090 (0.33)	0.777 (0.46)	0.107 (0.89)	0.422 (0.65)	1.685 (0.01)
BPG_{HETRO}	2.485 (0.03)	2.538 (0.03)	14.088 (0.00)	4.854 (0.00)	20.240 (0.00)
RESET	1.431(0.23)	0.858 (0.39)	0.678 (0.41)		
JB_{NORM}	57.452(0.00)	292.58 (0.00)	2933.8(0.00)	659.74 (0.00)	5361.21(0.00)
CUSUM	Y	Y	Y	Y	Y
LR	0.128	-0.146	-0.096***	0.099***	0.100

Notes: ***,**,* indicates significant at 1 percent, 5 percent, and 10 percent respectively; F_{PSS} stands Pesaran, Shin, and Smith, (2001) joint F-statistics; LM_{AUTO} stands for" Breusch-Godfrey serial correlation LM test"; BPG_{HETRO} stands for "Breusch-Pagan-Godfrey Heteroskedasticity test"; RESET stands for Ramsey RESET method; JB_{NORM} standsfor Jarque-Bera test for normality; CUSUM stands for the cumulative sum of squares suggested by Brown *et al*., (1998); values in the parenthesis () denotes p-value; Y signifies stable relationship; maximum 12 lag were selected based on the Akaike Information Criteria (AIC).

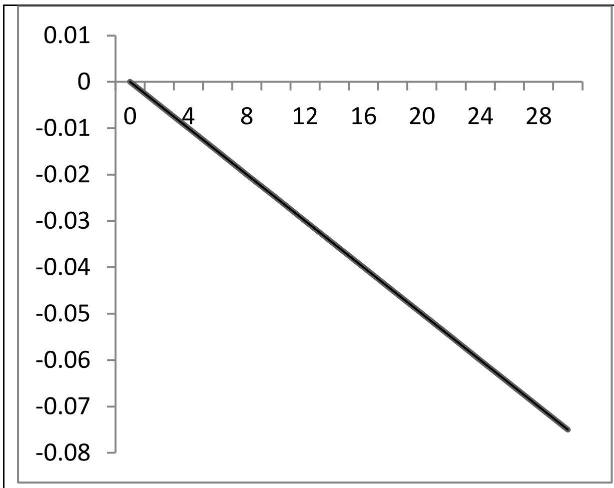
The result presented in Table 5 revealed that the null hypothesis of no Co-integration‖ is discarded in 2 out of 4 samples. Further, the model passes the diagnostic test such as DW statistics for a spurious model, LM_{AUTO} for autocorrelation, JB_{NORM} test for normality, BPG_{HETRO} for Heteroskedasticity, RESET and CUSUM test for parameter stability, except for normality and Heteroskedasticity in all the models.

4.3. FEVD and IRF

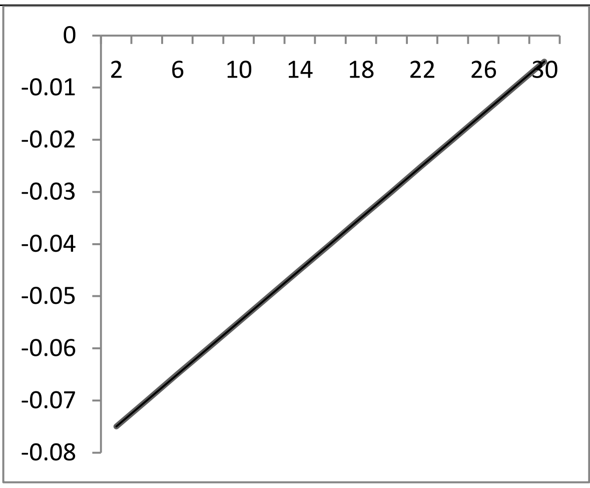
In addition to the ARDL model, the researcher also adopted the Innovation Accounting Approach, which comprises of FEVD and IRF to estimate the forecasted impact of international crude oil price on Rupee-Dollar exchange rates.

4.3.1. IRF

Based on the VAR framework, the study firstly conducted an IRF technique to measure the dynamic marginal effect of one standard deviation shock on the present and future values of all the endogenous variables over a period of time. The results of the same are provided in



Accumulated Response of lexc to loil Innovation using Generalized Impulse Response Function



Response of lexc to loil Innovation using Generalized Impulse Response Function

Figure 2: GIRF

Source: Authors calculation using Eviews, version 10.

The study adopted GIRF over Choleski fractionalization innovations deliberately to avoid the ordering problem built in the orthogonalized impulse responses (Shahbaz, Hye, Tiwari, and Leitão, 2013; Pesaran and Shin, 1998; Koop, Pesaran, and Potter 1996). Figure 2 demonstrates the negative response in the exchange rate due to one standard deviation shock stemming from oil prices in the first three sample periods. This indicates that oil prices have a negative impact on the exchange rate in our large sample period. However, the contribution of oil prices is positive to the exchange rate in the fourth sample period.

4.3.2. FEVD

Although the IRF gauges the effect of one standard deviation shock of endogenous variables in a VAR framework, it does not measure the magnitude/percentage of such shocks. To access this, the study incorporated the FEVD, which accounts for measuring the relative percentage of each shock to the h-step ahead forecast error variance of the exogenous variable. Further, Ibrahim (2005) and Engle and Granger (1987) documented the superiority of FEVD over other traditional techniques as it produces reliable and better results. Table 6 reports the FEVD results.

Table 6: FEVD Estimation Results

Variable	Period (Days)	lexc	loil
Sample 1	7	92.32	1.21
	30	96.41	1.52
	120	91.52	4.32
	365	60.25	21.22
Sample 2	7	89.28	1.23
	30	92.32	1.14
	120	90.24	1.24
	365	92.25	1.37
Sample 3	7	91.22	0.04
	30	96.21	1.42
	120	70.24	19.28
	365	38.28	42.24
Sample 4	7	89.24	8.21
	30	79.54	11.62
	120	74.21	21.42
	365	62.08	12.76

Source: Authors; calculation using Eviews, version 10.

The study allows one year (365 days) forecasting horizon. Beginning with the 1st sample, about 60.25 percent of the variation in the exchange rate is accounted by its own innovations, and the rest 21.22 percent by the oil prices. However, the contribution of the oil prices drastically decreases to 1.37 percent in the 2nd sample, depicting the exchange rate largely influenced by its own shocks, which account for 92.25 percent

The large fluctuation can be seen in sample 3rd (between 2013- 2016), when oil prices entered in a most dramatic period, falling deep down to 26$ per barrel in January 2016 from 115$ per barrel in September 2013. In that period, the variation in the exchange rate by its own innovative shocks drastically decreases to 38.28 percent, while the responses of the exchange rate to the one standard deviation shock in oil prices alone rise to 42.42 percent. In the last sample, the forecast variance error of the exchange rate explains itself by around 62.82 percent, while the oil price forecast error variance explains the exchange rate forecast error variance by around 12.76 percent.

5. CONCLUSION

The present paper analyzed the time-varying Co-integration between the INR-USD bi-lateral exchange rate and oil prices including the background information of the study. The study found that both of the underlined variables are non-stationary in nature, hence, contain unit root. The BP test statistics suggested that the oil-exchange relationship suffered from multiple structural breaks, i.e. 10/10/2011, 10/6/2013, and 12/4/2016 respectively. Thereafter, the study incorporated five VAR systems to estimate the causality pattern, four for each-sub- sample and one for the whole sample. The study found a strong unidirectional causality pattern running from oil prices to exchange rate, however, weak bidirectional causality between the oil prices and exchange rate in sample 1. To detect the long-run and short-run relationship, the study employed the ARDL model suggested by Pesaran, Shin, and Smith (2001), which failed to detect any Cointegration among the underlined variables for the whole sample. Thereafter, the researcher incorporated Bierens and Martins (2010) TVC procedure which suggested that the assumption of parameter constancy over entire time period might not be a decent choice. The null hypothesis of 2-dimential Cointegration vector is time-invariant was strongly rejected in most of the different lag order of Chebyshev polynomial except for lag order 1. The researcher has adopted an alternate methodology and divided the entire sample into different sub-samples based on Breakpoint analysis and then conduct the ARDL Bound testing procedure in each individual sub-samples. The null hypothesis of no Cointegration is rejected in 2 samples out of 4 samples which shows that the Rupee was decoupled from oil price shocks in the first 2 samples. However, the oil pass-through effect becomes stronger in the 3rd and 4th samples. Further, the GIRF reveals the negative response in the exchange rate due to one standard deviation shock stemming from oil prices in the first three samples. However, the contribution of the oil prices turns positive to the exchange rate in the fourth sample period. To measure the relative percentage of each shock FEVD has been applied. The result reveals that in the 3rd sample, 38.28 percent of the variation in the exchange rate is accounted by its own innovations and the rest 42.42 percent by the oil prices. However, in the 4th sample, the exchange rate explains itself by around 62.82 percent, while the oil price explains the exchange rate forecast error variance of around 12.76 percent.

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