PREDICTING VOLATILITY AND DYNAMIC RELATION BETWEEN STOCK MARKET, EXCHANGE RATE AND SELECT COMMODITIES

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Abstract

Commodities play a vital role in the development of emerging economies, like India. From this perspective, the study presents dynamic correlation in the prices of gold, crude oil, exchange rate and Indian stock market from April 01, 2014 to March 28, 2018. VARMA-BEKK-GARCH model is estimated for return and volatility spillovers across markets. Bidirectional returns spillover was found between Nifty and WTI and WTI and Gold pair. Whereas the bidirectional volatility spillover between Nifty and Gold pair. From the DCC-GARCH correlational analysis, Gold was found to be effective hedging commodity for Indian stock investors than Crude Oil. The asymmetric impact of shocks in covariance is observed between Nifty 50 and all other variables. The study focuses to aid investors and portfolio diversifiers while taking investment decisions.

Keywords: crude oil price, exchange rate, gold price, stock market, DCC-GARCH, BEKK-GARCH, correlation

INTRODUCTION

With the advent of financial liberalization and integration of capital markets, financialization of commodity markets has been witnessed (Arfaoui and Rejeb, 2017; Tang and Xiong, 2012). Since then commodity market development has paved the way for international cross market diversification (Domanski and Heath, 2007; Dwyer, Gardner and Williams, 2011; Sadorsky, 2014). Abanomey and Mathur (2001) low return correlation of commodities with other asset classes. Therefore, a sound understanding of cross market correlation becomes vital for effective diversification strategies.

Among the actively traded commodities, Gold and Oil are the most popular (Yaya, Tumala and Udomboso, 2016). Gold provides safety and acts as a store of wealth during uncertain time periods (Aggarwal and Lucey, 2007). Baur and McDermott

(2010) and Lombardi and Robays (2011) opined that investment in Gold is widely considered by investors when concern for inflation hovers. Further, Gokmenoglu and Fazlollahi (2015) viewed that Oil price volatility is critical due to its ability to create inflation. Jaffe (1989) observed that Gold has been considered to be an effective hedge against inflation. Since commodities are traded in US dollars (USD) too, hence exchange rate plays a vital role. USD depreciation leads to the growth in demand for crude oil and results in increase in crude oil price (Pindyck and Rotemberg, 1990; Sadorsky, 2000), which further creates unfavorable environment by reducing the country's equity prices (Basher and Sadorsky, 2006). This becomes vital for emerging economy like India where 70% of its crude oil requirement is met through exports and its gold import bill constitutes 10% of its total

imports. India is the largest oil and gold consumers ranking third[1] and second in the world[2].

Fluctuations in oil price often have serious consequences for oil importing nations like India. As a result, investors have shifted towards Gold as an investment asset in the portfolio. Inflation underpins the linkages between Gold and oil markets as suggested by Hooker (2002). Basher, Haug, and Sadorsky (2012) suggested the importance of emerging economies on the global frontiers has made the study of asset market linkages vital.

Ross (1989) advocated that information flows through volatility tend to vary with time. Silvennoinen and Thorp (2013) have further pointed that with the integration of commodity and conventional asset markets, the possible systematic shocks can cause time varying correlation to rise by dominating commodity returns.

This paper attempts to focus on the relationship among Crude Oil, Gold, Exchange Rate and Indian Stock Market in a time-varying domain. Such linkages were earlier limited to the return's aspect of the series and to the developed stock markets. However, the present study focussed on volatility and co-volatility aspect and an emerging market like India. Both the returns and volatility linkages were observed using the non-linear methodology to suite the time behaviour clustering and heteroscedasticity dynamics as a research contribution. Further, such relation has not been studied extensively from 2014, the onset of commodity slump and global market slowdown. Understanding such linkages among the proposed variables provides valuable implications for both the policy makers and investors which will help them in appropriate hedging and portfolio decisions.

The structure of the paper is as follows: Section 2 details out the literature review followed by the gap in the existing literature. Section 3 presents the data and methodology adopted followed by objectives. Section 4 presents the results and discussion which is ultimately followed by Conclusion section.

Literature Review

The conventional asset pricing models has ignored the higher moments in the OLS framework which was incorporated in the study done by Sharpe (1964), Lintner (1965) and Black (1972). These studies classified the markets as isolated. Further studies by Solnik (1983) and Dumas and Solnik (1995) assumed that markets are interdependent through the international markets under consideration. But in late 1990's it was observed that volatility does play a vital role in modelling as volatility interdependence

was much pronounced than returns. It was felt that the market's interdependence varies over time. The study done in this context was by Bekaert and Harvey (1995) where the time dependent weights to variance and covariance was added in the integration model. This study however didn't find conclusive evidence of complete integration between 12 emerging and 18 developed markets, but presented a seminal work on allowing for multiple risk factors in the standard asset pricing model. The study also presented that economic development of a country leads to integration of financial markets which offers better diversification opportunities to different set of investors. Further Fama (1970) reinforced the presence of volatility clustering and seconded on the ARCH behavior of financial time series. Study done by Baillie and Bollerslev (1991) has shown that volatilities vary across time and asset classes. Wide literature has reiterated the volatility spillovers and cross market volatility across same asset classes as well as among different asset classes in the recent past.

The empirical study on crude oil and gold prices relation was done by Zhang and Wei (2010) from January 2000 to March 2008 found that in the long run changes in price of crude oil cause fluctuations in gold prices. Crude oil has greater contribution than Gold prices depicted by Information Share and Permanent Transition from the Engle and Granger approach of cointegration, Granger causality and VECM was used. Further, the causal relation between energy prices and exchange rate was examined by Wang and Wu (2012) over 2003 to 2011. The whole study period was divided to show the effect of financial crisis. The linear granger test results revealed that crude oil prices granger caused exchange rates. Exchange rate caused natural gas prices in nonlinear causal test on pre-crisis period. And post crisis, the nonlinear feedback relationship could be displayed between exchange rate and crudeoil. Spillover in volatility measured through GARCH-BEKK was major contributor for existence of nonlinear causality. Prasad Bal and Narayan Rath (2015) in their study unveiled the crude oil prices and effective exchange rate in real terms in China and India. They used nonlinear granger causality test and exhibited the presence of feedback relationship between oil prices and exchange rate in India. However exchange rate caused oil prices in China over a period from 1994 to 2013.

While Basher, Haug and Sadorsky (2016) have used nonlinear model (Markov-Switching Model) to examine the influence of oil demand and supply shocks along with oil price shocks on real exchange

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1   https://www.eia.gov/tools/faqs/faq.php?id=709&t=6

2   Times News Network, (2016, May 02). Learning with the Times: India 2nd biggest gold consumer, China tops list The Economic Times. Accessed on 2018, March 20. https://economictimes.indiatimes.com/wealth/invest/learning-with-the-times-india-2nd-biggest-gold-consumer-china-tops-list/articleshow/52073142.cms

rates. The study covers a period till February 2014 with different beginning period for different countries. The importing countries included are South Korea, Japan and India. While the exporting countries include Russia, Mexico, United Kingdom, Brazil, Norway and Canada. It was found that the global demand shocks could significantly impact the exchange rates for both the classified countries. However, oil supply shocks have shown no clear evidence in affecting exchange rate for either of the two classified nations. Markov-Switching model was able to capture significant results for the impact of oil shocks on real exchange rate in both the classified nations. In a study by Tudor and Popescu-Dutaa (2012) done for a sample of 13 economies from 1997 to 2012, feedback relationship between exchange rate and Korean stock market. One-way granger causality existed from exchange rate to Brazilian and Russian stock market. UK's stock market granger caused exchange rate. Ingalhalli, and Reddy (2016) studied the linkages between oil prices, gold prices, exchange rate and Indian stock market from 2005 to 2015. The study was conducted through Granger Causality test. It was found that presence of unidirectional causality from oil prices to gold prices and exchange rate. However, Sensex caused fluctuations in oil prices. Movement between the return and volatility in stock market and gold returns were examined by Choudhry, Hassan and Shabi (2015) during the period from 2000 to 2014. Three stock market indices were employed namely FTSE (UK), NIKKEI (Japan) and S&P (US). Nonlinear bidirectional causality was found prevalent among all nations particularly during crisis period. Incorporation of gold in the portfolio may not provide an attractive alternative for hedging.

The linkages between energy prices, exchange rate and emerging stock markets examined by Basher, Haug and Sadorsky (2012) from 1988 to 2008 and by Fang and You (2014) from 2001–2012. The SVAR model was applied to capture the linkages. It was also found that oil prices rose with prices in emerging stock market in the former study and in the latter one, shocks in prices of oilhave impacted the Indian economy negatively. Supply shocks in oil prices positively affect Russia. Demand shocks display an insignificant impact on Chinese economy. found by employing SVAR model that from the period 2001–2012.

Balcilar, Gupta and Miller (2015) studied the long run relation between crude oil with that of US stock marketfrom the years 1859 to 2013. Cointegrating relationship was established through Johansen Cointegration technique. Further, to capture crisis-recovery phase which occurred in both the time series, two state Markov Regime Switching Behavior technique was adopted. Linear MS-VECM was not found indicating the presence of non-linearity. Regime of high volatility was prevalent before Great Depression and post 1973 OPEC oil price shock. Study also gauged effect of oil shocks on stock prices in both the regimes separately. Negative effect was observed in high volatile regime only. The effect of oil price shocks to the stock market returns has been studied widely.

Cong, Wei, Jiao, and Fan (2008) found that both Chinese and world oil price shocks can explain stock market manufacturing sector's returns. The interest rate and oil shocks are relatively less vital for stock returns in China for the time period from 1996 to 2007 using VAR model. Diaz, Molero, and Perez de Gracia (2016) investigated the fluctuations in oil prices and G-7 stock market returns' relationship during 1970 to 2014. They observed the period from 1986 could better capture the volatility in both the variables. Thus the period of study was divided into two parts. VAR model was used in the study with economic activity and rate of interest as additional two variables. It was found that the fluctuation in oil prices lead to a decrease in stock market returns. Stock markets are more affected by the world oil prices as compared to oil prices quoted in terms of domestic currency.

Study done by Park and Ratti (2008) from 1986 to 2005 with monthly data applied to real world oil prices and national real oil prices on U.S. and 13 European nations including Belgium, Finland, Austria, Greece, Norway, Spain, Italy, U.K., France, Netherlands, Germany, Denmark and Sweden. Using VAR model it was found that oil exporting country like Norway experienced positive returns on stock with rise in oil prices. But for rest of European nations, oil price volatility negatively affected stock returns. Shocks in oil prices contributed significantly in stock return volatility in most nations along with U.S. Both rate of interest and oil prices are strongly linked in US and most European nations. Oil importers exhibited negligible asymmetric effect of both positive and negative shocks in oil on returns of stock market. Malik and Hammoudeh (2007) investigated mechanism of shock and volatility spillover in stock markets of US, Saudi Arabia, Bahrain and Kuwait and crude oil market over the period from 1994 to 2001 using GARCH-BEKK model. It was found that oil market was dominant in passing volatility in most of Gulf markets except for Saudi Arabia where the case was just opposite. Mensi, Beljid, Boubaker and Managi (2013) examined the spillover in volatility between gold price, beverages price, crude oil price, wheat price and S&P 500 during 2000 to 2011 using daily closing figures. Multivariate- GARCH technique was employed in the study. Stock market and prices of oil display a significant volatility transmission. Commodities are important source of diversifying the stock risk associated with portfolio. The combination of long wheat and short Stock prices was most economical hedge. Olson, Vivian, and Wohar (2014) tried to analyze the linkage between energy (energy index

given by Goldman Sach) and stock market (S&P 500) from 1st January, 1985 to 24th April, 2013. The study was conducted using VAR and multivariate BEKK-GARCH model through impulse response function. Stock market returns could weakly explain shocks in energy index. Energy cannot be used as a reliable hedging tool for minimizing risk. Caporale, Menla Ali and Spagnolo (2015) performed a disaggregated analysis of volatility in oil prices on Chinese stock prices over a period from 1997 to 2014. Sectors like Consumer goods, oil and gas, Consumer services, Utilities, Telecommunications, Financial, Technologies, Basic Materials, Healthcare and Industrials. These stock returns were affected positively by volatility in oil prices in period of demand shocks examined through VAR-GARCH (Mean model). Exceptions were observed in Oil and gas, Financials and Consumer service sectors. While the supply shocks had opposite impact. Precautionary shocks did not have non-significant impact. Bouri, Chen, Lien, and Lv (2017) global oil prices and its impact on Chinese stock market was investigated for the period from 2005 to 2013 using CCF test. The results exhibited the Base Materials, Financials, Gas and Energy sectors were majorly affected by global shocks in prices of oil. Ewing and Malik (2016) felt the need to account the volatility dynamics in presence of structural breaks which has the potential to cause significant changes in characteristics of time series data. Results without checking for structural changes could produce a misleading result. Thus, in the present study on oil prices and US stock market, the volatility concerns using univariate and bivariate GARCH model are adjusted through incorporating structural breaks. The time period used in the study was from 1st July, 1996 to 30th June, 2013.The study found significant volatility spillover, in the presence of structural breaks, between oil and US stock prices. Moreover, the importance of model selection in favor of structural breaks was highlighted in designing optimal portfolio weights and dynamic hedge ratios for diluting the risk in the optimal portfolio. Yaya, Tumala and Udomboso (2016) were interested in analyzing the persistence in volatility and presence of returns spillover in the two asset class: oil and gold over a period from 1986 to 2015. The study period was bifurcated in two periods to delve into the effect of onset of financial crisis marked by February 2008. The CCC model was used to show that bidirectional returns spillover present in pre-crisis was transformed to unidirectional spillover from gold to oil market in the post- crisis period. Further the optimum hedge ratio estimates confirmed the fact that lesser volatile asset class should have maximum weights in the portfolio for minimizing risk favouring grater investments in gold. Singhaland Ghosh (2016) tried to investigate the association between crude oil and stock market in India for both, the economy as a whole and then

at sector level. Financial, Automotive, Energy, Metal, Gas and Power, Industrial and Oil were sector level variables. For aggregate analysis BSE-Sensex was used. The study was conducted for a period from 2006 to 2015. The entire period was divided into three phases. The symmetric and asymmetric aspects of correlations were studied using DCC-GARCH models. The transmission of volatility was seen in finance, auto and power. Sectoral stock indices on fluctuations in prices of oil show the presence of different time varying parameters. Jainand Biswal (2016) in their study to examine relationship among oil and gold prices, exchange rate and stock market from 2006 to 2015 employed DCC-GARCH model and nonlinear granger causality test. It was found that oil and gold prices fall caused the INR and Sensex to fall. Turhan, Sensoy, and Hacihasanoglu (2014) investigated the time varying correlation between exchange rates and prices of oil for G-20 nations. Strong negative correlation was found between the pair of variables from 2000 to 2013 using DCC method. Such nature of correlation is usefulfor diversification of risk. The shift to negative correlation was observed in 2003 and 2008 quoting Iraq invasion by US and global financial meltdown respectively. Sui and Sun (2015) studied the linkages between foreign exchange rates, interest rate differentials, domestic stock returns and returns on S&P 500 over a period from 2005–2014 in BRICS nations. In short run strong evidence of spillover is observed from exchange rate to stock return. A shock in S&P 500 affects China, South Africa and Brazil. The study was conducted using VAR, Variance Decomposition and ARDL cointegration technique.

The review is presented in three sections. The seminal studies from market independence to integration has been discussed in the first section along with importance of volatility in market integration. The second section was focussing on studies of cross market linkages and causal relation through SVAR, Granger Causality, Johansen Cointegration and Markov Switching Models. In the Final section, the returns and volatility spillover studies was presented using multi-variate techniques like VAR, GARCH-BEKK, DCC models.

MATERIALS AND METHODS

The study has been conducted using secondary data from April 01, 2014 to March 28, 2018.

Tab. I shows the stock index, exchange rate, gold prices and crude oil price which constitute the sample for our study along with their sources. The natural logarithm of all variables is taken. The statistical computations are performed in R.

We have used Augmented Dickey Fuller and Phillip Perron Test to check the stationarity of the series of four variables used in the study.

I: *List of Variables*

SL. NO.	Variables	Symbol	Source
1	West Texas Intermediate Crude Oil	WTI Crude	quandl.com
2	Gold Spot Prices USD/troy ounce	Gold	World Gold Council
3	USD vs. INR Exchange rate	USD/INR	rbi.org.in
4	Nifty 50 Index	Nifty 50	nseindia.com

We apply Multivariate Simultaneous Generalized ARCH formerly proposed by (Engle and Kroner, 1995) and later on reformed by (Ling and McAleer, 2003).

VARMA-GARCH model is applied to estimate returns and volatility spillover across the markets under consideration. The VAR model is expressed as:

$$r_{it} = v_{i0} + \sum_{j=1}^{4} v_{ij} r_{jt-1} + \varepsilon_{it}, \, \varepsilon_{it} \,|\, \varphi_{t-1} \sim N(0, h_{it}), \, i = 1, 2, 3, 4; \quad (1)$$

$$\varepsilon_{it} = \mu_{it} \sqrt{h_{it}}, \, \mu_{it} \sim N(0, 1); \quad (2)$$

$$h_{it} = K_{i0} + \sum_{j=1}^{4} \alpha_{ij} \varepsilon_{jt-1}^2 + \sum_{j=1}^{4} \beta_{ij} h_{jt-1}. \quad (3)$$

The basic GARCH-BEKK model is then specified in the following manner:

$$H_t = C'C + B'H_{t-j} B + A' \varepsilon_{t-i} \varepsilon'_{t-i} A, \quad (4)$$

r_{it} is the return vector of four series. ε_{it} is the residuals with conditional variance h_{it}. φ_{t-1} is the lagged market information set. Equation (9) shows the GARCH (1, 1) model in VARMA framework. The α coefficients specifies the effect of innovations from market i to j. While β shows the volatility transmission from i to j.

To estimate the time-varying conditional correlation among the variables we use Multivariate DCC-GARCH model. The model has taken care of the issue of dimensionality i.e. with the inclusion of more variables in the model, the parameters estimated increases linearly. Further to investigate the effect of asymmetric correlation along with asymmetric volatility two models has been introduced: DCC-GJR-GARCH model and ADCC-GJR-GARCH model.

The mean equation for the DCC-GARCH model given by Engle, Robert F and Sheppard (2001):

$$r_t = v_t + \lambda 1 r_{t-1} + \varepsilon_t, \quad (5)$$

where r_t represents return of Nifty, Gold prices, WTI Crude Oil prices and Exchange-rate over t periods. Thus r_t is 4X1 vector of variable's return. ε_t represents $(\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t} ..., \varepsilon_{nt})$ where $\varepsilon_t \,|\, \varphi_{t-1} \sim N(0, h_t)$. v_t is constant mean vector conditioned on φ_{t-1} information set. h_t is matrix of conditional variance – covariance. $\lambda 1$ are the lag one autoregressive coefficients of r_t. For estimating DCC model, two step process has to be followed. GARCH coefficients are estimated in

first step. Then the correlations are obtained in the final step. h_t can further be written as:

$$h_t = d_t r_t d_t, \quad (6)$$

where, $d_t = diag(c_{it}^{\frac{1}{2}})$: represents matrix of standard deviation. r_t is matrix representing conditional correlation. c_{it} follows the GARCH(1,1) specification on conditional volatility.

For DCC-GARCH univariate GARCH(1,1) specification is used.

$$c_{it} = v + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i c_{i,t-1}. \quad (7)$$

For DCC-GARCH-GJR and ADCC-GARCH univariate GARCH (1,1) in GJR is followed.

$$c_{it} = v + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i c_{i,t-1} + \delta_i \{(\min \varepsilon_{i,t-1}, 0)\}^2. \quad (8)$$

The estimator for correlation is denoted as

$$\rho_{ij,t} = q_{ij,t}/(q_{ii,t} q_{jj,t})^{\frac{1}{2}}$$

and r_t can written in terms of $P_t = q_{it,t}$ as follows:

$$r_t = (diag(P_t))^{-\frac{1}{2}} P_t (diag(P_t))^{-\frac{1}{2}}. \quad (9)$$

$$P_t = (1 - A - B)p + A\varepsilon_{t-1}\varepsilon_{t-1}^T + BP_{t-1}$$

and is square (nXn) symmetric matrix.

$$p = Cov[\varepsilon_t \varepsilon_t^T] = E[\varepsilon_t \varepsilon_t^T]$$

is unconditional standard error covariance matrix.

$$p = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_t \varepsilon_t^T \text{ and } A + B < 1.$$

However, with ADCC proposed by Cappiello, Engle, and Sheppard (2006) process P_t is presented as:

$$P_t = p + A * (\varepsilon_{t-1}\varepsilon_{t-1}^T - p) + B * (P_{t-1} - p) + C * (u_{t-1}u_{t-1}^T - U). \quad (10)$$

A, B, C are positive symmetric square matrix. * is Hadamard product. $u_t = \min(\varepsilon_t, 0)$, and $U = E[u_t u_t^T]$

$$U = \frac{1}{T} \sum_{t=1}^{T} u_t u_t^T. \quad (11)$$

The tests can be conducted to estimate the models using log-likelihood function.

If q represents the coefficients in d_t and p represents the coefficients in r_t, the function can be expressed as:

$$L(q, p) = L_v q + L_c p,$$ (12)

where

$$L_v(q = -\frac{1}{2}\sum_t (\log(2\pi) + 2\ln|d_t| + r_t d_t^{-2} r_t); \text{ volatility term and}$$

$$L_c(p) = -\frac{1}{2}\sum_t (-\varepsilon_t^T \varepsilon_t + \ln|r_t| + \varepsilon_t^T r_t^{-1}\varepsilon_t); \text{ correlation term.}$$

The objective is to maximize the log-likelihood function.

Objectives of the Study

Objectives are presented as under:
1. To determine the return and volatility spillovers among the variables.
2. To determine the time-varying conditional correlations among the variables.

RESULTS AND DISCUSSION

Descriptive Statistics

Tab. II shows the summary of Nifty 50 Index, USD/INR Exchange Rate and WTI Crude Oil and Gold.

Nifty 50 gives highest mean return followed by Gold and USD/INR Exchange Rate. WTI Crude gives the lowest mean return. USD/INR Exchange Rate is least volatile as its standard deviation is 3.81% which is lowest of all the other two variables. While WTI Crude Oil is the most volatile with 29.68% standard deviation. Here Nifty 50 Index is negatively skewed while other three i.e. Gold, USD/INR and WTI Crude Oil are positively skewed. The skewness of USD/INR Exchange rate and Gold are negative while the other two variables have positive skewness. Kurtosis is positive only for WTI Crude oil. The skewness reflects presence of fat-tails and non –normality in the data. Jarque-Bera test shows that all the variables are not normally distributed reaffirmed by the findings of Mensi, Beljid, Boubaker and Managi (2013). Further, we test the presence of heteroscedasticity for each series with ARCH test and serial correlation with Ljung-Box test. It was found that all series had heteroscedasticity and serial correlation issues as the null hypothesis of these tests gets rejected at 1% significance level.

Unconditional Correlation Matrix

Tab. III displays the correlation matrix of all the variables along with their p-values.

It can be inferred that the correlation of USD/INRwith Nifty 50 is positive and significant as the p-value is less than 5% and null hypothesis of no significant correlation gets rejected. Also the correlation of Nifty 50 with WTI Crude Oil is negative and significant. And the correlation of Nifty 50 with Gold is positive and is significant. The correlation of WTI Crude Oil and Gold with USD/INR is negative and significant. The study by Turhan, Sensoy and Hacihasanoglu (2014) also found the same relation. And the correlation of WTI Crude Oil and Gold is positive and significant as found by Zhang and Wei (2010). The correlations results need to be reaffirmed through sophisticated econometric tests.

II: *Characteristics of Distributions of the Variables*

	LNIF	LER	LWC	LGO
Mean	9.053	4.1667	3.9879	7.1165
Median	9.0358	4.1677	3.9144	7.1261
Maximum	9.3174	4.2309	4.6817	7.218
Minimum	8.8028	4.0678	3.2654	6.956
Variance	0.0121	0.0015	0.0881	0.0036
Std. Dev.	0.11	0.0381	0.2968	0.0596
Skewness	0.3473	-0.4867	0.7961	-0.6401
Kurtosis	-0.433	-0.6185	0.3848	-0.2649
Jarque-Bera	27.334	54.254	109.46	69.715
P-Value	(0.00)*	(0.00)*	(0.00)*	(0.00)*
Total Sample	979	979	979	979
Arch	9143.2	9333.14	9295.32	8609.37
P-Value	(0.00)*	(0.00)*	(0.00)*	(0.00)*
LB(12)	10833	11095	11040	10073
P-Value	(0.00)*	(0.00)*	(0.00)*	(0.00)*

Parentheses ( ) shows the p-values of the correlation coefficients of the variables respectively
*Shows significance at 1% level

III: *Correlation & P-values of the Variables*

	LNIF	LER	LWC	LGO
LNIF	1			
	(NA)			
LER	0.09	1		
	(0.0044)*	(NA)		
LWC	-0.12	-0.81	1	
	(0.0002)*	(0.00)*	(NA)	
LGO	0.36	-0.21	0.37	1
	(0.00)*	(0.00)*	(0.00)*	(NA)

Parentheses ( ) shows the p-values of the correlation coefficients of the variables respectively
*Shows significance at 1% level

Unit Root Tests

In order to prevent existence of any spurious relationship among the variables that can potentially distort the results, it is necessary to ensure that the variables are stationary. This is a necessary property of time series to enable forecasting of time series data. Thus two test of unit root (non stationarity) was employed: Augmented Dickey Fuller test and Phillip Perron Test.

Thus, the Tab. IV shows that all the variables suffer from unit root in the time series. Thus the data needs to be transformed to create first order differenced series of all the respective variables. The first order series exhibit stationarity for all the variables considered for study. Thus it can be concluded that each variable under study are integrated in first order i.e. I(1). Results are supporting findings of Ingalhalli and Reddy (2016), Mensi, Beljid, Boubaker and Managi (2013).

VARMA-BEKK-GARCH Model

The Tab. Va represents the estimated VAR-BEKK-GARCH parameters. The rows represent markets *j*

and columns represents markets *i*. Thus, the transmission takes places from *i* to *j*. In the returns or mean specifications, the current returns of Nifty are significantly influenced by one period lag of Nifty in the first row and first column (expressed as 1,1 henceforth). Further, a bidirectional returns transmission takes places between Nifty and WTI pair i.e. the past returns of WTI can predict future Nifty returns through a significant parameter (1,3) and past returns of Nifty can predict future WTI returns (3,1) unlike Ghosh and Kanjilal (2016) who found evidence for unidirectional spillover. However, the Nifty returns could strongly predict the WTI returns due to higher coefficient value. This signifies that India's consumption demand for oil can boost its prices. Such results was also found by Basher, Haug and Sadorsky (2012). Similarly, bidirectional returns transmission takes place between Gold and WTI returns but the past Gold returns can strongly predict future WTI returns (3,2) as was found by Yaya, Tumala and Udomboso (2016). The past Nifty returns can negatively influence future Exchange rate returns (4,1). This means that when Indian market booms, then rupee

IV: *ADF and Phillip Perron Unit Root Tests*

Variables	ADF (with intercept and no trend)		Phillip Perron (with intercept and no trend)		Level of integration
	Level	First Difference	Level	First Difference	
LNIF	-2.1574	-10.287	-9.1743	-838.29	I (1)
	(0.5117)	(0.01)*	(0.598)	(0.01)*	
LER	-1.6144	-9.4411	-5.1425	-924.42	I (1)
	(0.7415)	(0.01)*	(0.8229)	(0.01)*	
LWC	-1.5107	-9.9994	-3.6298	-1027.2	I (1)
	(0.7854)	(0.01)*	(0.9059)	(0.01)*	
LGO	-2.6338	-10.455	-12.599	-1017.7	I (1)
	(0.31)	(0.01)*	(0.4069)	(0.01)*	

Parentheses ( ) shows the p-values of the correlation coefficients of the variables respectively
*Shows significance at 5% level

Va: *VARMA-BEKK-GARCH Results*

Mean Equations				
	LNIF	LGO	LWC	LER
LNIF	0.072618	0.03024933	0.012613	-0.05034
	(0.0233)**	(0.1788)	(0.0022)*	(0.2428)
LGO	0.01085	0.00278	0.015573	-0.07293
	(0.8102)	(0.9303)	(0.003)*	(0.1945)
LWC	0.45162	0.26317	-0.04123	-0.03596
	(0.0033)*	(0.0048)*	(0.1816)	(0.8613)
LER	-0.10094	-0.07598	-0.014212	-0.04764
	(0.00002)*	(0.00003)*	(0.1858)	(0.3512)
Variance Equation				
ARCH terms				
	LNIF	LGO	LWC	LER
LNIF	-0.02026	-0.1908	-0.01235	-0.00955
	(0.552)	(0.00172)*	(0.9439)	(0.91572)
LGO	0.014415	-0.014415	-0.4282	-0.03399
	(0.01702)*	(0.63764)	(0.0138)*	(0.2428)
LWC	0.009945	0.014256	0.300146	-0.00361
	(0.1819)	(0.111)	(0.00)*	(0.4763)
LER	-0.12699	-0.18876	0.043938	0.246746
	(0.14907)	(0.0085)*	(0.8031)	(0.00124)*
GARCH terms				
	LNIF	LGO	LWC	LER
LNIF	1.003935	-0.44024	-0.486836	-0.05971
	(0.00)*	(0.00)*	(0.0036)*	(0.1729)
LGO	0.279636	0.86969	0.00358	-0.05856
	(0.00)*	(0.00)*	(0.9813)	(0.1941)
LWC	0.004454	-0.00264	0.958293	0.001735
	(0.271)	(0.6837)	(0.00)*	(0.458)
LER	0.19699	0.066612	-0.302558	0.691477
	(0.04804)**	(0.7043)	(0.2705)	(0.00024)*

( ) parentheses shows P-values at significance at 1% and 5% level denoted by * and ** respectively
Log likelihood is 20225.9786

Vb: *Diagnostics of BEKK-GARCH Model*

	LNIF	LER	LWC	LGO
LB (12)	18.63843	37.36711	10.36356	17.1166
P-Value	(0.545)	(0.0106)	(0.9611)	(0.6454)
ML	22.19627	9.99584	10.58129	18.0089
P-Value	(0.3299)	(0.9682)	(0.9563)	(0.5868)

appreciates by attracting Investments due to which the dollar-rupee exchange rate decreases as is also found by Ingalhalli and Reddy (2016). Finally, the past Gold returns can negatively influence future Exchange rate (4, 2). This means that if the Gold prices falls, it makes the Gold cheaper and stimulate

the demand for Gold in India. Thus, raising the Gold imports leads to domestic currency depreciation and US dollar appreciation. No spillover was found between Exchange rate and WTI unlike Wang and Wu (2012), who found evidence for unidirectional spillover.

In the volatility specification, the ARCH parameters are mostly sifnificant. The past squared errors in WTI and Exchange rate increases the conditional variances of their own returns in the future periods through significant positive parameters (3,3) and (4,4). Further, past innovations in WTI have significant influnece in next period's volatility of Gold (2,3) and past innovations in Gold negatively influences future volatility of Exchange rate (4,2). Shocks in Gold market negatively effects future conditional volatility of Nifty (1,2) but past innovations in Nifty positively effects future volatility of Gold (2,1). This means that uncertainty in the relationship of Gold and Nifty prevails.

The GARCH parameters are also mostly significant. The lagged variances stimulate the future variances of their own returns. The own spillover effects are stronger than the cross spillover effect. In comparison to ARCH terms, the GARCH terms are highly peristant. However, it is lowest for Exchange rate. The negative volatility transmission takes places from Gold to Nifty i.e. the lagged varainces of Gold negatively influences the future variances of Nifty returns (1,2). Similar patterns is observable between Nifty and WTI returns series (1,3). This means, that if the volatility in Gold and Crude market increases/decreases, it leads to reduction/ surge in Nifty volatility. Investors then consider investments in these assets simultaneously. Further, lagged variances in Nifty returns causes variances in Gold (2,1) and Exchange rate (4,1) returns in the future period.

Tab. Vb shows thediagnostic results of VAR-BEKK-GARCH model suggests that the Ljung Box test statistics for 12 lags for all series except Exchange rate are free from autocorrelation but the results with squared residuals tells that none of the series have serial correlation problem.

DCC-GARCH Model

Tab. VIa shows the DCC-GARCH results for the four variables Nifty 50, Gold, WTI Crude and USD/INR exchange rate. The results of DCC parameters A and B shows significance. That means the variables exhibit time varying co-movement. Also the conditional correlation exhibits a high level of persistence through the summation of A and B. The coefficient A + B is 0.942592, which fulfils the non- negativity criteria for DCC model to hold good. A reflects significant short run persistence and B reflect significant long run persistence of shocks on time-varying conditional correlation. The coefficients of ARCH term are positive but insignificant but GARCH term coefficients are positive and significant implying that conditional volatility of all the variables are influenced by their yesterday's variance rather than their yesterday's squared residuals. The variables exhibit high persistence in volatility which is denoted by $\alpha + \beta$ is adequately captured by GARCH (1,1) process.

The Tab. VIb shows the DCC-GARCH-GJR results, where δ term shows the asymmetric effect in volatility in variable's return. Only the Nifty 50 displays a positive significant asymmetric effect in the conditional volatility which highlights the fact that Nifty 50 responds differently to negative and positive shocks in its returns. None of the variables exhibit significant asymmetric shocks. The ARCH terms are not significant. But GARCH terms are

VIa: *DCC-GARCH estimation results*

	Returns-Equations		Variance-Equations			
	μ	λ1	φ	α	B	α+β
Nifty	0.000062	0.115025	0	0.051547	0.933824	0.985371
	(0.136)	(0.00034)*	(0.9935)	(0.6089)	(0.0000)*	
Gold	0.000001	0.056772	0	0.029023	0.967122	0.996145
	(0.9889)	(0.1265)	(0.9968)	(0.1914)	(0.0000)*	
WTI Crude	-0.000004	-0.022448	0	0.111423	0.885988	0.997411
	(0.98728)	(0.5189)	(0.98079)	(0.82201)	(0.044189)*	
Exchange Rate	0.000024	0.019095	0	0.075712	0.908101	0.983813
	(0.3184)	(0.6516)	(0.9888)	(0.24577)	(0.000)*	
Multivariate DCC equations						
	coefficients		t-value		p-value	
A	0.019257		[3.059814]		(0.002215)*	
B	0.923335		[44.908418]		(0.0000)*	

VIb: *DCC -GARCH-GJR estimation results*

Returns	Returns-Equations		Variance-Equations				
	ν	λ1	φ	α	β	Δ	α+β
LNIF	0.000063	0.100575	0	0.018632	0.94046	0.06536	0.95909
	(0.043)***	(0.0014)*	(0.9875)	(0.5063)	(0.0000)*	(0.00207)*	
LGO	0	0.020351	0	0.041963	0.953591	-0.10524	0.99555
	(0.996)	(0.8072)	(0.9987)	(0.9023)	(0.00036)*	(0.951)	
LWC	-0.00009	0.024838	0	0.034331	0.90309	0.117631	0.93742
	(0.6382)	(0.4845)	(0.9625)	(0.818)	(0.000)*	(0.208)	
LER	0.000018	0.01298	0	0.065623	0.933246	-0.0255	0.99887
	(0.446)	(0.7559)	(0.9894)	(0.1162)	(0.000)*	(0.2866)	

DCC-GARCH-GJR model				ADCC-GARCH model		
Multivariate DCC equations				Multivariate DCC equations		
	coefficients	t-value	p-value		coefficients	t-value	p-value
A	0.019171	[3.4176]	(0.0006)*	A	0.019243	[3.43019]	(0.0006)*
B	0.931273	[52.875]	(0.000)*	B	0.929757	[50.1557]	(0.000)*
				C	0.00155	[0.36376]	(0.716)

Parentheses ( ) shows the p-values of the correlation coefficients of the variables respectively
*, ** and *** shows significance at 1%, 5% and 10% level respectively

VIc: *Model Selection Criteria*

	Akaike Information Criteria	Hannan-Quinn Information Criteria	Log-likelihood
DCC-GARCH-GJR model	-41.225	-41.164	20170.26
DCC-GARCH model	-41.194	-41.141	20151.29

VId: *Diagnostics of Selected GARCH Model*

	LNIF	LGO	LWC	LER
LB (12)	12.034	12.834	4.066	7.7121
P-Value	(0.4429)	(0.3812)	(0.9822)	(0.1728)
ARCH	0.98135	36.5693	88.738	0.123198
P-Value	(0.3218)	(0.0633)	(0.000)	(0.725)

significant in all the variables with high level of persistence in conditional volatility.

Finally a comparison is made between the Asymmetric DCC model and DCC model with GJR specification to decide whether the ADCC model can capture the asymmetric nature of joint conditional correlation among the variables. But since the C parameter is insignificant that captures the asymmetry in dynamic conditional correlation, therefore we drop the possibility of determining asymmetric conditional correlation through ADCC model. The DCC-GARCH-GJR model parameters A and B are significant and display high level of persistence in conditional correlation both short and long run. Their sum is also less than unity.

However on the basis of Tab. VIc we shall decide which of the two will better capture the time varying conditional correlation. The AIC and HQ criteria has lower values in favour of DCC-GARCH-GJR model. Also the log-likelihood estimate shows that the highest value in DCC-GARCH-GJR model indicating it to be a better fit out of the three models for our study.

The Tab. VId shows the diagnostics results of DCC-GACRH-GJR model. It was found that all the models were free from serial correlation from Ljung-Box test on the residuals of each uni-variate series. The ARCH effect was absent for all series except for WTI Crude.

VII: *DCC -GARCH-GJR estimation results*

Returns	Returns-Equations		Variance-Equations				
	ν	λ1	φ	α	β	δ	α+β
LIVIX	0.00022	0.02578	0	0.12506	0.83487	-0.11937	0.95909
	(0.6823)	(0.5169)	(0.012)**	(0.063)***	(0.0000)*	(0.066)***	
LGO	0	0.013	0	0.04233	0.95294	-0.0099	0.99555
	(0.9984)	(0.9546)	(0.9995)	(0.9689)	(0.2658)	(0.984)	
LBC	-0.00019	0.06515	0	0.01719	0.93432	0.09496	0.93742
	(0.3775)	(0.1083)	(0.9835)	(0.7977)	(0.000)*	(0.0164)**	
LER	0.000018	0.01298	0	0.06746	0.93401	-0.0306	0.99887
	(0.446)	(0.7559)	(0.989)	(0.117)	(0.000)*	(0.2145)	

Multivariate DCC equations			
	coefficients	t-value	p-value
A	0.00772	[2.58237]	(0.00981)*
B	0.93657	[39.98953]	(0.000)*

Parentheses ( ) shows the p-values of the correlation coefficients of the variables respectively
*, ** and *** shows significance at 1%, 5% and 10% level respectively

Robustness

For the robustness check, we repeat our analysis on dynamic correlation estimates. We adopt India VIX in place of Nifty 50 and Brent Crude in place of WTI crude oil in daily frequencies. India VIX was chosen due to its negative correlation with Nifty 50.On comparison of ADCC-GARCH and GARCH models, it was found that DCC-GARCH-GJR model was found to be apt with highest log likelihood and minimum AIC. The DCC parameters are significant and less than unity i.e. the DCC model is mean-reverting. The results of the new DCC-GARCH-GJR (M1) model presented in Tab. VII are not significantly different from the former DCC-GARCH-GJR (M0) model. Further, the time varying of the two models are presented in the following section.

Time-Varying Conditional Correlation

The figures from 1 to 6 shows conditional correlation between the different pair of variables over time. We can observe that all the pairs exhibit fluctuations in their correlations over time that has been obtained form A and B parameters of the DCC-GARCH-GJR models fit (M0 and M1). The results obtained from dynamic conditional correlation gives the true nature of correlation that exists among the pair of variables with time. These results when compared with unconditional correlation can reveal the true scenario that prevails over time.
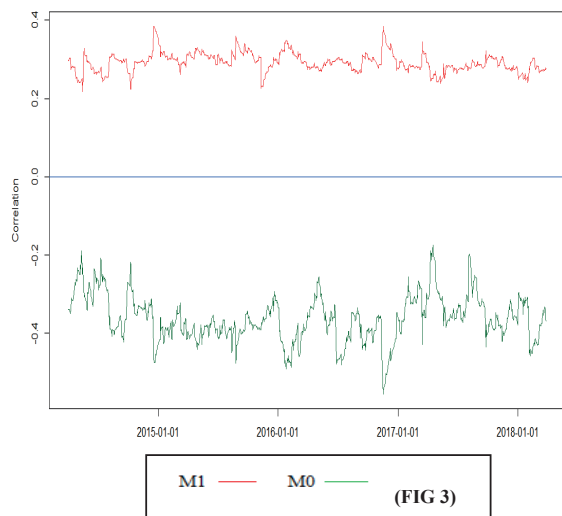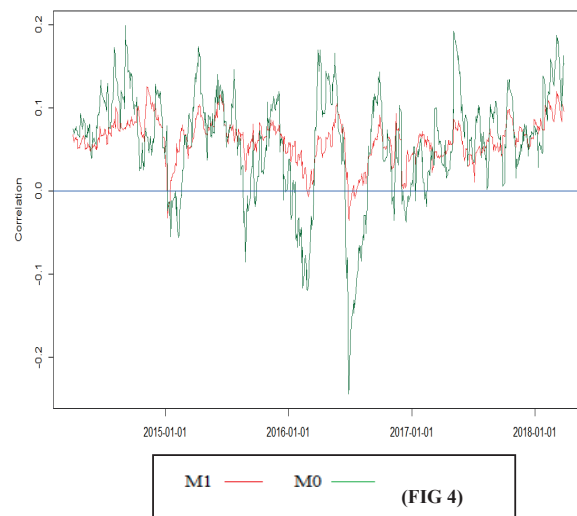
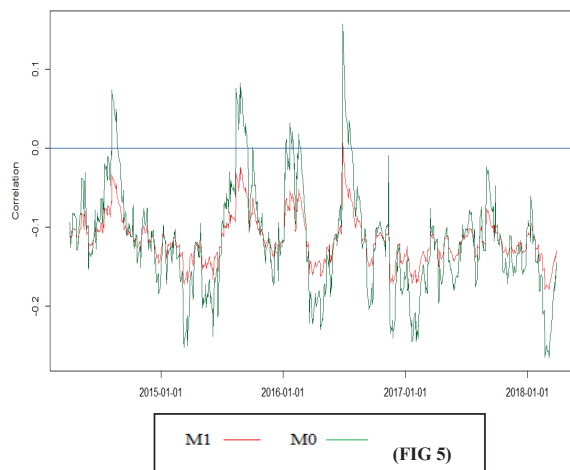

1: *DCC between Nifty 50/IVIX & GOLD*
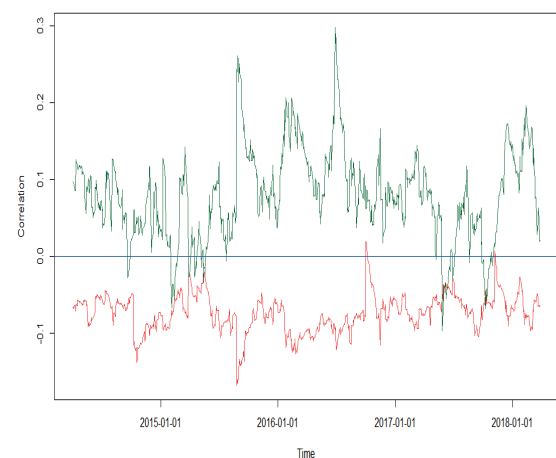
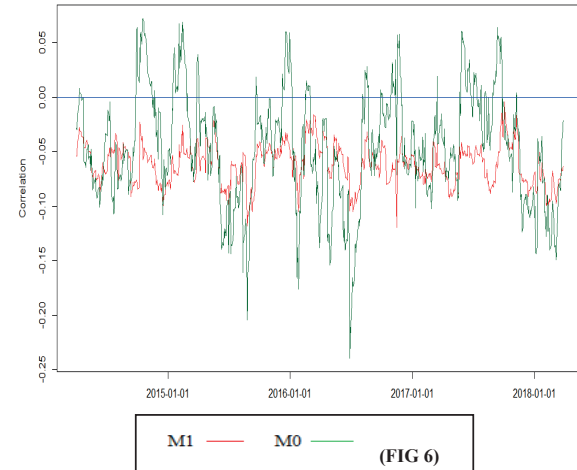2: *DCC between Nifty 50/IVIX & Brent Crude*

3: *DCC between Nifty 50/IVIX & Exchange Rate*

4: *DCC between Gold & WTI/Brent*

5: *DCC between GOLD & Exchange Rate*

6: *DCC between WTI/Brent & Exchange Rate*

In Fig. 1, contemporaneous correlation was found between Nifty 50 and Gold. Overtime, the correlation of this pair was negative as is found in literature. Gold is considered as a safe investment option when stock markets tremors. So the Nifty 50 was down from start of June 2015 as it experienced trembles from China's stock market. And as the global scenario worsened, Nifty 50 performed badly and people started withdrawing money from stock to invest in safer investment such as Gold. Thus, in the middle of 2015 the correlation between the two was negative. Also during early 2016, with the event of "Brexit", the global market became jittery. The demand for gold investment increased worldwide which lead to usurious prices of international Gold. Due to which the strong negative correlation could be observed. In Nov 2016, two major events hit the Nifty 50 high. These were demonetisation of Indian Currency notes and President Donald Trump's election in US. This has also contributed to strong negative correlation. And finally, global market slowdown and expectation of India's growth as predicted by International Financial Institutions has resulted in rallying of Nifty 50. So lesser investment in Gold was desirable which has again contributed to such correlation as is also supported by Jain and Biswal (2016) in their study

Fig. 2 reflects the contemporaneous correlation between Nifty 50 and WTI Crude oil. The relationship of Nifty 50 with that of WTI Crude is interesting as India is an emerging nation with high requirement of Crude Oil. Literature says that when prices of Crude Oil increase the Stock market performs badly implying a negative correlation between the two. However, with the global slowdown, rise in demand for crude has been witnessed as stimulating factor for growth of Indian economy. Such expectations further caused stock market's upturn. Following this argument, a positive correlation can be seen. However, recently the International Crude Oil price has been rising and Nifty 50 has been falling. The India VIX in M1 has shown a negative time-varying correlation indicating incorporating India VIX in the portfolio

will result in suitable hedging strategies against the volatile oil prices.

Fig. 3 reflects the contemporaneous correlation between Nifty 50/India VIX and USD/INR exchange rate. With the rise in the index value, the investors get attracted to investment in stock market particularly the investments by FII's boosts the demand for rupees leading to depreciation of USD/INR exchange rate. Ideally, the correlation of this pair is negative. This nature can be seen in the figure. But the India VIX and Exchange rate showed positive correlation, indicating that whenever, Indian market become jittery, it gets immediately reflected in the investments by foreigners and thereby in the Exchange rates.

Fig. 4 depicts the contemporaneous correlation between Gold and WTI Crude oil. Overtime the dynamic correlation between the two is positive as is observed by Arfaoui and Rejeb (2017). This relationship follows from the literature which states that whenever due to high oil prices, companies are hit by inflation which further raises the demand for safer asset i.e. gold which ultimately increases the price. This co-movement is observed among the two assets in most of the time period except for during 2016. 2016 was a period when due to gold demand was high due to China's stock market crash and other commodity prices plummeted particularly oil due to alternatives available and China's fall in manufacturing sector lowering the demand of oil.

Figs. 5 and 6 depicts the contemporaneous correlation between WTI Crude oil and USD/INR pair and Gold and USD/INR pair. We observe strong negative correlation between these pairs throughout the sample period. This relationship is followed from the literature that when dollar depreciates, commodities being quoted in US dollar become cheaper. This raises the price of these commodities, thus showing negative correlation between them also observed from Jain and Biswal (2016).

CONCLUSION

The study exhibits USD/INR exchange rate is least volatile and WTI crude oil is the most volatile according to their standard deviation. Unconditional correlation matrix shows that all the variables are significantly correlated. The returns and volatility spillovers were estimated through VARMA-BEKK-GARCH model. Evidences with significant unidirectional and bidirectional returns and volatility spillover coefficients was found. Bidirectional returns spillover was found between Nifty and WTI and WTI and Gold pair. Whereas the bidirectional volatility spillover between Nifty and Gold pair. The GARCH effect was stronger than the ARCH effect. For determining whether the variables are correlated over time, we employed DCC-GARCH-GJR model that appeared to be best model of others. It was found that the model was mean-reverting. And significant conditional correlation was present between the pairs of variables over time.

The asymmetric impact of shocks in covariance is observed between Nifty 50 and all other variables. Over the time period from April 2014 to March 2018, the positive correlation was found between Nifty 50 and WTI crude oil pair and between Gold and WTI Crude oil pair indicating that post crisis of 2008 the correlation of these markets have increased. This increase in correlation was not due to contagion but strengthened market interdependence. While negative correlation was found between Nifty-Gold pair indicating that Gold can be a safe hedge against stock price volatility Choudhry, Hassan and Shabi (2015). Further, negative time varying correlation was found between all variables with Exchange rate.

The results can be used for better portfolio diversification and hedging decisions based on true nature of correlation among the variables. The linkages of Exchange rate with all other variables are crucial for monetary authorities and policy makers. The returns spillover of WTI to Nifty 50 and vice-versa highlights that International Crude oil prices are no longer an exogenous variables unlike (Ghosh and Kanjilal, 2016) effecting Exchange rate and Stock markets. Hence proper strategies are needed to be framed by policy makers to insulate the economy from factors that causes exchange rate volatility.

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