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Interest Rate And Exchange Rate Volatility In India, 2011-2020

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Abstract

In this study, we have empirically investigated the role of interest rate on the volatility of the exchange rate using monthly data starting from January 2011 to January 2020. The conditional standard deviation of the GARCH (1,1) based on the ARIMA (1,1,0) model is used as a proxy for exchange rate volatility. To test the causal effect of the interest rate on the exchange rate volatility, we employed the Granger causality test, Shannon's transfer entropy causality test, and the bootstrap impulse response function. Each test is performed with two separate lag lengths. The results of the study suggest that the interest rate has a positive causal effect on the exchange rate volatility unanimously supported by the Granger causality test and Shannon Transfer Entropy causality test. The IRF revels that a shock in the interest rate positively influences the exchange rate volatility between a lag of two to four months.

Keywords: Granger Causality, Transfer Entropy, Impulse Response Function, GARCH, Exchange rate volatility, Interest rate.

Introduction:

Exchange rate being one of the crucial factors in the free market economy, plays a vital role of an economy's level of international trade. According to FRED[1] Indians' spot exchange rate of rupee against US dollar is 83.39 rupees per us dollar in April, 2024 and 83.11 in January 2024, 82.94 in February, 2024 and 83.02 in March 2024, indicating fluctuating exchange rate. Over the past two decades, the Indian foreign exchange market has gradually liberalized. Since adopting a market-determined exchange rate in 1993, the rupee has experienced several periods of increased volatility, the most recent of which occurred after May 22, 2013, due to concerns about the US Federal Reserve tapering its quantitative easing program (Prakash, 2012). An economy can encounter exchange rate volatility for a number of important reasons. Trade volume may decrease as a result of traders' confusion about the exchange rate caused by the exchange rate's volatility, which also makes import and export more unpredictable. Exchange rate volatility can also effect the foreign direct investment and portfolio investment moreover investors might be cautious about the currency risk, potentially leading to lower capital inflows. For businesses, this uncertainty can impact long-term planning and investment decisions, which could slow economic growth. The ongoing exchange rate volatility can weaken economic stability. It can heighten uncertainty in financial markets, impact asset prices, and potentially cause broader financial instability. More importantly central banks might struggle to manage monetary policy effectively during volatility exchange rate periods. Sudden and unpredictable exchange rate fluctuations can complicate efforts to control inflation and sustain economic stability. The main objective of central bank is to maintain a stable price level, keeping a stable piece of growth along with

[1] Federal Reserve Economic data, URL-https://fred.stlouisfed.org/series/EXINUS

an eye on exchange rate, interest rate has been is an important tool to control the inflation rate and the growth rate stability to the extreme. Numerous recent research that used the framework of monetary models of exchange rate determination have shown that some of the major causes of exchange rate volatility are the money supply, inflation rate, interest rates, and real output growth rate. (Phuc and Duc, 2021; Mpofu, 2021; Xie and Chen, 2018). According to the international Fisher effect theory, disparities in interest rates between two countries have an impact on capital transfers between them and play a decisive role in exchange rate volatility. Investors typically shift their investments to countries offering higher interest rates to maximize their returns. This capital movement can result in fluctuations in exchange rates. Keeping these points in minds it is inevitable to ask whether a country should increase its interest rates compared to another, expecting a strengthen currency as investors chase greater yields, thereby boosting demand for that currency. A rise in interest rates can increase exchange rate volatility by impacting the movement of capital, initiating the unwinding of carry trades, shaping market anticipations, prompting responses from central banks, and changing risk perceptions within financial markets. However, raising interest rates can also potentially restrict the exchange rate volatility by drawing in foreign investment, tempering speculative behavior, enhancing the credibility of central banks, diminishing carry trade practices, and managing inflation expectations. However, the precise direction of the exchange rate's impact on volatility varies across nations due to various economic and market factors, making it subject to empirical validation. Thus, it would be worthwhile to investigate the relationship between interest rates and exchange rate volatility empirically.

Literature Review:

The factor effecting volatility of exchange rate has been an important question among the macroeconomist over last few decades. However, the research in this particular area is quite narrower especially in the Indian case. Some of the works are highlighted here. Behera *et al.*, (2008) empirically investigated the connection, within the framework of the Indian foreign currency market, between central bank action and exchange rate behavior. The authors in this paper employed GARCH (1,1) on the monthly data ranging from June 1995 to December 2005 on bilateral exchange rate of rupee against dollar, instead of only changing the direction of the rupee's value relative to the US dollar, they noted that the central bank's intervention in the treasury bill rate has been extremely beneficial in lowering the volatility of the exchange rate. The issue of whether Inflation Targeting (IT) adoption lowered Indonesia's currency rate volatility was investigated by Kuncoro (2020). The Autor in this paper used Johansen co-integration tests and an Autoregressive Distributed Lag (ARDL) model on monthly data from July 2005 to July 2016. The author discovered that the foreign exchange intervention and interest rate policy were ineffective in lowering Indonesia's exchange rate volatility. Ansari et al. (2011) conducted an empirical analysis to determine how Malaysia's currency rate volatility was impacted by interest rates and inflation rates. Using monthly data from January 1999 to January 2009, the authors in this paper employed the Impulse response function time series approach, Granger Causality, and Vector Error Correction Model (VECM). They discovered that interest rates significantly reduce the volatility of exchange rates. Similarly, study is found on Pakistani economy by Ali *et al.* (2015) where the authors empirically investigated the impact of money supply, inflation and interest on the exchange rate variability in Pakistan. They too employed Granger Causality, Vector Error Correction Model (VECM) and Impulse response function etc. time series techniques on the monthly data ranging from July 2000 to June 2009, they found the contrasting result that the interest along with the money supply have been negatively affected the exchange rate volatility. Another study is conducted by Rai.et al., (2023) where the authors addressed some issue regarding the exchange rate of rupee against dollar. Here authors employed ARIMA, VAR model on the monthly data spanning January 2005 to December 2020, they found that the exchange rate volatility is mostly affected by the lag value of exchange rate itself then the variable like rate of inflation and the interest rate. Other research, like Petrica et al. (2016) and Ouyang (2011), has shown that one important factor influencing exchange rate volatility is the exchange rate's lag value.

The available literature, especially extent of the studies on the factors effecting exchange rate volatility is limited. Moreover most of the studies are conducted by using traditional research methods, this study contributes fresh insights in this field, and here we applied a recently trending transfer entropy causality technique to empirically verify interest rates' impact on exchange rate volatility. Moreover this study conduct Granger causality and Vector Autoregressive model based Impulse response function to achieve a more robust conclusion.

Methodology:

Volatility of exchange rate:

Specialists in finance and Economics often utilize the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to predict and model time series data volatility, such as stock returns. Measured as the variability or dispersion of returns, volatility is an essential tool for financial market analysis, option pricing, and risk management. A simple standard GARCH (p, q) with ARMA (p,q) mean equation takes the form

$$\Delta Z_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta Z_{t-i} + \sum_{i=1}^{q} \gamma_i \mu_{t-i} + \mu_t$$

$\mu_t = \sigma_t v_t$

Where,

v_t is a white noise process

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \varphi_i \, \mu_{t-i}^2 + \sum_{i=1}^{q} \theta_i \, \sigma_{t-1}^2 + \epsilon_t$$

Where,

ΔZ_t = The first difference of the exchange rate

α = The intercept term in the mean equation

β_i = The autoregressive coefficients of exchange rate

γ_i = The moving coefficients

μ_t = The error term at time t, which is assumed to be normally distributed with mean zero and variance σ_t^2

σ_t^2 = The conditional variance at time t

ω = The constant term

φ_i = the coefficients of the lagged squared errors μ_{t-i}^2 (ARCH terms)

θ_i = The coefficients of the lagged conditional variances σ_{t-1}^2 (GARCH terms)

ϵ_t = standardized residual

Using conditional variance as a proxy of the volatility leaves some extreme value where the volatility is relatively high, and the regression results are affected by those extreme values, therefore instead of using conditional variance of exchange rate we use the conditional standard deviation of the of the exchange rate as a proxy of the exchange rate volatility, which have relatively lesser extreme values.

Granger Causality:

The Granger causality test (Granger, 1980) is the standard method for examining causal relationships between time series data. To determine if interest rate say r_t causes exchange rate volatility σ_t , the Granger causality test involves two predictions: one using only σ_t 's past values and another using both σ_t 's and r_t's past values. The test then compares these predictions to assess whether including r_t 's history improves the prediction of σ_t , indicating a causal effect of interest rate r_t on the volatility of exchange rate σ_t .

To test whether the exchange rate volatility is caused by interest rate r_t , following Hmamouche,(2020) we estimated two equation as follows

$\sigma_t = \delta + \sum_{i=1}^{p} \rho_i \sigma_{t-i} + e_t$

$$\sigma_t = \delta + \sum_{i=1}^{p} \rho_i \sigma_{t-1} + \sum_{i=1}^{p} \varphi_i r_{t-i} + e_t$$

We calculated the Granger Causality Index (GCI) in the following manner to measure the causal relationship between the interest rate and exchange rate volatility.

$$GCI = \log\left(\frac{\tau_1^2}{\tau_1^2}\right)$$

Where,

The variances of the errors of equations 3 and 4 are, respectively $\tau_1^2 \, and \, \tau_1^2$ .In order to assess if there is a statistically significant difference between these variances, the Fisher test was computed as follows.

$F = \frac{(RSS_1 - RSS_2)/p}{RSS_2/(n-2p-1)}.$

RSS_1 and RSS_2 are the residual sum of squares of equation 3 and 4 respectively and n is the size of the lagged interest rate, accordingly two hypotheses are considered

i. $H_0: \forall_i \in \{1,2, \dots \dots, p\}, \varphi_i = 0$

$H_1: \exists_i \in \{1,2, \dots \dots, p\}, \varphi_i \neq 0$

H_0 is the hypothesis that interest rate (r) does not cause exchange rate volatility σ_t . Under H_0, F follows the Fisher distribution with (p, n − 2p − 1) as degrees of freedom.

Transfer Entropy:

Shannon entropy is a concept from information theory that measures the uncertainty or unpredictability of a random variable. It is defined as-

$$H(X) = -\sum_i P(x_i) \log P(x_i)$$

Where,
$P(x_i)$ is the probability of the occurrence of the event x_i. In the context of causality, Shannon entropy can be used to understand the relationship between variables by measuring how the uncertainty of one variable changes when we know the value of another variable. Following Behrendt *et al* (2023). Let the exchange rate volatility be (σ) and interest rate be (r) are two discrete random variable with marginal probability distributions p(i) and $p(j)$, and a joint probability distribution $p(i,j)$. These variables have dynamic structures that correspond to stationary Markov processes of order k (for process σ) and order l (for process r). The Markov property indicates that the probability of observing σ in state i at time t+1, given the k previous observations, is $p(i_{t+1}|i_t,\ldots,i_{t-k+1})=p(i_{t+1}|i_t,\ldots i_{t-1})$.The average number of bits required to encode the observation in t+1,given the known lagged values of k is given by

$$h_I(k) = -\sum_i p\left(i_{t+1}, i_t^{(k)}\right).\log\left(p(i_{t+1}|i_t^k)\right),$$

Where, $i_t^{(k)}$ =$(i_t,\ldots,i_{t-k+1})$.h_r (σ) can analogously be derived for the process r . In our bivariate case the information flow from r to σ is measured by quantifying the deviation from the generalized Markov property $p(i_{t+1}|i_t^k) = p\left(i_{t+1}|i_t^{(k)}, r_t^{(l)}\right)$ relying on the Kullback-Leibler distance (Schreiber 2000).Thus Shannon transfer entropy is given by

$$T_{r\to\sigma}\ (k,l) = \sum_{ij} p\left(i_{t+1}, i^{(k)}, j_t^{(l)}\right).\,log\left(\frac{p\left(i_{t+1}|t_t^{(k)}, j_t^{(k)}\right)}{p\left(i_{t+1}|i_t^{(k)}\right)}\right)$$

$T_{r\to\sigma}$ measures the information flow from r to σ. To evaluate the statistical significance of transfer entropy estimates, we use a Markov block bootstrap method as suggested by Dimpfl *et al*.(2013) .Unlike shuffling, this method maintains the dependencies within each time series, thus generating the distribution of transfer entropy estimates under the null hypothesis of no information transfer i.e A simulated series is formed based on random drown block of observation of interest rate series (r),which keeps the univariate dependencies of interest rate (r) intact but removes the statistical dependencies between exchange rate volatility (σ) and interest rate(r),then Shannon Transfer Entropy(TE)is estimated on the simulated time series. Repeating this process produces the distribution of the transfer entropy estimate under the assumption that there is no information flow. Then we calculated the p-value corresponding to the null hypothesis of no information transfer as the number of times the transfer entropy estimates on shuffled data is greater than or equal to the transfer entropy estimates on the original dataset, then the number divided by the total number of shuffles. Another way to calculate the p-value corresponding to the null hypothesis of no information transfer as 1-q_{te}, where q_{te} is the simulated distribution that corresponds to the original transfer entropy estimate.(Behrendt et al, 2023).

Data and Results:
The current study uses sport exchange rate of Indian rupee against US dollar as a proxy for exchange rate and the call money rate (weighted average) as a proxy for interest rate. The data on both the variable are collected from Database on Indian Economy; RBI[2]. A significant portion of the Indian money market is the call or notice money market. Money is exchanged overnight in the call money market and on a notice basis in the notice money market. (Aashadha, 2005). By dividing the sum of all transaction volumes and their corresponding rates by the total of all transaction volumes, the Weighted Average Call Rate (WACR) is calculated. Under the current operating procedure of monetary policy, the Reserve Bank of India has adopted the weighted average call rate (WACR) as the operating target with the objective of aligning it to the policy repo rate through proactive liquidity management (PRESS RELEASES, 2023),therefore WACR is used as a proxy for interest rate in our empirical study.

Descriptive Statistics:
The mean of the exchange rate from December 2010 to January 2020 is 61.75 Indian Rupee against one US dollar having a standard deviation of 7.76 rupee. The mean of Interest rate is 7.71 percent with a standard deviation of 1.14 percent. The mean of the conditional standard deviation of exchange rate from GARCH model is 1.44 percent with 0.37 percent standard deviation. The coefficient of variation of Exchange rate, Interest rate and Conditional standard deviation of Exchange rate are 12.56 percent, 14.78 percent and 25.69 percent respectively. The test static with 2 degree of freedom revels that exchange rate and the conditional variance of exchange rate are not normally distributed while Interest rate is normally distributed. The descriptive statistics are presented by table-1.

The time series properties of the three series are represented by the table-2. Each series are checked for unit root using conventional Augmented Dickey Fuller (ADF) test and Zivot and Andrews test carry out unit root test by permitting a break at an unidentified location in either the point of intercept in the linear trend, or both. The lag

[2] Reserve Bank of India, URL- https://cimsdbie.rbi.org.in/BOE/OpenDocument/2311211338/OpenDocument/opendoc/openDocument.jsp?logonSuccessful=true&shareId=22

length of the test are selected based on the lag order selection criteria such as Akaike's information criterion (AIC), , Hannan–Quinn information Criterion(HQ) ,Schwarz's information

Table 1:

Variables/Statistics	*Exchange rate(Z)*	*Interest rate(I)*	*Conditional SD of Z*
Observation	110	110	109
Mean	61.75	7.71	1.44
Median	63.82	6.92	1.32
Standard Deviation	7.76	1.14	0.37
Max	73.37	10.23	2.93
Min	44.16	4.94	1.04
Skewness	-0.79	0.25	1.86
Kurtosis	-0.37	-083	3.38
Coefficient of variation	12.56	14.78	25.69
Jarque-Bera test	Chi-square-12.13 P-value -0.0023	Chi-square-3.97 P-value - 0.13	Chi-square-137.54 P-value - 00

Table 2:

Variable	Test		Lags	Test statistic	Critical Value			Decision
					1%	5%	10%	
Exchange rate	ADF	With Trend	1	-2.6051	-3.99	-3.43	-3.13	I(1)
	ZA	With intercept and trend	1	-4.4669	-5.57	-5.08	-4.82	
ΔExchange rate	ADF	With intercept	1	-8.06	-3.46	-2.88	-2.57	
	ZA	With intercept	1	-8.5198	-5.34	-4.8	-4.58	
Interest rate	ADF	With intercept	3	-0.3227	-3.46	-2.88	-2.57	I(1)
	ZA	With intercept	3	-4.0578	-5.34	-4.8	-4.58	
Δ Interest rate	ADF	With intercept	2	-9.6135	-3.46	-2.88	-2.57	
	ZA	With intercept	2	-9.9702	-5.34	-4.8	-4.58	
Conditional SD of exchange rate	ADF	With intercept	1	-3.0362	-3.46	-2.88	-2.57	I(0)
	ZA	With intercept	1	-4.1755	-5.34	-4.8	-4.58	

Criterion (SIC) and Akaike's Final Prediction Error (FPE). Taking excessive lag reduces the degrees of freedom of the estimated parameter and taking too few lags will leave correlated residuals therefore we selected the optimal lag length by comparing four criteria. The test results suggest that the exchange rate series and Interest rate series are integrated of order one or have a unit root at level however both the series are stationary at the first difference. The conditional standard deviation of the exchange rate based on the GARCH model is stationary at level. The time series plot of the exchange rate and Interest rate series are depicted by figure-1 and figure-2

Figure-1

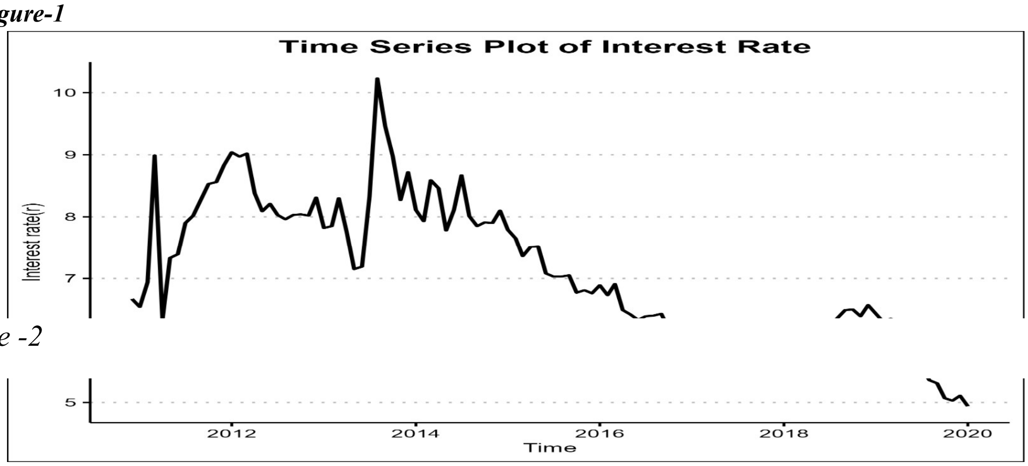
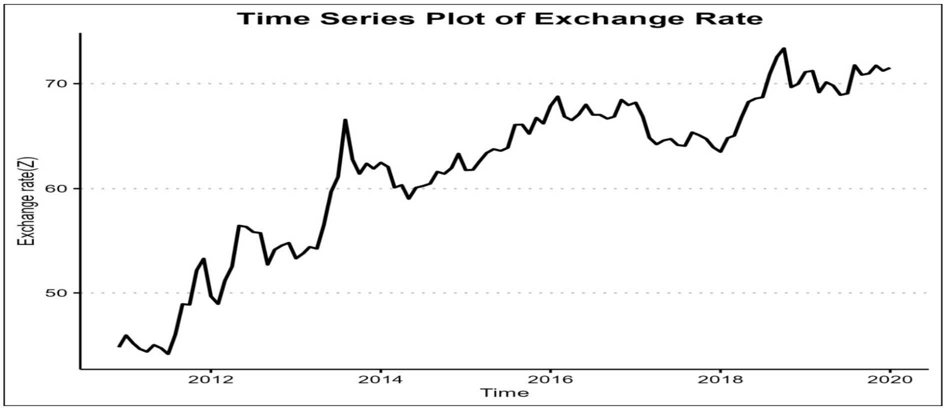


Figure -2



Conditional standard deviation of Exchange Rate:

To extract the conditional standard deviation of exchange rate a GARCH (1,1) with a ARIMA (1,1,0) specification is selected by taking into account the lowest Akaike's information criterion (AIC) value.

Some possible ARIMA models are listed by the table-3.

Table 3:

Models ARIMA(p,d,q)	Akaike's information criterion (AIC) values
ARIMA(1,1,0)	394.78
ARIMA(0,1,1)	394.78
ARIMA(2,1,0)	395.36
ARIMA(1,1,1)	395.83
ARIMA(2,1,1)	396.51

For the appropriate GARCH model we computed Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of some possible combinations of GARCH type model with two types of distribution such as sGARCH, GJR-GARCH, Component GARCH, eGARCH and distribution such as normal distribution and students' t distribution. Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) value associated with some possible models are listed in table-4. Based on the lowest RMSE and MAE, we estimated the standard GARCH (sGARCH) model with normally distributed standardized residuals.

Table -4:

GARCH/distribution	Root Mean Square Error (RMSE)		Mean Absolute Error (MAE)	
	norm	snorm	norm	snorm
sGARCH	0.5977756	0.7246576	0.4852852	0.5565530
gjrGARCH	0.7176020	0.7695401	0.5642673	0.5892593
csGARCH	0.5957217	0.6869874	0.4840998	0.5362730
eGARCH	0.7378703	0.7352801	0.5627372	0.5606857

The mean equation and variance equation of the GARCH are given below-

$Z_t = 0.146 - 0.062Z_{t-1} + \varepsilon_t$

(0.193) (0.56)

$\sigma_t^2 = 0.355 + 0.213\sigma_{t-1}^2 + 0.632\varepsilon_{t-1}^2 + \mu_t$

(0.11) (0.05) (0.00)

Note: Values are in parenthesis is the p-value

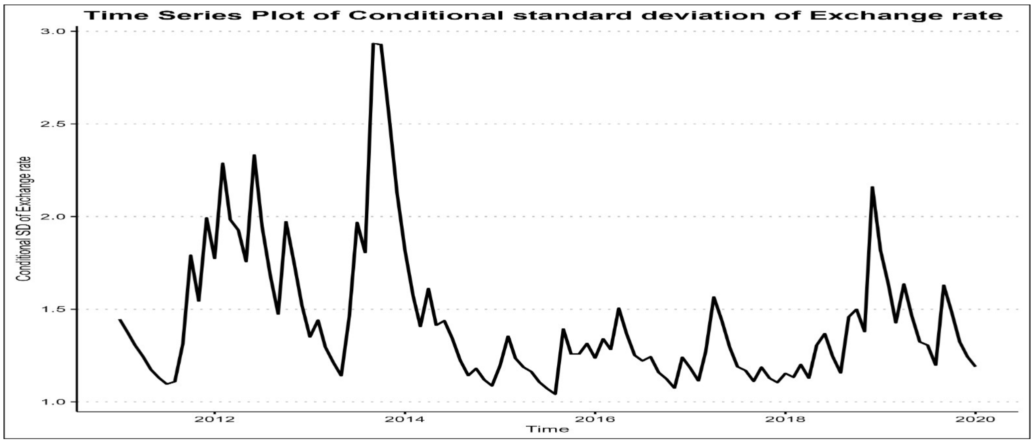
Diagnostics

Table 5:

Test	Lags	Statistics	P-value
Ljung-Box Test	1	0. 756	0.38
	2	1.14	0.65
	5	2.17	0.65
ARCH LM test	3	0.00	0.97
	5	2.74	0.32
	7	3.89	0.36

The autoregressive coefficient in the mean equation of the exchange rate is -0.062 with standard error of 0.10 therefore it is not statistically significant even at 10 percent level of significance. The model is stationary because the sum of the ARCH and GARCH parameter (0.21+0.63) less than unity. If the sum equals or exceeds 1, the model may become non-stationary, indicating that volatility could explode or be highly persistent. Moreover the sum of the ARCH and GARCH parameter being close to unity indicates that the volatility in the exchange rate takes a long time to die up after a shock. The Ljung-Box test suggests that the GARCH model do not suffer from autocorrelation, The ARCH-LM test suggest that the standardized residuals do not suffer from ARCH effect. The estimated conditional standard deviation of the GARCH model is depicted by the figure-3

Figure-3:



Granger Causality test:

Science the Granger causality test is sensitive to the lag length, therefore we used optimal lag length of the VAR (p) model based on the interest rate (r_r) and volatility of the exchange rate(σ_t). The AIC and FPE suggest lag order of 9,while HQ and SC suggest 2 lag order we have performed two Granger causality test once using 9 months lags and another time using 2 months lag length separately. The results are reported by the table-5,The results of the Granger Causality test shows that the Granger Causality Index is 0.088 when we use lag 2 compared to 0.456 when used 9 lags. The F-statistic are higher than the critical values at 5% level of significance, therefore we have sufficient evidence against the null hypothesis, which indicates that the lag values of interest rate is significant in predicting the exchange rate volatility. Hence interest rate Granger Causes exchange rate volatility. Results are reported in table-6

Table- 6:

Lags	GCI	F-statistic	Critical value at5%	P-value
2	0.088	4.735	3.087	0.010
9	0.456	5.213	1.999	0.000

Transfer entropy:

Shannon Transfer Entropy estimates in both direction i.e from interest rate to exchange rate volatility and from exchange rate volatility to interest rate, the effective transfer entropy estimates, the standard errors along with the p-value and the quintiles of the bootstrap samples are reported in table-6. The lag length of the Shannon Transfer Entropy (TE) is chosen by the optimal VAR lag for the two variable, like the Granger Causality test we used two lag length 2 and 9 for the estimation of transfer entropy. The results suggest that there is a significant information flow form interest rate to exchange rate volatility at lag 2.The value of transfer entropy (TE) 0.12361 indicates that the lag values of interest rate add 0.12361 bits of additional information in predicting the future values of the exchange rate volatility or the conditional standard deviation of the exchange rate. However the information flow from exchange rate volatility to interest rate is not statistically significant when used 2 lag length of each series. However the results of the transfer entropy suggest that there is not a significant information flow from interest rate to exchange rate volatility or from exchange rate volatility to interest rate we used lag length of 9 of each series. Since transfer entropy is asymmetric measure that means that the information flow from interest rate to exchange rate volatility is not identical with the information flow from exchange rate volatility to interest rate, the difference between the two is known as net information flow and which allows the quantification of the directional coupling between systems (How to Measure Statistical Causality: A Transfer Entropy Approach with Financial Applications, 2109).The net information flow is the direct measure of dominant information flow, in other words a positive value of 0.068 (0.1261-0.0575) indicates that a dominant information flow exist from interest rate to exchange rate volatility compared to other direction. More explicitly the system of interest rate provides more predictive information about the exchange rate volatility system (Michalowicz, Nichols, & Bucholtz, 2013).The effective transfer entropy (ETE) is calculated to account the bias existed in the transfer entropy. The ETE is determined by first calculating the transfer entropy of a randomized series where the elements of the time series are individually drawn randomly so that the dependencies between the series and other series are destroyed (shuffling) while maintaining the probability distribution of the shuffled series and then subtracting the shuffled transfer entropy from the transfer entropy (Osei & Adam, 2020). The number of shuffles used to calculate the effective transfer entropy in our case is 100.The ETE help us to determine the directionality of the causality too, in this case the effective transfer entropy from interest rate to exchange rate volatility is positive irrespective of the lag length but the value of ETE from exchange rate volatility to interest rate is zero indicating the unidirectional causality from interest rate to exchange rate volatility. The p value is calculated by counting how many times the transfer entropy estimates on shuffled data is greater than or equal to the transfer entropy estimates on the original dataset, then the number divided by the total number of shuffles in our case is 100.The p-value associated with the transfer entropy are reported in the table. We have also calculated the bootstrap transfer entropy with 2000 replications for each direction of the estimated transfer entropy.

Shannon Transfer Entropy Results

Table -7:

Direction	At lag 2				At la 9					
	TE	ETE	Std.error	p-value	TE	ETE	Std.error	p-value		
$\sigma \rightarrow r$	0.0575	0.0000	0.0363	0.3675	0.0091	0.0000	0.0575	0.9960		
$r \rightarrow \sigma$	0.1261	0.0761	0.0319	0.0285	0.1470	0.0105	0.0370	0.1060		
Bootstrapped Transfer Entropy (TE) Quantiles (300 replications)										
Quantile	0%	25%	50%	75%	100%	0%	25%	50%	75%	100%
σ→r	0.0000	0.0221	0.0433	0.0712	0.2415	0.0000	0.0969	0.1403	0.1814	0.3163
r→σ	0.0022	0.0303	0.0484	0.0712	0.2293	0.0039	0.0779	0.1007	0.1266	0.2180

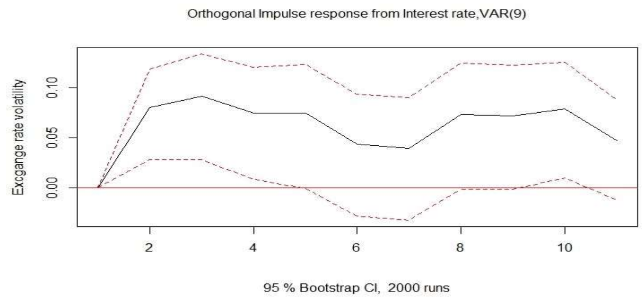
Impulse Response Function:

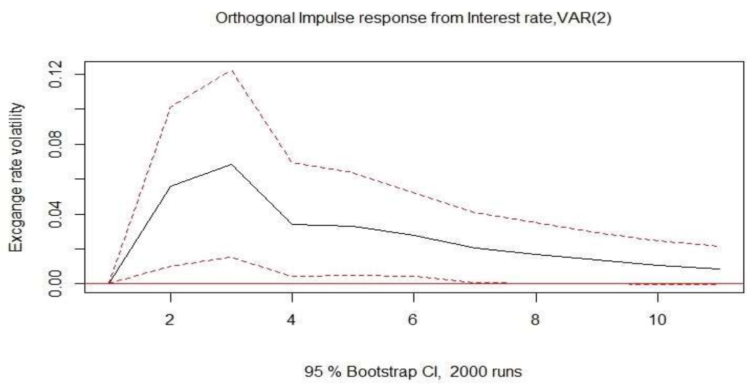
Since Granger causality and estimates of Shannon Transfer Entropy reveals the existence of causality from interest rate to the exchange rate volatility at lag length of 2, but the Shannon Transfer Entropy rejects the existence of this causality when 9 lag lengths is used. Therefore to achieve more robust results we estimated the Impulse Response Functions(IRF) by estimating two VAR models, VAR(2) and VAR(9) .We estimated the bootstrap confidence interval of the IRF with 2000 replications since bootstrap require relatively less assumptions, and therefore more accurate results. The estimated IRFs up to 10 months are depicted by the figure-4 and figure-5. From the IRF plot it can be observed that the bootstraps confidence intervals are different from zero between month 2 and month 4 for IRFs extracted VAR(2) and VAR(9) models. Which indicates that irrespective to the lag length of 2 and 9,shoch in the rate of interest has a positive impact on the exchange rate volatility.

Figure-4:

Figure-5:

Conclusion:





In this study we have empirically investigated the role of interest rate on the volatility of the exchange rate using monthly data starting from January 2011 to January 2020.The conditional standard deviation of the GARCH (1,1) based on ARIMA (1,1,0) model are used as a proxy for the exchange rate volatility and the weighted average call rate is used as a proxy for the interest rate. To test the causal effect of the interest rate on the exchange rate volatility we have employed Granger Causality test, Shnnon's Transfer Entropy causality test and bootstrap Impulse Response Function with 2000 replications based on the two VAR models one with two lag periods 2 and another with 9 lag periods separately. The results of the study suggest that the interest rate have a positive causal effect on the exchange rate volatility supported by the Granger causality test, Shannon Transfer Entropy causality test, at lag length of 2.The IRF revels that a shock in the interest rate positively influences the exchange rate volatility between a lag of two to four months. The results of our findings are in line with the studies such as Ansari et al., (2011), Behera et al., (2008).Therefore we are recommending a lower interest rate, lower interest rate not only helps to keep pace the economic growth rate but also will significantly reduce the exchange rate volatility thereby reducing the possible harmful effects of the exchange rate volatility.

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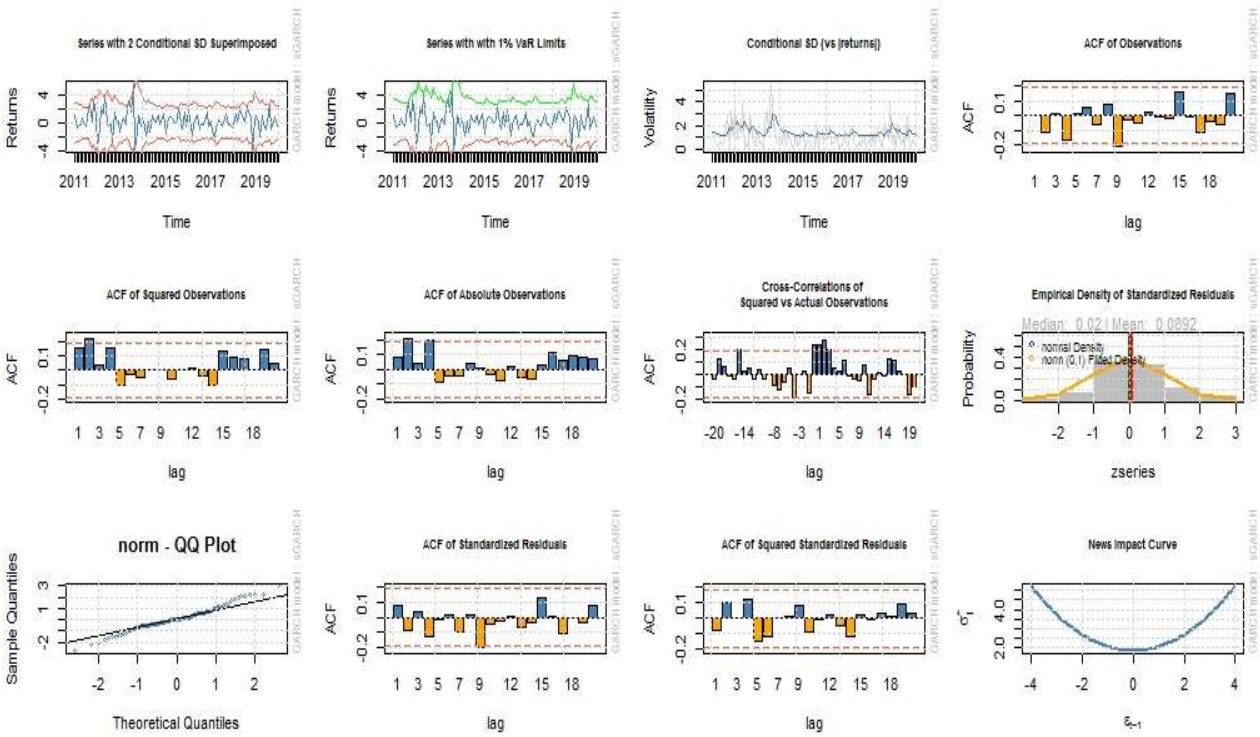
Appendix:

Kruskall-Wallis test for seasonality in the data:

Series	Test statistics	p-value
Exchange rate	2.44	0.9962716
ΔExchange rate	14.19	14.19
Interest rate	2.32	0.9969987
Δ Interest rate	28.71, 2.85*	0.002516124, 0.2399576*
Exchange rate volatility	4.78	0.9413423

Note: H_0: The mean ranks of the groups are the same
Asterisk(*) denotes welch seasonality test statistics, and p-value
H^*_0: The two population means are the same but the two population variances may differ.

ARIMA-GARCH residuals:
VAR results:



VAR (2) results:

	Dependent variable:	
	(Exchage_volatility)	(Interest rate)
Exchage_volatility.l1	0.689***	0.177
	(0.097)	(0.201)
interest.l1	0.123***	-0.326***
	(0.046)	(0.096)
Exchage_volatility .l2	0.126	-0.339*
	(0.097)	(0.202)
interest.l2	0.105**	-0.204**
	(0.047)	(0.098)
Constant	0.267***	0.209
	(0.091)	(0.189)
Observations	107	107
R2	0.660	0.126
Adjusted R2	0.646	0.092
Residual Std. Error (df = 102)	0.222	0.461
F Statistic (df = 4; 102)	49.432***	3.678***

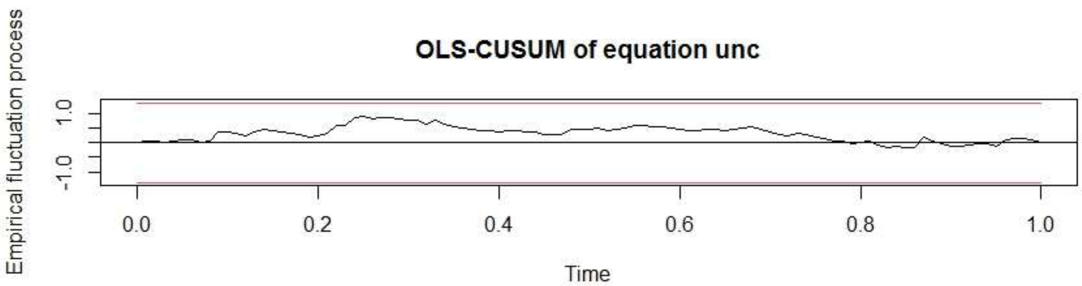
Note: *p<0.1; **p<0.05; ***p<0.01

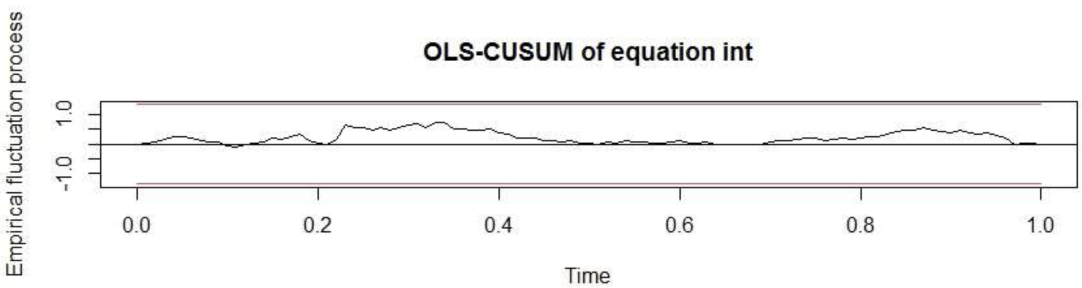
VAR (9) results:

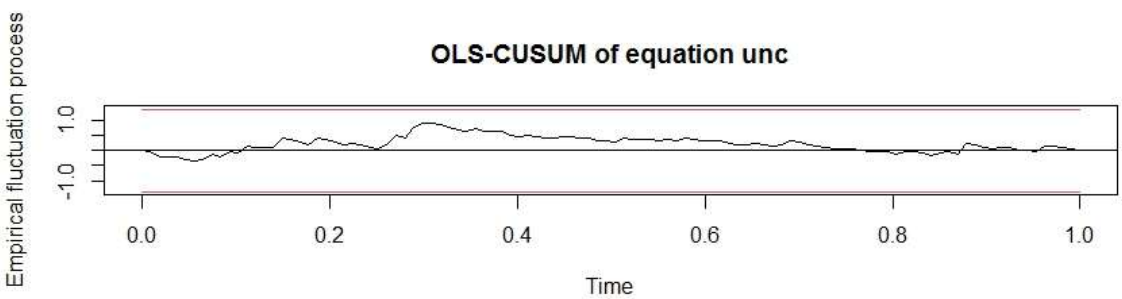
	Dependent variable:	
	(Exchage_volatility)	Interest rate
Exchage_volatility .l1	0.670***	0.314*
	(0.107)	(0.167)
interest.l1	0.265***	-0.016
	(0.071)	(0.112)
Exchage_volatility.l2	0.072	-0.222
	(0.124)	(0.194)
interest.l2	0.130*	-0.394***
	(0.072)	(0.112)
Exchage_volatility.l3	0.042	0.154
	(0.123)	(0.193)
interest.l3	0.109	-0.268**
	(0.077)	(0.120)
Exchage_volatility.l4	0.196	-0.527***
	(0.119)	(0.187)
interest.l4	0.147*	-0.015
	(0.080)	(0.126)
Exchage_volatility.l5	-0.291**	0.100
	(0.130)	(0.203)
interest.l5	-0.081	-0.022
	(0.073)	(0.114)
Exchage_volatility.l6	-0.115	0.043
	(0.123)	(0.192)
interest.l6	0.050	0.119
	(0.073)	(0.114)
Exchage_volatility.l7	0.046	-0.550***
	(0.121)	(0.190)
interest.l7	0.181***	0.236**
	(0.066)	(0.103)
Exchage_volatility.l8	0.156	0.493**
	(0.126)	(0.198)
interest.l8	0.038	0.167*
	(0.061)	(0.095)
Exchage_volatility.l9	-0.003	0.148
	(0.105)	(0.165)
interest.l9	0.165***	0.140
	(0.054)	(0.084)

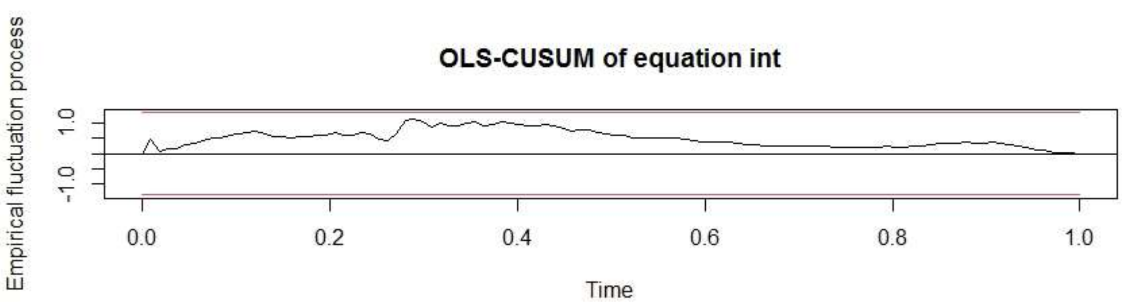
constant	0.350***	0.025
	(0.116)	(0.182)
Observations	100	100
R2	0.779	0.361
Adjusted R2	0.730	0.219
Residual Std. Error (df = 81)	0.197	0.309
F Statistic (df = 18; 81)	15.890***	2.544***
Note:	*p<0.1; **p<0.05; ***p<0.01	

OLS-CUSUM test for st ability of VAR models









Note: ‘int’ =Interest rate, ‘ unc’=Exchange rate volatility