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Do daily oil and gold prices beat the random walk model? A tale of INR/USD exchange rate using restricted and un-restricted VAR.

Lubhanshu Bartaria

Research Scholar, Department of Accounting and Finance, MDI Gurgaon, India

[*] *Corresponding author: fpm19lubhanshu_b@mdi.ac.in*

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Abstract: It is said that the foreign exchange market never sleeps. Thus, we see that there are continuous fluctuations in the exchange rates during the 24 hour duration. These are keenly watched not only by exporters and importers but by investors and policy makers also, before doing any international transaction. They also deploy forecasting models of exchange rates to look into the future trends of the currency pairs, so that they can earn more domestic currency in case of exporters or save domestic currency in case of importers. The aim of my study is to develop forecasting models for the INR/USD exchange rate by employing time series methodologies that can predict it better than the Random Walk model. Earlier forecasting models of the INR/USD exchange rate employed univariate models that had monthly data, and similar studies on the multivariate models employed macroeconomic variables that appeared monthly. I have employed daily data of commodity prices viz. oil and gold from 1st March 2020 to 31st May 2021 in my study to predict the INR/USD exchange rate by incorporating them in the Vector Auto regression (VAR) framework. The unrestricted VAR model predicts better than the Random Walk model, and previous day oil prices are playing a significant role in predicting the INR/USD exchange rate. Volatility in the INR/USD currency pair can be reduced by looking for the alternative sources of energy.

Keywords: Forecasting, INR/USD exchange rate, VAR, Random walk, volatility

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1. Introduction

By the year 2024-25, India's economy is expected to reach its US$ 5 trillion target. To achieve the target, India has already launched Make in India and Production-linked incentive schemes. These schemes will make India the manufacturing hub of the world. In 2020 we became the fifth largest recipient of FDI in the world, and for the financial year 2020-21, we have received a total of US$81,722 million as Foreign Direct Investment (FDI). FDI leads to economic growth in India (Kang, Ritu.2021). Hence, a higher level of FDI is desirable in India. According to data from the Ministry of Commerce and Industry website, in the financial year 2020-21, India's total import value was US $ 393610.52 million and export value was US $ 291163.53 million. Since the exchange rate impacts both the FDI (Gupta, Kirti and Ahmed, Shahid. 2020) and cross-border trade in India (Hashmi, Shabir and Chang, Bisharat. 2020) therefore, it is important to study exchange rate market and forecasting models in detail.

The exchange rate market changed significantly after the collapse of the Bretton-Woods system in 1971. A floating exchange rate mechanism was introduced in which the price of a nation's currency is based on the supply and demand in the foreign exchange market relative to other currencies. Further exchange rates are one of the sought-after economic indicators in the world (Frankel, J and Saravelos, G.2012) and any fluctuation in it may bring serious economic consequences. These consequences may affect corporate decisions and macro-economic variables (Bofinger,P et al.2003). Hence, to mitigate these risks, a dependable forecast is required. Forecasting is a formal process of generating expectations by using economic theory, mathematics, statistics, and econometrics (Kallianiotis, J. 2013).It is required by Multinational Corporations (MNCs) for their hedging decisions, short-term investment decisions, and capital budgeting decisions. Thus, to evaluate the risks and benefits associated with transactions in the international market, they need accurate and reliable forecasts of the foreign currency.

In the first such seminal paper by Meese and Rogoff (1983), they figured out that the econometric model based on macroeconomic fundamentals failed to outperform the random walk model. Boothe and Glassman (1987) confirmed that random walk models performed better in forecasting than other fundamental models. There were other methods like the economy-wide macroeconometric model proposed by Gandolfo et al. (1990) that captured all macro-economic variables which could possibly affect exchange rate movements. Their model beat the random walk model for the out-of-sample forecasting of exchange rates. A study by McDonald and Taylor (1991,1993, 1994) found that in the long-run, a monetary model of the exchange rate could beat the random walk model. Mark and Sul (2001) confirmed that monetary models are effective in the long run. For a forecasting horizon of 1 to 3 year monetary models did not perform well (Sarno and Taylor, 2002)

To improve forecasting performance of spot exchange rates, researchers focused their attention towards time series and non-linear models. Results were encouraging when univariate time series models beat the random walk model (Brooks, 1997). Min Qi et al.(2003) employed Artificial Neural Networks (ANN), a non-linear model, to forecast exchange rates but couldn't beat the random walk model. A contrary result was obtained when both the ANN and linear autoregressive models beat than the random walk model (Narasimhan and Panda, 2003).

The purpose of this study is to model, forecast and compare the forecasting performance of the linear, non-linear and hybrid time series models for the INR/USD exchange rate.

2.Literature Review

Hoque et al. (1993) studied the forecasting performances of Restricted Vector Auto regression (VAR) model with the unrestricted VAR for the Australian Dollar and US Dollar currency pair. The periodicity of their data was quarterly and the sample period was from 1976: I to 1990-I. They figured out that for the out-of-sample forecasting Restricted VAR performed better than unrestricted VAR. Te-Ru Liu et al. (1994) confirmed the same findings. The currency pairs in their model were US dollar / yen, US dollar/ Canadian dollar, US dollar/ Deutsche mark. The VAR specification was based on a monetary model of the exchange rate specification. The data were collected monthly and the sample period was from 1973:3 to 1982:12.Choudhry and Lawler (1997) employed monthly data of the US dollar/ Canadian dollar from 1950 to 1962 in the VAR model based on the monetary theory of exchange rate. They found out that the VAR model beat the random walk model in the out-of-sample forecasting of exchange rates. Chen and Leung (2003) employed Bayesian Vector Error Correction (BVECM) model based on the uncovered interest parity theorem. The currency pairs in their study were Australian dollar / US dollar, Japanese Yen / US dollar and Korea Won/ US dollar. The periodicity of the data was monthly and sampled from January 1980 to December 1994. For out-of-sample forecasting, their model beat the random walk model. Cuaresma and Hlouskova (2004) employed various models of the VAR methodology for forecasting the exchange rates of Central European countries. The VAR model was specified on the basis of the monetary theory of exchange rate determination. The exchange rates in their study were Czech koruna, Hungarian forint, Polish zloty, Slovak koruna and Slovenian tolar. Their model could not beat the random walk model for out-of-sample forecasting. Zita and Gupta (2007) employed Dornbusch model in the VAR framework and found out that their model beat the random walk model for the Mozambique metical/ South African rand exchange rate. ANN model performed well for the forecasting of INR/USD exchange rate (Gupta, Sanjiv and Kashyap, Sachin. 2016). Monthly data on INR/USD exchange rate was collected from April 1999 to October 2013 in this research. In a study of 40 years from 1977-78 to 2015-16, it was found that the inflation rate and the balance of trade is significantly affecting INR/USD exchange rate (Jeelani, S et al.2019). After comprehensively employing macro-economic variables for exchange rate predictions, researchers focused their attention towards the relationship between exchange rates, stock markets, and commodity prices. Some interesting results emerged for the Indian-specific studies and they are

- Oil prices and precious metals have the informational content to predict INR/USD exchange rate (Jain, A & Ghosh,S .2013; Jain, A & Biswal,P.C. 2016; Naceur, K et al. 2020).
- Stock markets have shown the predictive ability to explain INR/USD exchange rate (Shiva,A & Sethi,M.2015; Kumar, M.2016).
- Currency pairs viz. INR/USD, INR/EUR, INR/GBP and INR/JPY have shown to explain each other movements (Dua, P & Suri, R. 2019).

3.Research Objective and Questions

Most of the macroeconomic variables data are available on the monthly basis and previous studies have employed them in the time series models for exchange rate forecasting, but the data on oil and precious metals are available on daily, hourly or even minute-wise also. So according to the best of our beliefs, no present-day research papers have employed the daily data of the oil and gold to forecast the INR/USD exchange rate. Thus, the research objective of this study is to develop VAR models to forecast the INR/USD exchange rate using the daily prices of gold and oil, and then compare their forecasting accuracy against the benchmark (Random walk model).

3.Existing theories

Purchasing Power Parity (PPP) Theorem: It is a theoretical exchange rate that allows for buying the same amount of goods and services in every country. Macro-economic analysts use a "basket of goods" approach to compare different currencies. It was observed initially that the PPP model deviates in the short run, but in the long run the PPP model holds true. However, studies by the Jacobson et al. (2002) figured out that in the long run the PPP theorem does not hold true. The failure of the PPP model in the long run gave way to the monetary models.

Monetary Models: The monetary model of exchange rate determination took into account capital/bond market arbitrage along with the goods market arbitrage assumed in the PPP theorem. According to the monetary model, it is the money supply in relation to the money demand in both the home and foreign countries which determines the exchange rate. Monetary models are of 4 types

- Flexible price monetary model
- Sticky price monetary model
- Real interest differential model
- Hooper-Morton's extension of the sticky price model

The flexible monetary model (Frenkel. 1976) assumes that prices are flexible. Changes in the nominal interest rate reflect changes in the expected inflation rate. An increase in the domestic interest rate with respect to the foreign interest rate implies that the domestic currency will depreciate in value due to inflation. The model further assumes that the increase of the domestic money supply with respect to the foreign currency will cause the domestic currency to depreciate.

In the sticky price monetary model (Dornbusch, 1976) changes in the nominal interest rate reflect changes in the tightness of monetary policy. When the domestic interest rate rises with respect to the foreign country's interest rate, it reflects the crunch of the money supply in the economy. The higher interest rate attracts a capital inflow which results in the appreciation of the domestic currency.

Hooper and Morton (1982) modified the sticky-price formulation by incorporating the trade balance term into the exchange rate determination equation. Thus, a domestic trade balance deficit indicates depreciation of the exchange rate and vice versa.

Therefore, a single equation for the exchange rate determination by combining all the theorems is shown below

$$\widehat{e}_t = a + b(m_t - m_t^*) + c(y_t - y_t^*) + d(i_t - i_t^*) + e(\pi_t - \pi_t^*) + f(TB_t - TB_t^*) + \varepsilon_t --- (1)$$

Where e = price of foreign currency in domestic currency

m= money supply

y=real output

i=nominal interest rate

[]=inflation

TB=trade balance

And starred variables denote foreign counterpart

Random Walk Model

It is one of the most important models in time series forecasting. This model states that in each period a variable takes a random step away from its previous value, where each step is independently and identically distributed (i.i.d). At period'‘t’, forecast from the random walk model for ‘h’ time period ahead is

$$\widehat{Y}_{t+h} = Y_t --- (2)$$

4.Empirical Methodologies

Time Series: A time series is a sequence of observations taken sequentially in time. An important feature of time series is that typically adjacent observations are dependent. Thus, the time series analysis is concerned with the methodologies to study this dependent behaviour.

Stationary Time Series: A time series is said to be stationary if its mean and variance are constant over time, and the value of covariance between two time periods depends only on the distance or lag between the two time periods. The statistical methods used to determine the stationarity of a time series are known as “unit root tests”. We have employed Augmented Dicky Fuller (ADF) test, Phillips-Perron and, Kwiatkowsky-Phillips-Schmidt-Shin (KPSS) test in this study to test for the stationarity in the time series.

Vector Auto Regression (VAR) Model

This model allows feedback causality among the dependent and independent variables using their own past values. In VAR models all variables are endogenously determined. For example- let us consider a VAR (1) model with 2 variables

$$y_{1t} = a_{10} + a_{11} y_{1,t-1} + a_{12} y_{2,t-1} + \varepsilon_{1t} --- (3)$$

$$y_{2t} = a_{20} + a_{21} y_{1,t-1} + a_{22} y_{2,t-1} + \varepsilon_{2t} --- (4)$$

In the VAR framework, each variable is expressed as a linear combination of the lagged value of itself and the lagged values of all other variables in the group. a_{12} denotes the linear dependence of y_{1t} on $y_{2,t-1}$ in the presence of $y_{1,t-1}$. Therefore, if $a_{12} \equiv 0$ then y_{1t} depends on its past values. In general, VAR (p) model can be written as

$$y_t = a_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + u_t$$

Where $y_t, a_0 \,\&\, u_t$ are (k*1) vector

φ_i is a (k*k) matrix

u_t is a sequence of serially un-correlated random vectors with mean zero and covariance matrix ∑

Choosing the appropriate lag length is important in VAR modelling. Optimal lag lengths are selected by using appropriate lag length criteria and they are

- Akaike Information Criteria (AIC)
- Schwartz Bayesian Criteria (SC)
- Hannan Quinn Criterion (HQ)

For our studies series log(INR/USD), log(gold) and log(oil) are stationary at first difference. Hence, we shall be employing the first difference series in our VAR model

ΔUSD = log(INR/USD)-log(INR/USD)(-1)

Δgold= log(gold)-log(gold)(-1)

Δoil=log(oil)-log(oil)(-1)

$$\Delta USD_t = \delta_1 + \alpha_{11}\Delta USD_{t-1} + \alpha_{12}\Delta gold_{t-1} + \alpha_{13}\Delta oil_{t-1} + \beta_{11}\Delta USD_{t-2} + \beta_{12}\Delta gold_{t-2} + \beta_{13}\Delta oil_{t-2} + \varepsilon_{1t} --- (5)$$

$$\Delta gold_t = \delta_2 + \alpha_{21}\Delta USD_{t-1} + \alpha_{22}\Delta gold_{t-1} + \alpha_{23}\Delta crude_{t-1} + \beta_{21}\Delta USD_{t-2} + \beta_{22}\Delta gold_{t-2} + \beta_{23}\Delta crude_{t-2} + \varepsilon_{2t} (6)$$

$$\Delta oil_t = \delta_3 + \alpha_{31}\Delta USD_{t-1} + \alpha_{32}\Delta gold_{t-1} + \alpha_{33}\Delta oil_{t-1} + \beta_{31}\Delta USD_{t-2} + \beta_{32}\Delta gold_{t-2} + \beta_{33}\Delta oil_{t-2} + \varepsilon_{3t} --- (7)$$

Co-integration

When we regress to two or more non-stationary time series, then their regression results may be spurious. Hence, we need to determine whether the long-term relationship exists between the variables; if there exists a long-term relationship, then the series are said to be co-integrated. We will employ Johansen (1988), Johansen and Juselius(1990) cointegration methodology to test for the long-run relationship between the variables. This method is based on the relationship between the characteristics roots of a matrix and its rank.

Johansen and Juselius Co-integrated VAR model

In general, VAR(p) can be written as

$$y_t = a_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + u_t$$

Where $y_t, a_0 \,\&\, u_t$ are (k*1) vector

φ_i is a (k*k) matrix

u_t is a sequence of serially un-correlated random vectors with mean zero and covariance matrix $\sum$

Let $\Delta y_t = y_t - y_{t-1}$ then Vector Error Correction Model (VECM) can be written as

$$\Delta y_t = a_0 + a_1 t + \sum_{i=1}^{p-1} \Pi_i^* \Delta y_{t-i} - \Pi^* y_{t-1} + u_t --- (8)$$

The test for co-integration between the y's is calculated by looking at the rank of the $\prod$ matrix via its eigen values. The rank of a matrix is equal to the number of its characteristic roots (eigen values) that are different from zero. Π^* is the long-run multiplier matrix and Π_i^* captures the short-run dynamic effects.

5.Model Performance

Various measures have been proposed to measure the predictive accuracy of the forecasting models. Most of these measures are designed to evaluate ex-post forecast. The smaller the values of these measures better is the forecast of the model. Following are the measures

- **Root Mean Square Error (RMSE)**: It is calculated by the formula $\sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}}$ where n is the number of periods being forecasted, y_i is the actual value and $\hat{y}_i$ is the forecasted value.

- **Mean Absolute Error (MAE):** It is calculated by the formula $\frac{1}{n}\sum_i |y_i - \hat{y}_i|$, where n is the number of periods being forecasted, y_i is the actual value and $\hat{y}_i$ is the forecasted value.

- **Mean Absolute Percentage Error (MAPE):** It is a measure of prediction accuracy of a forecasting model. It is calculated by the formula

$$\frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

where n is the number of periods being forecasted, y_i is the actual value and $\hat{y}_i$ is the forecasted value.

6.Results and Discussions

Sample Data Description

The daily data of the INR/USD exchange rate was obtained from the National Stock Exchange of India website starting from 1st March 2020 to 31st May 2021. Similarly, data on the daily oil and gold prices were obtained from the Multi Commodity Exchange of India Ltd website. Prices for gold are in INR per 10 gram, whereas crude oil prices are in INR per Barrel. All the variables are transformed to natural logarithms and the descriptive statistics of the transformed variables are provided in table number 1. Oil prices show the highest volatility during the sampling period.

Table 1: Descriptive statistics

	INR/USD	Oil	Gold
Mean	4.31	8.05	10.76
Std. Dev	0.01	0.33	0.08
Skewness	0.32	-1.14	-0.57
Kurtosis	1.99	4.79	2.33
Jarque-Bera	18.82 (0.00)	112.35 (0.00)	23.56 (0.00)
Observations	319	319	319

Table 2 reports the correlation between the variables. All the correlations are significant at the 1% level. Oil and gold prices have negative correlations with the exchange rate, indicating that consumers in India were demanding gold and oil only when the INR was strong.

Table 2: Correlation matrix, significant at 1% level

Correlation	Oil	Gold	INR/USD
Oil	1.00		
Gold	0.45	1.00	
INR/USD	-0.68	-0.36	1.00

For testing the variable on stationarity, we have employed Augmented Dicky Fuller test (Dicky and Fuller.1979) along with Phillips and Perron(1988) and Kwiatkowski et al.(1992). Table numbers 3,4 and 5 present the results of the stationarity testing on the natural logarithm of the level variables, whereas table numbers 6, 7 and 8 present the test results of stationarity testing on the first difference level variables. In level analysis, all tests are unable to reject the null hypothesis of non-stationarity. In the first difference variables, all the tests rejected the null hypothesis of non- stationarity. Thus all our I(1) variables are stationary.

Table:3, ADF Test, null hypothesis = series is non-stationary

Level variables (intercept only)	t- statistic	probability	Level variables (intercept and trend)	t- statistic	probability
Log(INR/USD)	-1.93	0.32	Log(INR/USD)	-4.25	0.00***
LOG(Gold)	-1.64	0.46	LOG(Gold)	-1.43	0.85
Log(oil)	-1.77	0.39	Log(oil)	-3.07	0.11

*** significant at 1%, ** significant at 5%, * significant at 10%

Table:4, Phillips Perron Unit Root test, null hypothesis = series is non-stationary

Level variables (intercept only)	t- statistic	probability	Level variables (intercept and trend)	t- statistic	probability
Log(INR/USD)	-2.05	0.26	Log(INR/USD)	-4.32	0.00***

LOG(Gold)	-1.70	0.43	LOG(Gold)	-1.52	0.82
Log(oil)	-1.31	0.63	Log(oil)	-3.81	0.02**

*** significant at 1%, ** significant at 5%, * significant at 10%

Table:5, Kwiatkowski Phillips Schmidt Shin Unit Root test, null hypothesis = series is stationary

Level variables (intercept only)	LM- statistic	Critical value at 5%	Level variables (intercept and trend)	LM- statistic	Critical value at 5%
Log(INR/USD)	1.28***	0.46	Log(INR/USD)	0.149**	0.146
LOG(Gold)	0.59**	0.46	LOG(Gold)	0.41***	0.146
Log(oil)	1.55***	0.46	Log(oil)	0.07	0.146

*** significant at 1%, ** significant at 5%, * significant at 10%

Table:6 ADF Test

Ist diff variables (intercept only)	t-statistic	probability
Log(INR/USD)	-18.08	0.00***
LOG(Gold)	-16.98	0.00***
Log(oil)	-4.38	0.00***

*** significant at 1%

Table:7, Phillips Perron test

Ist diff variables	t-statistic	probability

(intercept only)		
Log(INR/USD)	-18.08	0.00***
LOG(Gold)	-17.01	0.00***
Log(oil)	-18.12	0.00***

*** significant at 1%

Table:8, Kwiatkowski Phillips Schmidt Shin Unit Root test

Ist diff variables (intercept only)	LM-statistic	Critical value at 5%
Log(INR/USD)	0.26	0.46
LOG(Gold)	0.19	0.46
Log(oil)	0.11	0.46

The first step in the VAR model is to check for cointegration between the variables. We have employed Johansen and Juselius method to check for cointegration and the result is displayed in table numbers 9 and 10. From the results it is clear that there is no cointegration between the variables; hence we will employ a VAR model on the first difference variables. For our sample size from 01/03/2020 to 01/04/2021, table 11 shows the result of the lag selection criteria. Akaike Information Criteria (AIC) suggest 2 lags; hence, after employing 2 lags to each of our endogenous variables in the VAR framework, the results for the unrestricted VAR framework are shown in equation numbers 9, 10 and 11, respectively. We have imposed restrictions on our VAR model by selecting only significant variables at a 5% level or less. The results of INR/USD forecasting for one month ahead i.e., from 01/04/2021 to 30/04/2021 are shown in table number 12, 13 and 14, respectively.

Table: 9, Un-restricted co-integration rank test (Trace)

Number of CE	Eigen value	Trace statistic	0.05 critical value	probability
None	0.04	21.37	29.79	0.33
At most 1	0.01	7.07	15.49	0.56
At most 2	0.005	1.79	3.84	0.17

Table: 10, Un-restricted co-integration rank test (Maximum Eigen Value)

Number of CE	Eigen value	Max. Eigen statistic	0.05 critical value	probability
None	0.04	14.31	21.13	0.34
At most 1	0.01	5.27	14.26	0.71
At most 2	0.005	1.79	3.84	0.17

Table 11: Lag selection criteria

Lag	AIC	SC	HQ
0	-17.6292	-17.58913*	-17.61312*
1	-17.6069	-17.4465	-17.5425
2	-17.65135*	-17.3707	-17.5387
3	-17.6024	-17.2015	-17.4414
4	-17.6346	-17.1134	-17.4252
5	-17.6215	-16.9801	-17.3639
6	-17.5959	-16.8342	-17.29
7	-17.5637	-16.6817	-17.2095
8	-17.5063	-16.504	-17.1038

$$\Delta USD_t = -1.032 \times 10\text{^}{-5} - 0.02\ \Delta USD_{t-1} + 0.02\ \Delta gold_{t-1} + 0.008^{***}\ \Delta oil_{t-1} + 0.004\ \Delta USD_{t-2} + 0.001\ \Delta gold_{t-2} - 0.004\ \Delta oil_{t-2} + \varepsilon_{1t} --- (9)$$

$$\Delta gold_t = 0.0001 - 0.04\,\Delta USD_{t-1} + 0.04\,\Delta gold_{t-1} - 0.001\,\Delta oil_{t-1} - 0.1\,\Delta USD_{t-2} + 0.083\,\Delta gold_{t-2} + 0.005\,\Delta oil_{t-2} + \varepsilon_{2t} --- (10)$$

$$\Delta oil_t = 0.001 - 0.05\,\Delta USD_{t-1} - 0.27\,\Delta gold_{t-1} - 0.02\,\Delta oil_{t-1} - 1.74\,\Delta USD_{t-2} + 0.36\,\Delta gold_{t-2} - 0.25^{***}\,\Delta oil_{t-2} + \varepsilon_{3t} --- (11)$$

Table 12: Forecasting result from un-restricted VAR

Forecasting period	RMSE	MAE	MAPE
01/04/2021-30/04/2021	0.0027	0.002	0.0479

Table 13: Forecasting result from restricted VAR

Forecasting period	RMSE	MAE	MAPE
01/04/2021-30/04/2021	0.0027	0.002	0.0485

Table 14: Forecasting result from the Random Walk Model

Forecasting period	RMSE	MAE	MAPE
01/04/2021-30/04/2021	0.0028	0.0021	0.049

Table 15: ARCH-LM test

lag	Coefficient	Prob.
1	0.006	0.91
2	0.38***	0.00
3	0.12*	0.06
4	-0.066	0.33
5	0.001	0.98
6	-0.025	0.70
7	0.01	0.87

8	0.01	0.91
9	0.02	0.67
10	-0.01	0.81

To test for heteroskedasticity in our USD equation we have employed Autoregressive Conditional Heteroskedasticity- Lagrange Multiplier (ARCH-LM) method. The results from the test are presented in table 15. Clearly, on lags 2 and 3, the ARCH effect is present. Thus, after modelling the variance equation by employing Generalized Autoregressive Conditional Heteroskedasticiy (GARCH) model, result of forecasting INR/USD from the hybrid VAR-GARCH(1,1) model for a month ahead i.e., from 01/04/2021 to 30/04/2021 is shown in table number 16.

Table: 16, Forecasting result from un-restricted VAR-GARCH (1,1)

Forecasting period	RMSE	MAE	MAPE
01/04/2021-30/04/2021	0.0028	0.002	0.0481

We have checked for the heteroskedasticity in our restricted VAR model and the result is presented in table number 17

Table:17, ARCH-LM test on restricted VAR

lag	Coefficient	Prob.
1	-0.003	0.95
2	0.39***	0.00
3	0.09	0.14
4	-0.07	0.25
5	0.039	0.56
6	0.004	0.94
7	0.002	0.96
8	-0.006	0.92

9	0.025	0.68
10	-0.016	0.78

In table number 18, we have presented the forecasting results of INR/USD using restricted VAR-GARCH (1, 1) model for a month ahead period.

Table : 18

Forecasting period	RMSE	MAE	MAPE
01/04/2021-30/04/2021	0.0027	0.002	0.0485

Rolling Regression One Month Forward

Now we have rolled our sample data one month forward, hence our new sample estimation period is from 01/03/2020 to 01/05/2021. AIC criteria suggested 2 lags to use in the VAR model, therefore INR/USD equation from the unrestricted VAR model is shown in equation number 12.

$$\Delta USD_t = 5.77 \times 10\text{^}{-6} - 0.009\,\Delta USD_{t-1} + 0.02\,\Delta gold_{t-1} + 0.008^{***}\,\Delta oil_{t-1} + 0.028\,\Delta USD_{t-2} + 0.00\,4\Delta gold_{t-2} - 0.004\,\Delta oil_{t-2} + \varepsilon_{1t} --- (12)$$

Forecasting of INR/USD exchange rate from the un-restricted VAR model is shown in table number 19

Table 19, forecasting from un-restricted VAR

Forecasting period	RMSE	MAE	MAPE
01/05/2021-31/05/2021	0.0025	0.0019	0.0447

The ARCH-LM method for testing the presence of heteroskedasticity in the INR/USD equation is shown in table number 20.

Table: 20, ARCH-LM test result

lags	Coefficient	Prob.
1	0.018	0.76
2	0.319	0
3	0.099	0.11
4	-0.024	0.70
5	0.015	0.80
6	-0.042	0.50
7	0.024	0.70
8	0.026	0.67
9	0.024	0.68
10	-0.041	0.49

From the result it is clear that the heteroskedasticity is present in lag 2. Hence we have employed the GARCH method to model the variance in the system. After modelling the variance we have employed the hybrid of VAR-GARCH (1,1) method to forecast the INR/USD exchange rate. Result for the month ahead forecasting is shown in table number 21.

Table:21, forecasting result from unrestricted VAR-GARCH

Forecasting period	RMSE	MAE	MAPE
01/05/2021-31/05/2021	0.0025	0.0019	0.0447

Restrictions were imposed on the VAR model by selecting only significant values at a 5% level or less. Forecasting results obtained from restricted VAR models are shown in table number 22.

Table 22: Forecasting result from restricted VAR model

Forecasting period	RMSE	MAE	MAPE
01/05/2021-31/05/2021	0.0026	0.0019	0.0451

ARCH-LM results for testing the presence of heteroskedasticity in the restricted VAR model are shown in table number 23.

Table 23: ARCH-LM Test

Lag	Coefficient	Prob.
1	0.007	0.90
2	0.35	0
3	0.076	0.23
4	-0.057	0.37
5	0.048	0.44
6	-0.003	0.96
7	0.0133	0.83
8	0.016	0.79
9	0.022	0.71
10	-0.044	0.44

After modelling for heteroskedasticity by employing the GARCH (1,1) model, forecast of INR/USD exchange rate obtained from restricted VAR-GARCH (1,1) model is shown in table number 24.

Table 24: forecast from restricted VAR-GARCH model

Forecasting period	RMSE	MAE	MAPE
01/05/2021-31/05/2021	0.0026	0.0019	0.0451

Forecasting result of the INR/USD exchange rate obtained from the random walk model is shown in table number 25.

Table 25: Random walk model

Forecasting period	RMSE	MAE	MAPE
01/05/2021-31/05/2021	0.0026	0.0019	0.0454

7.Conclusion

Forecasts of INR/USD exchange rate obtained from un restricted VAR model are better than the forecasts obtained from the Random walk model. These results are obtained after employing the daily data of oil prices, gold and exchange rates in the VAR framework. Clearly VAR models using daily prices of oil and gold can outperform the Random walk models for a month ahead forecasting. Further if we impose restrictions on the VAR models even than they are forecasting better than the Random Walk model but the results are inconclusive for the combination of VAR-GARCH models.

Another interesting point that emerged from this study is the predictive ability of previous day oil prices to forecast today's exchange rate. So if there is an increase in previous day oil prices then Indian Rupee (INR) will depreciate relative to USD and vice versa. Policymakers should look into crude oil prices closely as sustained increases in crude oil prices will not only depreciate INR with respect to the USD, but there is an upside risk of inflation in the economy too, as our imports will get costlier too.

Owing to the daily fluctuations in the oil prices there is volatility in the INR/USD currency pair as well. ARCH test confirms the same. Since the aim is to become the $5 trillion economy by 2024-25 and to achieve this target a substantial investment has to come in the form of FDI but the volatility in the INR/USD currency pair will not attract the FDI from the off shore investors. Thus it is pertinent for the policy makers to develop alternative sources of energy so that the dependence on the oil as a energy source is reduced, this will not only reduce volatility in the INR/USD currency pair but will also pave the way for the increase FDI in India.

8.References

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