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Model Selection and Forecasting Performances of Advance Univariate Time Series Models during the Pandemic Period: A Case of Inr/Usd Exchange Rate

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Abstract: Through this paper, we have determined the best time series model to forecast the INR/USD exchange rates during the pandemic period. The daily closing prices of the INR/USD exchange rate were modelled using various ARIMA models viz. SARIMA, SARIMA-GARCH (1,1) ,and ARIMAX. The models performance was compared against the benchmark model, the Random Walk model using the root mean square error. We recommend using the SARIMA- GARCH (1,1) for forecasting the INR/USD exchange rate during the pandemic period. For a week ahead, this model has outperformed the Random Walk model continuously for 4 days and is superior to both SARIMA and ARIMAX models regarding its forecasting abilities. Further, Nifty50 is not a good indicator to predict the INR/USD exchange rates during the pandemic period.

Keywords: SARIMA, SARIMA-GARCH, ARIMAX, Exchange Rates, INR/USD

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1. Introduction

India's trade deficit was US $9.37 Billion during June 2021[1]. The trade deficit was attributed mainly to the purchase of oil. Since crude oil is purchased in US Dollar hence, our trade deficit can also be attributed to the USD-INR exchange rates. Thus, it has become inevitable to forecast USD-INR exchange rates so that it can help the importers to decide when to pay USD to the suppliers. Another aspect to forecast exchange rates (read USD-INR) is to select the best econometric model, in terms of forecasting abilities, from the plethora of available time series models. If the model is known to the practitioner a priori, then their

[1] Website source : *Trading Economics* https://tradingeconomics.com/india/balance-of-trade (accessed July 2021)

precious time is saved and further it will also be a cost- saving mechanism for them as they don't have to incur cost to procure the services of a professional forecaster.

Literature Review

Meese and Rogoff (1983) in their seminal paper propose that Random Walk models are superior in out- of - sample forecasting in comparison to structural time series models. This paper set the tone for developing time series models which can predict better forecasts than random walk models. The key to a good forecast is to outperform the Random Walk model on a consistent basis. Further, the pandemic period has provided us with a wonderful opportunity to forecast exchange rates, particularly INR/USD using the various time series models.

Howrey (1994) used Michigan Quarterly Econometric model to produce both an ex post and ex ante forecast for the lira/$ exchange rate. The ex ante forecast of the currency pair could not outperform the Random Walk model.

Panda and Narasimhan (2007) used neural networks to forecast the INR/US $ exchange rate. The time horizon for forecasting was a day ahead. The out- of- sample forecasting results were compared against the forecasting results of the linear autoregressive and random walk models. Their model outperforms the random walk model.

Sun and et. al (2020) used a new ensemble deep learning approach known as LSTM-B for forecasting US Dollars against four currencies GBP, EUR, JPY(Japanese Yen) and CNY(Chinese Yuan). Their model outperformed the RW and ARMA models for a single forecast.

Vadivel (2020) studied the causal relationship between INR/USD and Sensex. He found out that the capital inflow in the Sensex appreciated INR while the outflow of capital from the Sensex depreciated INR.

Thus, we present in this paper advance time series univariate models like Seasonal ARIMA, a hybrid of Seasonal ARIMA with GARCH and ARIMA-X, where X stands for the exogenous variable. To the best of our knowledge these hybrid models have not been applied earlier for the forecasting of exchange rates and now with the advent of the covid-19 pandemic an opportunity has been created in which we can answer the following question 'which time series model works better to forecast the exchange rate in the pandemic situation'? .Further, our stock markets have constantly appreciated during the prevailing pandemic period and thus our paper will try to determine whether the Nifty50 is a good indicator to forecast the INR/USD exchange rates . Also, we have seen in previous studies that only a day ahead forecast is calculated, so in this paper we will calculate a 5 day ahead forecast and for each day of the week we will compare the forecasting performances of the model with the Random Walk model. RMSE values will be used for comparison purposes. Thus these are the novelties of this paper.

The paper is divided into the following sections:

Section 2, will discuss in brief the various time series models used in the paper.

In section 3, we will discuss the forecast results of the paper.

Section 4, we will conclude the paper.

2. Time Series Models

Seasonal Auto Regressive Integrated Moving Average (SARIMA)

SARIMA models come under the category of the univariate time series models. Univariate time series mean that a single observation is collected sequentially over a period. These models take into account the effect of trend and seasonality. The equation for the model is

$$\emptyset_p(L)^s \varphi_p(L)(1-L^s)^D(1-L)^d X_t = \vartheta_Q(L)^s \theta_q(L) u_t$$

Where L is a backward shift operator, $\emptyset$ and ϑ are seasonal autoregressive (AR) and moving average parameters (MA), φ and θ are non-seasonal autoregressive and moving average parameters, u_t is the white noise process; D and d are the order of seasonal and non-seasonal differencing.

SARIMA-GARCH (p,q) models

It is assumed for the variance of the residuals obtained from SARIMA models to be homoscedastic, but if the variance exhibits the property of the heteroscedasticity, then the Generalized Autoregressive Conditional heteroscedastic models (GARCH) models will be used to model the variance of the residuals. Hence the mean equation as obtained from SARIMA model will be

$$\emptyset_p(L)^s \varphi_p(L)(1-L^s)^D(1-L)^d X_t = \vartheta_Q(L)^s \theta_q(L) u_t$$

Where $u_t \sim$N(0,σ_t^2)

GARCH (p,q) for modelling the variance is given by

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2$$

The mean of the volatility equation is given by ω, α represents the size effect and β measures the persistence of the shock.

ARIMA model with an exogenous variable (ARIMAX)

ARIMAX – Transfer function model

Assuming X_t and Y_t are two stationary time series, then the transfer function model can be written as

$$Y_t = c + \vartheta(L) X_t + u_t$$

Where Y_t is the output series, X_t is the input series, L is the lag operator and u_t is the disturbance term.

$\vartheta(L)X_t$ is a transfer function which allows X to influence Y by a distributed lag. We can also write transfer function as follows

$$\vartheta(L)X_t = \frac{\omega_q(L)L^b}{\delta_p(L)}X_t$$

Where q is number of independent terms plus 1, p is the number of terms of the dependent variable included and b is the dead time. Disturbance term u_t can be written as follows

$$\emptyset_p(L)^s\varphi_p(L)(1-L^s)^D(1-L)^d u_t = \vartheta_Q(L)^s\theta_q(L)a_t$$

where the notations have their usual meaning as mentioned in the SARIMA model and a_t is a white noise process.

3. Empirical Analysis

Data Source: The daily closing prices of the INR/USD exchange rate and the Nifty50 have been obtained from the website of the National Stock Exchange of India. The period of the data was from 01/03/2020 to 28/02/2021. I have kept the last 5 values from February 2021 for our model validation purpose. Missing data in the series were filled using an interpolation technique. Further series was converted into natural log series to make them covariance stationary.

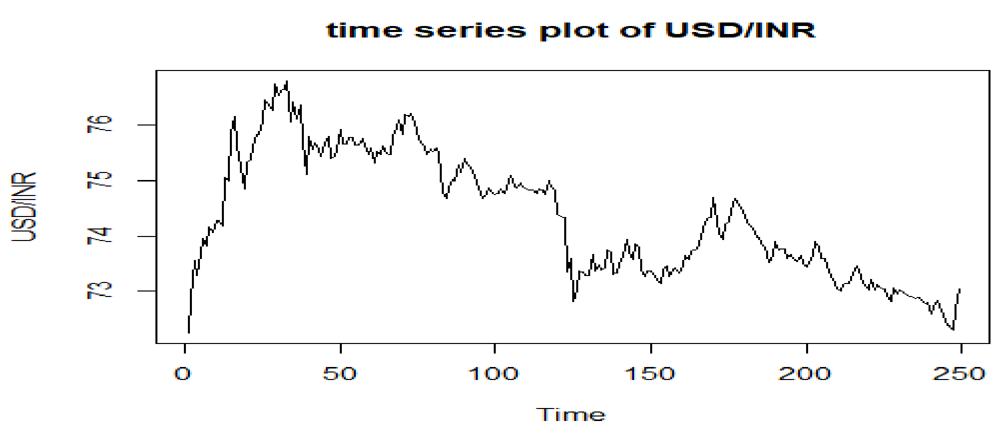

Figure 1

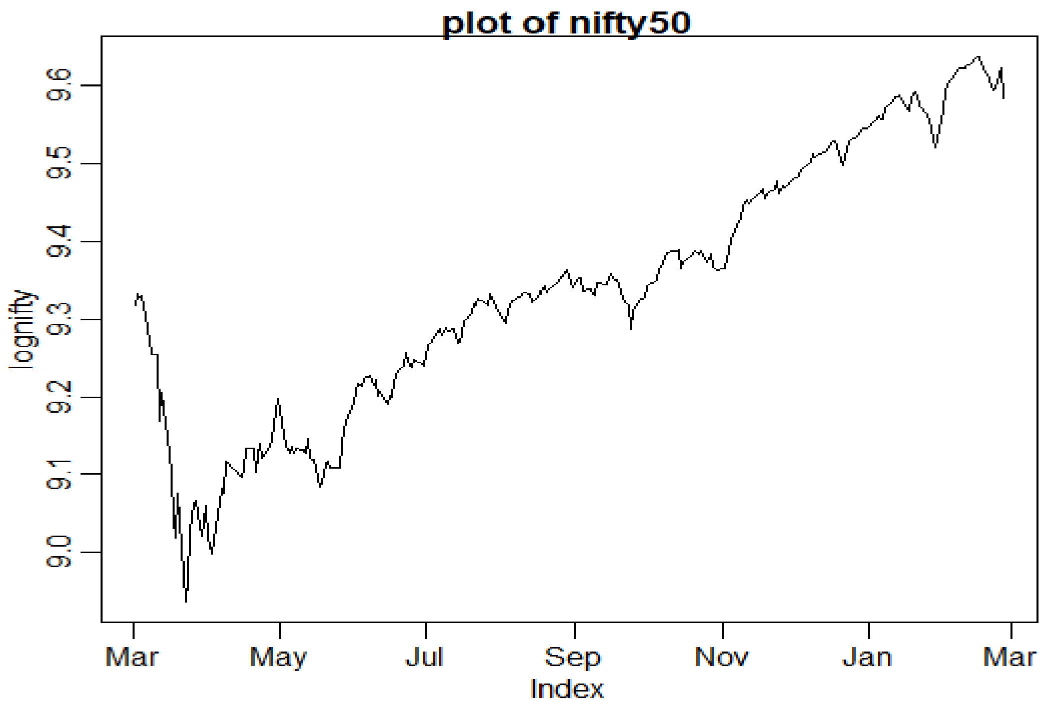

Figure 2

Figure 1 and figure 2, show the time series plot of the INR/USD and Nifty50 respectively.

Descriptive statistics of the INR/USD series (Table 1)

Parameter	Value
Mean	4.31
Median	4.31
Mode	4.29
Kurtosis	-1.12
Skewness	0.22
Count	249

Table 1

Descriptive statistics of the Nifty50 series (Table 2)

Parameter	Value
Mean	9.34
Median	9.33
Mode	9.26
Kurtosis	-0.78
Skewness	-0.06
Count	249

Table 2

From the result of table 1 and 2, it is clear that data in both the series are symmetrical and light tailed.

3. (i) SARIMA model

The first step is the determination of stationarity in a univariate time series, we have applied Augmented Dicky Fuller test for determining the stationarity. The result for the level series is shown below in the table 3.

S.No.	1%	5%	10%
Tau critical values	-3.46	-2.88	-2.57
Tau test statistic	-1.58		

Table 3

Thus the value of the test statistic is more than the critical values hence the level INR/USD series is non stationary. To make our series stationary we first de-seasonalize the series and then apply ADF test on the series. The results are presented in table 4 below

S.No.	1%	5%	10%
Tau critical values	-3.46	-2.88	-2.57
Tau test statistic	-5.72		

Table 4

Thus it is clear that the seasonal difference of the INR/USD series is stationary and then we proceed to determine the best fit model. Following is the result for the best fit model in table 5 below:

S.No.	Model (p,d,q)*$(P,D,Q)_S$	Akaike Information Criteria (AIC)
1	(1,0,0)*$(1,1,1)_5$	-8.4211
2	(1,0,0)*$(2,1,0)_5$	-8.2813
3	(1,0,1)*$(0,1,1)_5$	-8.4235
4	(1,0,0)*$(0,1,1)_5$	-8.4266
5	(9,0,0)*$(0,1,3)_5$	-8.39

Table 5

Based on the Akaike Information criteria, we have selected (9,0,0)*$(0,1,3)_5$ as the best fit model , in table 6, the values of the co-efficients along with their p-values are displayed

S.No	Parameters	Co-efficients	P-value
1	Constant	0	0.8885
2	ar1	0.9273	0***
3	ar2	0.1071	0.2329
4	ar3	-0.0138	0.8783
5	ar4	-0.1241	0.1371
6	ar5	-0.6092	0.0005***
7	ar6	0.5934	0.0002***
8	ar7	0.1923	0.0412.
9	ar8	-0.1605	0.0752.
10	ar9	0.0614	0.421
11	sma1	-0.1439	0.3813
12	sma2	-0.623	0***
13	sma3	-0.1224	0.126

Table 6, Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' , In table 7, we have presented the Ljung-Box test results for checking the auto-correlation in the residuals of the model. Null hypothesis is that the model does not show a lack of fit.

S.No.	Lags	P-value
1	5	0.98
2	10	0.94
3	15	0.88
4	20	0.94

Table 7

All the p values are insignificant hence the residuals are not correlated, hence we proceed for forecasting INR/USD series using the SARIMA model, and results are shown in Table 8 below

Time horizon	Actual values of INR/USD	Forecasted values from SARIMA model	Random walk series	RMSE of the SARIMA model	RMSE of the random walk model
t+1	73.2948	72.93789	73.0408	35.69%	25.40%
t+2	73.3507	72.90263	73.2948	40.51%	18.39%
t+3	73.0662	72.8143	73.3507	36.13%	22.25%
t+4	72.7126	72.88643	73.0662	32.47%	26.15%
t+5	72.7572	72.98694	72.7126	30.81%	23.48%

Table 8

Thus, based on the Root mean square error (RMSE) it is evident that the SARIMA model has failed to outperform the Random Walk model.

3 (ii) SARIMA – GARCH Model

It is imperative to check for heteroscedasticity in the residuals of the fitted model. To check for heteroscedasticity, Autoregressive Conditional Heteroskedasticity – Lagrange Multiplier (ARCH-LM) test was used. The null hypothesis of the test is – there is no ARCH effect. In table 9 below, the results from the test are presented.

S.No.	Lags	p-values
1	5	0.017.
2	10	0.003*
3	15	0.03.
4	20	0.05.

Table 9, Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

So all the p-values are significant, hence the heteroscedasticity is present in the residual series. Thus, we applied GARCH (1,1) to the residuals and the results of the test are shown in table 10 below.

S.No.	Parameter	Coefficients	P-values
1	omega	4.35*10^{-7}	0.1258
2	Alpha	1.079*10^{-1}	0.0354.
3	Beta	8.515*10^{-1}	0***
4	Ljung-Box test	Q(10)	0.97
5	Ljung-Box test	Q(15)	0.804
6	Ljung-Box test	Q(20)	0.813

Table 10, Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Alpha and beta are significant; hence the variance in the residual series is dependent on the previous day shocks and also on previous day variance. Ljung-Box test results are insignificant; thus the resultant residuals after fitting in the GARCH (1,1) model are not auto-correlated. Forecasting results from the SARIMA-GARCH (1,1) model are shown in Table 11 below

Time horizon	Actual values of INR/USD	Forecasted values from SARIMA – GARCH model	Random walk series	RMSE of the SARIMA-GARCH model	RMSE of the random walk model
t+1	73.2948	73.1753	73.0408	11.95%	25.40%
t+2	73.3507	73.12681	73.2948	17.94%	18.39%

t+3	73.0662	73.02643	73.3507	14.83%	22.25%
t+4	72.7126	73.08818	73.0662	22.75%	26.15%
t+5	72.7572	73.17949	72.7126	27.76%	23.48%

Table 11, Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Thus, from the RMSE values it is clear that the SARIMA-GARCH (1,1) model has outperformed the Random Walk series continuously for 4 days.

3 (iii) ARIMAX Model

For the ARIMAX model we have employed Nifty50 as our exogenous variable. In table 12 below we present ADF test results for the Nifty50 series.

S.No.	1%	5%	10%
Tau critical values	-3.46	-2.88	-2.57
Tau test statistic	-0.198		

Table 12

Clearly the Nifty50 series is non-stationary. Then we check for the correlation result between the various lags of Nifty50 series on the INR/USD series and result is presented in figure 3.

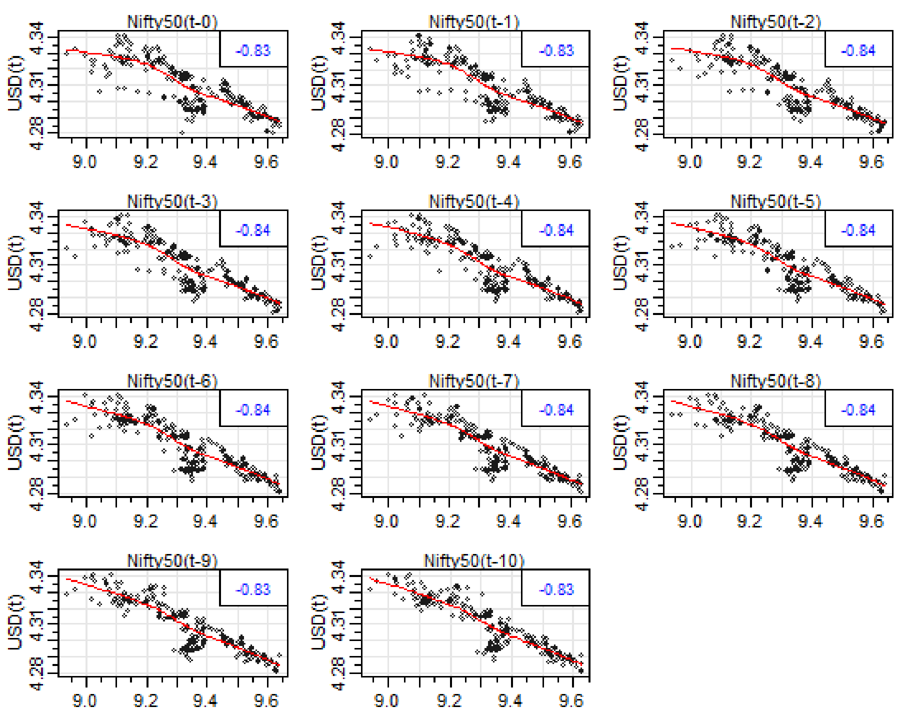

Figure 3

Clearly, Nifty50 is negatively correlated with the INR/USD series; thus till lag 10 values of the Nifty50 model is used in the final model; result of the model is presented in table 13 below

S.No.	Parameters	Co-efficients	P-value
1	Constant	0.61054	0***
2	Nift50	0.02181	0.1137
3	Nifty50(-1)	-0.0241	0.2028
4	Nifty50(-2)	0.01109	0.5587
5	Nifty50(-3)	-0.0069	0.711
6	Nifty50(-4)	0.00854	0.6389
7	Nifty50(-5)	-0.012	0.5027
8	Nifty50(-6)	0.03343	0.0432*
9	Nifty50(-7)	-0.008	0.59
10	Nifty50(-8)	-0.0098	0.4975
11	Nifty50(-9)	0.02373	0.1025
12	Nifty50(-10)	-0.0482	0***
13	INR/USD(-1)	0.88062	0***

Table 13, Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

R square = 0.9638, Adjusted R square = 0.9618

<u>Residuals Modelling</u>

Model Selected: (0,0,0)*$(1,1,1)_5$

S.No.	Parameters	Co-efficients	P-values
1	sar1	0.1041	0.1466
2	sma1	-0.9999	0***
3	constant	0	0.9926

Table 14, Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Auto-correlation test of the residuals using the Ljung-Box test (table 15)

S.No.	Lags	P-value
1	5	0.44
2	10	0.17
3	15	0.32
4	20	0.58

Table 15

From table 15, it is clear that the residuals are not auto-correlated. In table 16 below forecast of the INR/USD obtained from the ARIMAX model is presented

Time horizon	Actual values of INR/USD	Forecasted values from ARIMAX model	Random walk series	RMSE of the ARIMAX model	RMSE of the random walk model
t+1	73.2948	69.87007	73.0408	342.47%	25.40%
t+2	73.3507	67.10524	73.2948	503.66%	18.39%
t+3	73.0662	64.78487	73.3507	630.65%	22.25%
t+4	72.7126	62.84952	73.0662	735.86%	26.15%
t+5	72.7572	61.27744	72.7126	834.72%	23.48%

Table 16

Thus, from the result table it is evident that using Nifty50 as an exogenous variable to forecast the INR/USD series has failed to outperform the random walk model.

4. Conclusion

The present pandemic scenario across the world has provided us a unique opportunity to revisit time series models for forecasting purposes, especially during the pandemic period. In the prevailing volatile market conditions, a reliable forecast of the exchange rates definitely helps the banks, financial institutions, corporates and all other stake holders to save money. Some very interesting results have emerged from this paper which shall be helpful for all the stakeholders and these are:

- INR/USD currency pair is volatile in the current Covid19 pandemic condition. The value of the currency pair is affected by the previous day's news.
- The best way to forecast the INR/USD in the covid19 period is to employ a hybrid univariate time series models. Our recommendation is to use SARIMA-GARCH (1,1) model for predicting the daily prices upto 4 days ahead.
- Not to use any other high frequency indicator in the model to forecast INR/USD series because the volatility of the INR/USD currency pair is getting affected by previous day news and we cannot use all news sources in one model. We have tested this principle by incorporating Nifty50 series in our time series model, but the forecasts obtained from this model are not satisfactory.

Due to prevailing pandemic condition, only daily high frequency data is obtained, so the future research should be on ultra- high frequency data for forecasting the INR/USD series and other currency pairs as well.

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