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AN ARIMA ANALYSIS OF THE INDIAN RUPEE/USD EXCHANGE RATE IN INDIA

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ABSTRACT

This study uses annual time series data on the Indian Rupee / USD exchange rate from 1960 to 2017, to model and forecast exchange rates using the Box-Jenkins ARIMA technique. Diagnostic tests indicate that R is an I (1) variable. Based on Theil's U, the study presents the ARIMA (0, 1, 6) model, the diagnostic tests further show that this model is quite stable and hence acceptable for forecasting the Indian Rupee / USD exchange rates. The selected optimal model the ARIMA (0, 1, 6) model shows that the Indian Rupee / USD exchange rate will appreciate over the period 2018 – 2022, after which it will depreciate slightly until 2027. The main policy prescription emanating from this study is that the Reserve Bank of India (RBI) should devalue the Rupee, firstly to restore the much needed exchange rate stability, secondly to encourage local manufacturing and thirdly to promote foreign capital inflows.

Contribution/Originality:

This paper's primary contribution is finding that the Indian Rupee/USD exchange rate will appreciate over the period 2018 – 2022, after which it will depreciate slightly until 2027.

1. INTRODUCTION

Exchange rate is an important variable which influences decisions taken by the participants of the foreign exchange market, namely investors, importers, exporters, bankers, financial institutions, business, tourists and policy makers both in the developing and developed world as well (Dua and Ranjan, 2011). Forecasting of the exchange rate is essential for practitioners and researchers in the spree of international finance, particularly in the case of exchange rate which is floating (Hu, 1999). Since the breakdown of the Bretton Woods System of fixed exchange rate in 1973, the difficulty and desirability of obtaining reliable forecasts of exchange rates was highly demanding to earn income from speculative activities, to determine optimal government policies as well as to make business decisions (Newaz, 2008). The foreign exchange market in India is believed to have begun in 1978 when the government allowed banks to trade foreign exchange with each other. Today, it is almost unnecessary to reiterate the observation that globalization and liberalization have significantly enhanced the scope for the foreign exchange market in India. The Indian exchange rate is regime, as noted by Goyal (2018) is a managed float, where the central bank allows markets to discover the equilibrium level but only intervenes to prevent excessive volatility.

1.1. Research Objectives

i. To develop an optimal ARIMA model for the analysis of the Indian Rupee / USD exchange rate.
ii. To check whether the Random Walk Model out performs other ARIMA processes in forecasting the Indian Rupee / USD exchange rate.
iii. To predict the Indian Rupee / USD exchange rate over the period 2018 – 2027

1.2. Statement of the Problem

Foreign exchange markets are filled with uncertainty (Canova and Marrinan, 1993). Foreign exchange traders are constantly looking for ways to protect themselves against these uncertainties and unwanted fluctuations due to the effect that they have on the economic outlook of a country (Gali and Monacelli, 2005). There is no doubt; exchange rate stability contributes to the development of a safe macroeconomic environment which leads to growth and investment (Ames *et al.*, 2001). A number of forecasting techniques have been developed and yet the much needed exchange rate stability has not materialized (Tudela, 2004). It is important to understand how the exchange rate mechanism works and contributions can be made to any forecasting model so as to reach the desired level of confidence and trust the market needs (Grauwe and Schnabl, 2008). The importance of forecasting exchange rates in practical aspect is that an accurate forecast can render valuable information to the investors, firms and central banks for use in allocation of assets, in hedging risk and in policy formulation (Tindaon, 2015). The modeling and forecasting of the Indian Rupee / USD Exchange Rate is expected to go a long way in improving policy formulation in India.

2. LITERATURE REVIEW

2.1. Theoretical Literature Review

There are a number of theories of exchange rate determination, applied in exchange rate forecasting; in this study we will only consider three of them:

2.2. The Purchasing Power Parity (PPP) Model

The PPP framework, officially named and popularized by Cassel (1918) is an exchange rate model which is based on the famous "law of one price" and explains the movements of the exchange rate between two countries' currencies by the changes in the countries' price levels. The basic argument is that the goods-market arbitrage mechanism will move the exchange rate to equalize prices in the two countries. For example, if the United States (US) goods are more expensive than those in India, consumers in the US and India may tend to purchase more Indian goods. The increased demand for Indian goods will drive the Indian Rupee to appreciate with respect to the USD until the dollar-denominated prices of the US goods and Indian goods are equalized. The PPP model can be expressed as follows:

$$Ine_t = Inp_t - Inp_t \qquad (1)$$

where $e_t$is the nominal exchange rate, p_t and p_t^* are domestic and foreign prices respectively. Equation (1) is reffered to as the relative version of the PPP model, since price indices instead of actual price levels are used in estimations. Equation (1) is a "weaker" variation of the PPP theory, hence the term relative PPP theory and is different from the absolute version of the PPP theory which is based on a strict interpretation of the law of one price. However, the absolute PPP theory is unlikely to hold, probably due to the existence of transport costs, imperfect information as well as distorting effects of tariffs and other forms of protectionism and yet the relative PPP theory arguably holds even in the presence of such distortions. It is almost unnecessary to note that equation (1) points to the notion that the exchange rate will adjust by the amount of the inflation differential between two economies. However, the applicability of the PPP theory in exchange rate determination is subject to a hot debate, for example, Enders (1988); Corbae and Ouliaris (1990) and Tronzano (1992) amongst other argue that the PPP theory performs poorly while, on the other side of the same coin, researchers such as Abuaf and Jorion (1990); Kim (1990); Patel (1990) and Taylor (1990) have found out that the PPP theory is applicable, especially in developed countries and can therefore forecast exchanges very well, especially for the long-run.

2.3. The Uncovered Interest Rate Parity (UIP) Model

The UIP explains how the exchange rate moves according to the expected returns of holding assets in two different currencies. UIP ignores transaction costs and liquidity constraints and apparently gives an arbitrage mechanism that drives the exchange rate to a value that equalizes the returns on holding both the domestic and foreign assets. If the UIP holds, the arbitrage relationship gives the following expression:

$$E_t(Ine_{t+h} - Ine_t) = i_t - i_t^* \qquad (2)$$

where $E_t(Ine_{t+h} - Ine_t)$ is the market expectation of the exchange rate return from time *t* to time *t+h*, and i_t and i_t^* are interest rates of the domestic and foreign currencies respectively. Uncovered interest parity condition, as presented in equation (2), implies that market arbitrage will move the exchange rate to the point at which the expected rate of return on investments denominated in either the home or foreign currency is the same, with the exception of a possible risk premium. Essentially, equation (2) rules out the possibility of excess profits in asset markets, in the sense that the interest rate differential between the home and foreign country equals the anticipated change in the exchange rate. The applicability of the UIP model in forecasting exchange rates has been shown by Meredith and Chinn (1998); Alexius (2001) and Cheung *et al.* (2004) who noted that the UIP model is basically capable for forecasting at longer horizons.

2.4. The Sticky Price Monetary (SPM) Model

The SPM model, postulated by Dornbusch (1976) and Frankel (1979) is basically an extension of the PPP model by replacing the price variables in equation (Abdullah *et al.*, 2017) with macroeconomic variables that capture money demand and over-shooting effects. Frankel (1979) specifies the SPM model as follows:

$$Ine_t = Inm_t - Inm_t^* - \emptyset(Iny_t - Iny_t^*) + \alpha(Ini_t - Ini_t^*) + \beta(\pi_t - \pi_t^*) \quad (3)$$

where m_t is the domestic money supply, y_t is the domestic output, i_t is the domestic interest rate, π_t is the domestic current state of expected long run inflation, and all variables in asterisk denote variables of the foreign country. Equation (3) incorporates the short-run interest rate in order to capture liquidity effects and also assumes that the expected rate of depreciation of the exchange rate is positively related to the gap between the current exchange rate and the long-run equilibrium rate and the anticipated long-run inflation differential between the domestic and foreign countries. Equation (3) can also be explained as an overshooting model in the sense that the exchange rate tends to overshoot its new equilibrium level following some exogenous shock to the system. For instance, a shock which warrants depreciation of the exchange rate to a new long run level: overshooting means that in the short run, the exchange rate has a tendency of over-depreciating before appreciating towards its new long run equilibrium value.

2.5. Empirical Literature Review

A myriad of scholarly papers have been published on the area of exchange rate forecasting since the breakdown of the Bretton Woods System. Given the main thrust of this paper, Table 1 below provides a fair sample of relevant studies undertaken more recently:

Table-1. Reviewed Previous Studies

Author(s)/Year	Country	Period	Methodology	Main Findings
Alam (2012)	Bangladesh	July 2006 – April 2010	AR, ARIMA, ARMA, MA	AR and ARMA models outperform other models
Pacelli (2012)	Italy	January 1999 – December 2009	ANN, ARCH, GARCH	ARCH and GARCH models perform better than ANN
Ramzan *et al.* (2012)	Pakistan	1981 – 2010	ARIMA, ARCH, GARCH, EGARCH	GARCH (1, 2) is the best to remove the persistence in volatility while EGARCH (1, 2) successfully overcame the leverage effect in the exchange rate returns
Pedram and Ebrahim (2014)	Iran	November 2010 – June 2013	ARIMA, ANN	ANNs are far much better than ARIMA models
Nwankwo (2014)	Nigeria	1982 – 2011	ARIMA	AR (1) model (i.e ARIMA (1, 0, 0)) was the best.
Erdogan and Goksu (2014)	Turkey	2010 – 2013	ANN	ANNs can closely forecast the future EUR/TRY exchange rates
Babu and Reddy (2015)	India	January 2010 – April 2015	ARIMA, ANN, Fuzzy Neuron	ARIMA model performs better than complex non-

				linear models
Etuk and Natamba (2015)	Nigeria	July 1990 – November 2014	SARIMA	SARIMA (0, 1, 1)(0, 1, $1)_{12}$, SARIMA (0, 1, 1)(1, 1, $1)_{12}$ are preferred
Gupta and Kashyap (2015)	India	April 2014 – March 2015	ARIMA	The following models were found to be performing very well: ARIMA (0, 1, 1), ARIMA (2, 1, 1) and ARIMA (2, 1, 2)
Ngan (2016)	Vietnam	January 2013 – December 2015	ARIMA	VND/USD in 2016 tends to increase
Abdullah *et al.* (2017)	Bangladesh	January 2008 – April 2015	GARCH, APARCH, TGARCH, IGARCH	AR (2) – GARCH (1, 1) is the best model
Qonita *et al.* (2017)	Indonesia	January 2010 – June 2016	ARIMA	ARIMA method has an accuracy rate of 98.74%
Mustafa *et al.* (2017)	Malaysia	November 2010 – August 2016	Hybrid ARIMA-GARCH, hybrid ARIMA-EGARCH	ARIMA-EGARCH model fits the data better
Ganbold *et al.* (2017)	Turkey	2005 – 2017	ARIMA, SARIMA, ARCH, SVAR	EGARCH (1, 1) performs better
Mia *et al.* (2017)	Bangladesh	August 2004 – March 2016	ARIMA, ESM, ANN	ANNs perform better than ARIMA models
Nyoni (2018l)	Nigeria	1960 – 2017	ARIMA	ARIMA (1, 1, 1) is the optimal model

Source: Authors' analysis from literature review (2019).

3. METHODOLOGY

3.1. Autoregressive (AR) Models

A series R_t (*which represents the Indian Rupee / USD exchange rate at time, t*) is said to be an autoregressive process of order p, denoted by AR (p) if it can be expressed in the form:

$$R_t = \emptyset_1 R_{t-1} + \emptyset_2 R_{t-2} + \cdots + \emptyset_p R_{t-p} + \varepsilon_t \quad (4)$$

Equation (4) implies that the Indian Rupee / USD exchange rate, in this regard, is explained by the previous period values of the Indian Rupee / USD series, hence the term "autoregressive".
Using the backshift operator, equation (4), as noted by (Alexius, 2001); can be written as:

$$R_t\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) = \varepsilon_t \quad (5)$$

Where B is the backshift operator, $\emptyset_1 \ldots \emptyset_p$ are parameters of the model and ε_t is a normally distributed random process with mean 0 and a constant varience σ_ε^2 and is assumed to be independent of all previous process values $R_{t-1}, R_{t-2}, \ldots$

AR models are normally restricted to stationary data (Hyndman and Athanasopoulos, 2014). Therefore, it is necessary to check for stationarity of the data before fitting such models.

3.2. Moving Average (MA) Models

A series with a white noise process of mean 0 and varience σ_ε^2 is reffered to as a moving average process of order q, denoted as MA (q), if it can be expressed as a weighted linear sum of past forecast errors as follows:

$$R_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{6}$$

Equation (6) means that the Indian Rupee / USD exchange can be explained using the current and previous period disturbances (the random errors, or the socalled shocks such as unanticipated political events).
In backshift operator notation, equation (6), as noted by (Alam, 2012); can be written as:

$$R_t = \varepsilon_t \left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) \tag{7}$$

Where $\theta_0, \theta_1, \ldots\ \theta_q$ are coefficients of the lagged error terms and θ_0 is assumed to be equal to 1. B and ε_t are as previously defined.
The parameters of an MA process must be negative so that we can have characteristic operators of the same signs for both AR and MA processes, although this has no significant change to the interpretation of the model.

3.3. Autoregressive Moving Average (ARMA) Models

Combining both the AR (p) and MA (q) models gives rise to an Autoregressive Moving Average model (ARMA (p, q)) model which can be expressed as follows:

$$R_t = \emptyset_1 R_{t-1} + \emptyset_2 R_{t-2} + \cdots + \emptyset_p R_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{8}$$

Equation (8) means that the Indian Rupee / USD exchange rate can be explained by its previous period values as well as the current and past disturbances.
Re-arranging equation (8), as hinted by (Box and Jenkins, 1994); gives:

$$R_t - \emptyset_1 R_{t-1} - \emptyset_2 R_{t-2} - \cdots - \emptyset_p R_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{9}$$

Using the backshift operator equation (Canova and Marrinan, 1993) can be expressed as follows:

$$R_t\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) = \varepsilon_t\left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) \tag{10}$$

Equation (10), based on (Cassel, 1918); can be simplified to:

$$\emptyset(B) R_t = \theta(B) \varepsilon_t \tag{11}$$

Where:

$$\left.\begin{aligned} \emptyset(B) &= \left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) \\ \theta(B) &= \left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) \end{aligned}\right\} \tag{12}$$

Both the AR (p) and MA (q) are special cases of the ARMA model. An ARMA (p, 0) process is the same as an AR (p) process and an ARMA (0, q) process is the same as an MA (q) process. If the available data is stationary, it is better modeled using an ARMA (p, q) model than AR (p) or MA (q) models individually (Chin and Fan, 2005). This is because an ARMA (p, q) model in such as case uses fewer parameters than the individual models and gives a better representation of the data and this is reffered to as the principle of parsimony (Singh, 2002; Woodward *et al.*, 2011).

3.4. Autoregressive Integrated Moving Average (ARIMA) Models

Most time series data is not stationary due to seasonality and trend. Hence, once cannot apply AR, MA or ARMA models directly. The best way of obtaining stationarity when dealing with ARIMA models is differencing (Systematics, 1994). Basically, time series data can be differenced "d" times, until it becomes stationary. Most time series data become stationary after differencing, either once or twice, and in that case, "d" is either 1 or 2, respectively. By convention, differencing "d" times can be written as:

$$(1-B)^d R_t$$

If the original data series is differenced "d" times before fitting an ARMA (p, q) model, then the model for the original undifferenced series said to be an ARIMA (p, d, q), where "d" represents the number of times the data has been differenced (Hendry, 1995).

Differencing "d" times changes equation (11), as suggested by (Cassel, 1918); to:

$$R_t(1-\emptyset_1 B-\emptyset_2 B^2-\cdots-\emptyset_p B^p)(1-B)^d=\varepsilon_t\left(1+\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q\right) \quad (13)$$

Equation (13), following (Chin and Fan, 2005); can be simplified to:

$$\emptyset(B)(1-B)^d R_t=\theta(B)\varepsilon_t \quad (14)$$

Equation (13), as noted by (Corbae and Ouliaris, 1990); is reffered to as an ARIMA model. The white noise process (ARIMA (0, 0, 0)), random walk process (ARIMA (0, 1, 0)), autoregressive process (ARIMA (0, 0, q)) and autoregressive moving average (ARIMA (p, 0, q)) are special types of ARIMA models.

3.5. The Random Walk Model – The ARIMA (0, 1, 0) Model

The random walk model can be given by:

$$R_t=R_{t-1}+\varepsilon_t \quad (15)$$

where ε_t is as previously defined and apparently denotes a purely random process.

Equation (15) (Dornbusch, 1976) does not form a stationary process, however, the first difference: R_t-R_{t-1}, forms a stationary series.

Equation (15) (Dornbusch, 1976) can also be decomposed as follows:

$$\left.\begin{array}{r} R_1=\varepsilon_1 \\ R_2=\varepsilon_1+\varepsilon_2 \\ \vdots \\ R_t=\varepsilon_1+\varepsilon_2+\cdots+\varepsilon_t \end{array}\right\} \quad (16)$$

The mean function is given by:

$$\left.\begin{array}{c}\mu_t = E(R_t)\\ \mu_t = E(\varepsilon_1 + \varepsilon_2 + \cdots + \varepsilon_t)\\ \mu_t = E(\varepsilon_1) + E(\varepsilon_2) + \cdots + E(\varepsilon_t)\\ \therefore\\ \mu_t = 0 + 0 + \cdots + 0\\ such\ that:\\ \mu_t = 0\ \forall\ t\end{array}\right\} \quad (17)$$

$$\left.\begin{array}{c}Var(R_t) = Var(\varepsilon_1 + \varepsilon_2 + \cdots + \varepsilon_t)\\ Var(R_t) = Var(\varepsilon_1) + Var(\varepsilon_2) + \cdots + Var(\varepsilon_t)\\ Var(R_t) = \sigma_{\varepsilon_1}^2 + \sigma_{\varepsilon_2}^2 + \cdots + \sigma_{\varepsilon_t}^2\end{array}\right\} \quad (18)$$

Equation (17) implies that, on average, all errors or disturbances or shocks, sum up to zero. Hence the process varience increases with time, linearly as shown in equation (18).

Analysis of the Covariance Function

Given: $1 \leq t \leq s$, then:

$$\gamma_{t,s} = cov(R_t, R_s)$$
$$\gamma_{t,s} = cov(\varepsilon_1 + \varepsilon_2 + \cdots + \varepsilon_t, \varepsilon_1 + \varepsilon_2 + \cdots + \varepsilon_t + \varepsilon_{t+1} + \cdots + \varepsilon_s) \quad (19)$$

This can be written as follows:

$$\gamma_{t,s} = \sum_{i=1}^{s} \sum_{j=1}^{t} cov(\varepsilon_i, \varepsilon_j)$$
(20)

The covariates are normally equal to zero unless when i=j, and in that scenario, we have: $Var(\varepsilon_i) = \sigma_t^2$. There are t of these such that $\gamma_{t,s} = t\sigma_\varepsilon^2$. The purpose of equations (15) to (20) is to uncover the issue of covariance stationarity, which is an important issue when it comes to univariate analysis in econometrics. A stochastic process is thought of as stationary if its mean and varience are constant over time and the value of the covariance between the two time periods depends only on the gap or lag between the two periods and not the actual time at which the covariance is computed. The simplest example of a covariance stationary stochastic process is a white-noise process. Equation (17) is the mean function while equation (18) is varience function. Equations (19 – 20) show the covariance functions and that the covariance function is stationary since the value of the covariance between period t and s depends on the lag between the two periods and not the actual time at which the covariance is calculated.

3.6. The Box – Jenkins Technique

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage.

The process may go on and on until an appropriate model is identified (Nyoni, 2018i). The Box – Jenkins technique is accredited to Box and Jenkins (1970) and is widely used in many forecasting contexts. In this paper, we will use it for forecasting the Indian Rupee / USD exchange rates.

3.7. Data Collection

In line with Chatfield (1996) and Meyler *et al.* (1998) who argued that more than 50 observations are needed in order to build a reliable ARIMA model, this study is based on a data set of the Indian Rupee / USD[1] exchange rate (denoted as R) ranging over the period 1960 – 2017. All the data used in this study was extracted from the World Bank online database.

3.8. Diagnostic Tests and Model Evaluation

3.1.8. Stationarity Tests: Graphical Analysis

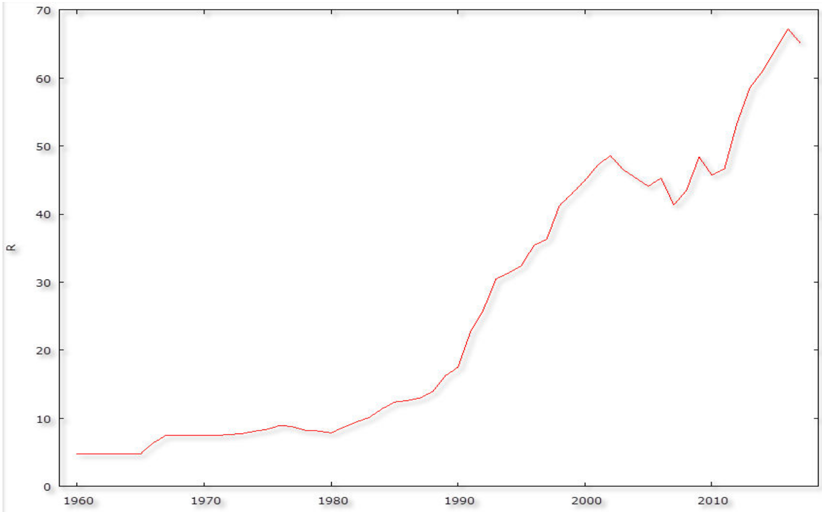

Figure-1. Graphical Analysis

Source: Author's Own Computation

3.9. The Correlogram in Levels

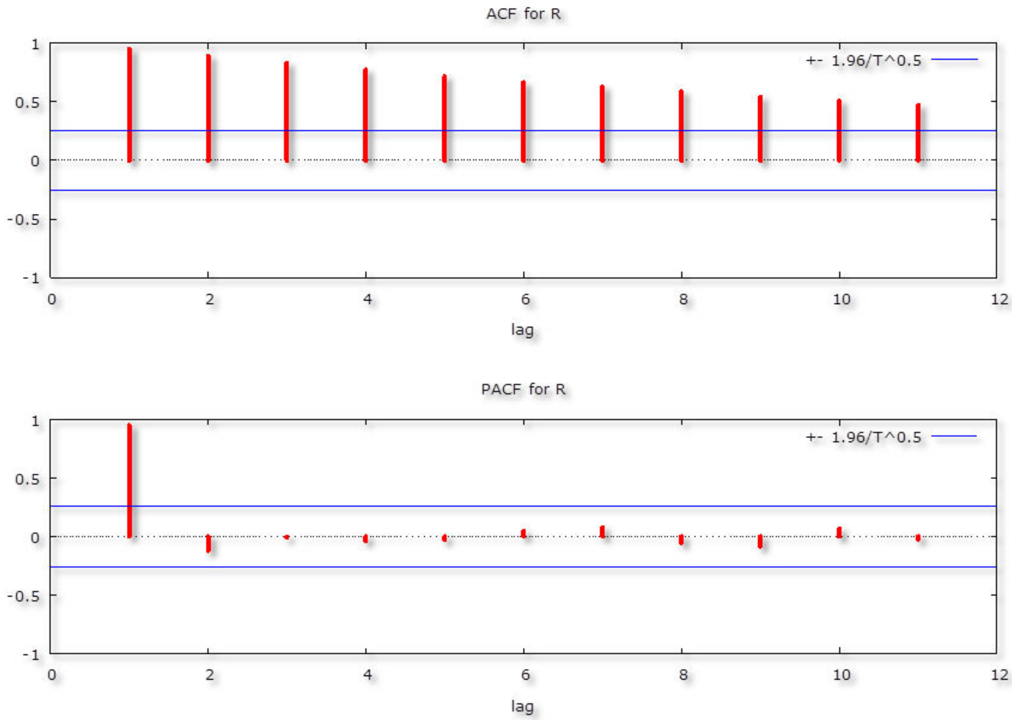

Figure-2. Correlogram in Levels

[1] *United States Dollar.*

Source: Author's Own Computation

3.10. The ADF Test

Table-2. Levels-intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	1.594465	0.9994	-3.550396	@1%	Not stationary
			-2.913549	@5%	Not stationary
			-2.594521	@10%	Not stationary

Source: Author's Own Computation

Table-3. Levels-trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-1.492394	0.8208	-4.127338	@1%	Not stationary
			-3.490662	@5%	Not stationary
			-3.173943	@10%	Not stationary

Source: Author's Own Computation

Table-4. without intercept and trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	4.159	1.000	-2.606163	@1%	Not stationary
			-1.946654	@5%	Not stationary
			-1.613122	@10%	Not stationary

Source: Author's Own Computation

3.11. The Correlogram at 1st Differences

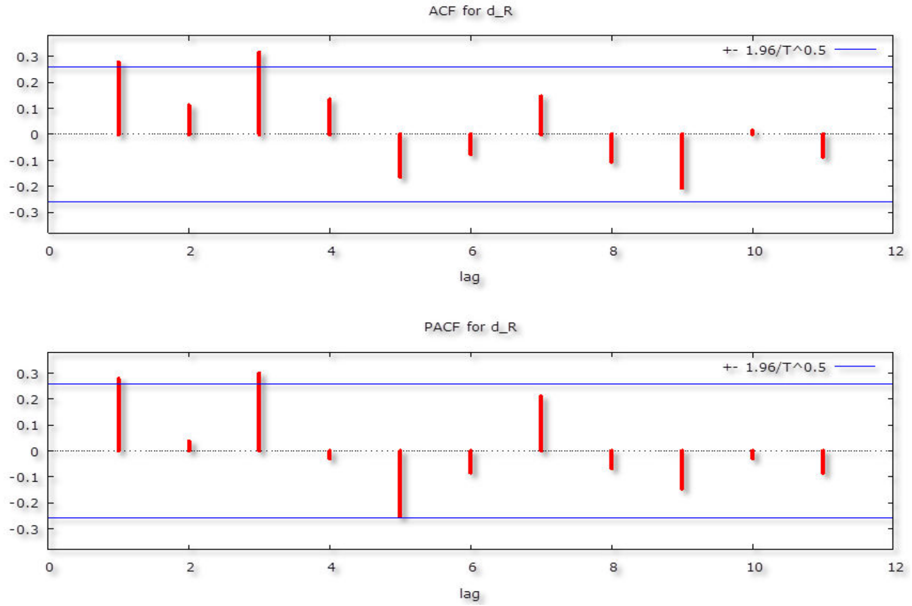

Figure-3. Correlogram in 1st Differences

Source: Author's Own Computation

Table-5. 1st Difference-intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(R_t)$	-5.329250	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Source: Author's Own Computation

Table-6. 1st Difference-trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(R_t)$	-5.570223	0.0001	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

Source: Author's Own Computation

Table-7. 1st Difference-without intercept and trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(R_t)	-1.961682	0.0484	-2.608490	@1%	Stationary
			-1.946996	@5%	Stationary
			-1.612934	@10%	Stationary

Source: Author's Own Computation

Figures 1, 2 and 3 and Tables 2 to 7 indicate that R is an I (1) variable.

3.12. Evaluation of ARIMA Models (without a constant)

Table-8. Evaluation of ARIMA models

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	243.6966	0.85192	0.37654	1.2341	1.9402	4.7461
ARIMA (0, 1, 2)	248.9982	0.88621	0.6934	1.349	2.0358	4.8727
ARIMA (0, 1, 1)	247.2181	0.89296	0.723	1.3598	2.0395	4.8946
ARIMA (0, 1, 3)	241.0277	0.87503	0.51926	1.2289	1.8535	4.899
ARIMA (0, 1, 4)	240.3721	0.85135	0.41417	1.1644	1.81	4.6827
ARIMA (0, 1, 5)	242.3710	0.85162	0.41753	1.1647	1.8101	4.6812
ARIMA (1, 1, 0)	245.3469	0.86294	0.56792	1.2857	2.0061	4.697
ARIMA (2, 1, 0)	246.4242	0.85609	0.50154	1.2545	1.9894	4.671
ARIMA (3, 1, 0)	240.4945	0.85664	0.35074	1.2009	1.8489	4.7601
ARIMA (4, 1, 0)	242.4934	0.85688	0.34981	1.2014	1.8489	4.7658
ARIMA (5, 1, 0)	241.6721	0.86423	0.38937	1.212	1.7994	4.8872
ARIMA (2, 1, 2)	246.0884	0.8434	0.36352	1.2081	1.9115	4.5822
ARIMA (0, 1, 6)	244.0862	**0.84203**	0.41489	1.1584	1.8012	4.6528
[2]ARIMA (0, 1, 0)	-	1	1.0589	1.5621	2.2498	5.7223
ARIMA (1, 1, 2)	245.4296	0.84583	0.34008	1.2492	1.9312	4.6125
ARIMA (1, 1, 3)	241.1691	0.85631	0.40144	1.1675	1.8231	4.7143
ARIMA (1, 1, 4)	242.3713	0.85154	0.41651	1.1646	1.8101	4.6817
ARIMA (2, 1, 1)	245.6751	0.85035	0.37414	1.2356	1.9399	4.7305
ARIMA (3, 1, 1)	242.4940	0.85675	0.35032	1.2012	1.8489	4.7627
ARIMA (4, 1, 1)	244.2591	0.85993	0.34178	1.2183	1.8448	4.846
ARIMA (5, 1, 1)	243.6160	0.86648	0.39433	1.2091	1.7984	4.8985
ARIMA (2, 1, 4)	244.3247	0.8518	0.44263	1.1663	1.8101	4.6637

Source: Author's Own Computation

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n) Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). In this paper, we rely mainly on the Theil's U as the criteria for choosing the best model. The Theil's U indicates that the random walk model performs poorly and is in fact, the worst, in the case of the Indian Rupee / USD exchange rate as shown in this regard. This means that the annual Indian Rupee / USD exchange rate does not follow a random walk. This is apparently inconsistent with Mussa (1979) and Meese and Rogoff (1983) who showed the superiority of the random walk model in out-of-sample exchange rate forecast. However, the Theil's U evaluation statistic shows that the ARIMA (0, 1, 6) model outperforms other ARIMA models and is therefore chosen as the best model.

3.13. Residual & Stability Tests

3.13.1. Residual Correlogram of the ARIMA (0, 1, 6) Model

[2] *Random Walk Model*

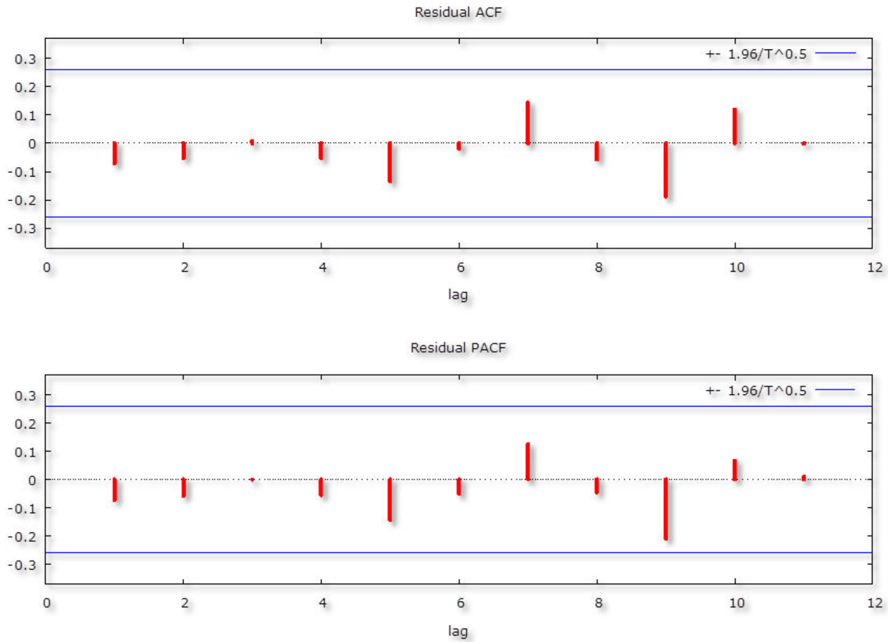

Figure-4. Residual Correlogram

Source: Author's Own Computation

3.14. ADF Tests of the Residuals of the ARIMA (0, 1, 6) Model

Table-9. Levels-intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.373411	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Source: Author's Own Computation

Table-10. Levels-trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.314221	0.0000	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

Source: Author's Own Computation

Table-11. without intercept and trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.077427	0.0000	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

Source: Author's Own Computation

Figure 4 and Table 9 to Table 11 indicate that the residuals of the ARIMA (0, 1, 6) model are stationary.

3.15. Stability Test of the ARIMA (0, 1, 6) Model

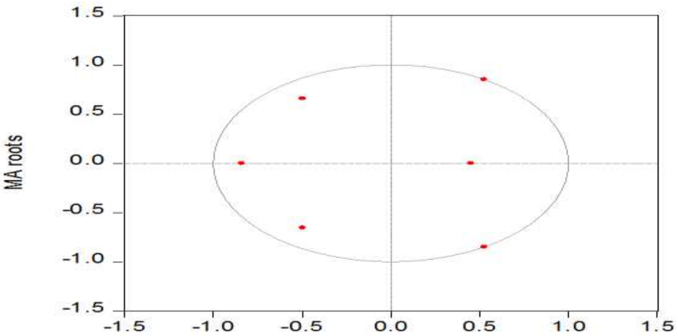

Figure-5. Stability Test

Source: Author's Own Computation

Because the corresponding inverse roots of the characteristic polynomial lie in the unit circle, we can safely conclude that the chosen ARIMA (0, 1, 6) model is indeed stable.

4. FINDINGS

Table-12. Descriptive Statistics

Description	Statistic
Mean	25.647
Median	15.075
Minimum	4.76
Maximum	67.2
Standard deviation	19.986
Skewness	0.52602
Excess kurtosis	-1.1889

Source: Author's Own Computation

As shown in Table 12 above, the mean is positive, i.e 25.647. The median is 15.075. The maximum is 67.2. The minimum is 4.76. Since skewness is 0.52602, it implies that variable R is positively skewed and non-symmetric. Excess kurtosis is -1.1889 and simply indicates that R is not normally distributed.

4.1. Results Presentation[3]

Table-13. Results

ARIMA (0, 1, 6) Model:

$$\Delta R_{t-1} = 0.375217\varepsilon_{t-1} + 0.232964\varepsilon_{t-2} + 0.455302\varepsilon_{t-3} + 0.333495\varepsilon_{t-4} + 0.0486549\varepsilon_{t-5} - 0.137725\varepsilon_{t-6} \quad (21)$$

Variable	Coefficient	Standard Error	z	p-value
θ_1	0.375217	0.136507	2.749	0.0060***
θ_2	0.232964	0.148769	1.566	0.1174
θ_3	0.455302	0.152045	2.995	0.0027***
θ_4	0.333495	0.156202	2.135	0.0328**
θ_5	0.0486549	0.158404	0.3072	0.7587
θ_6	-0.137725	0.148658	-0.9265	0.3542

Source: Author's Own Computation

Equation (21) is the estimated optimal model, the ARIMA (0, 1, 6) model. Only θ_1, θ_3 and θ_4 are significant, showing the importance of such disturbances or shocks (shocks experienced 1 year ago, 3 years ago as well as 4 years ago) in explaining exchange rate movements in India over the study period.

[3] ***, ** *and* * *means significant at 1%, 5% and 10% level of significance, respectively.*

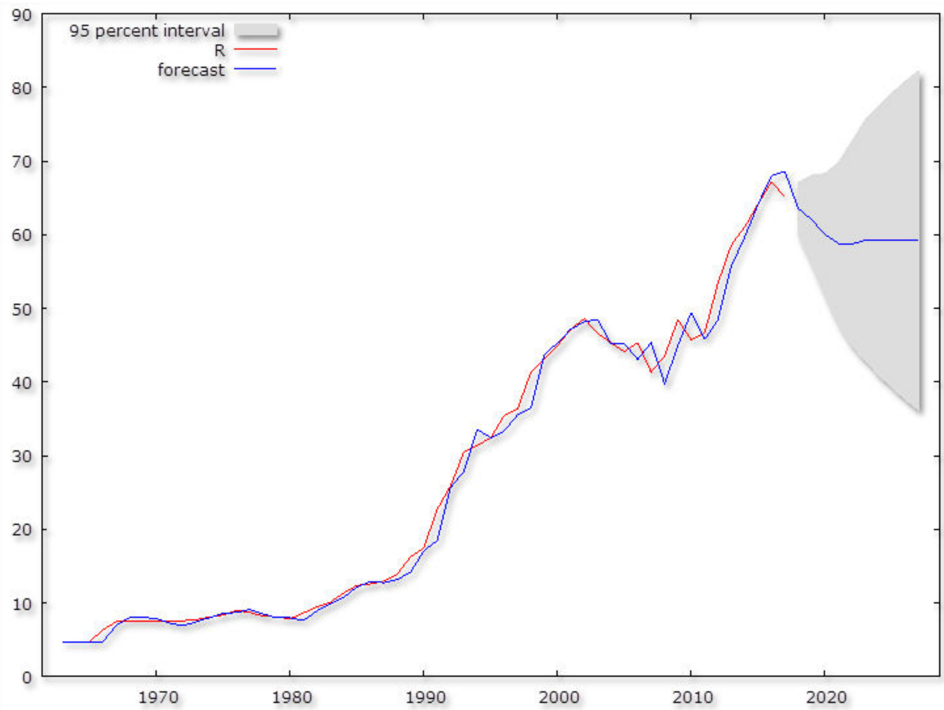

Figure-6. Forecast Graph

Source: Author's Own Computation

[4]**Table-14. Out-of-Sample Forecast**

Year	Predicted Indian Rupee / USD exchange rate	Standard Error	95% interval
2018	63.5526	1.80003	(60.0246, 67.0806)
2019	62.0545	3.06071	(56.0556, 68.0534)
2020	60.0088	4.21280	(51.7518, 68.2657)
2021	58.8002	5.61640	(47.7922, 69.8081)
2022	58.7415	7.08238	(44.8603, 72.6227)
2023	59.2223	8.33905	(42.8781, 75.5665)
2024	59.2223	9.31655	(40.9622, 77.4824)
2025	59.2223	10.2008	(39.2291, 79.2155)
2026	59.2223	11.0143	(37.6347, 80.8099)
2027	59.2223	11.7717	(36.1502, 82.2944)

Source:

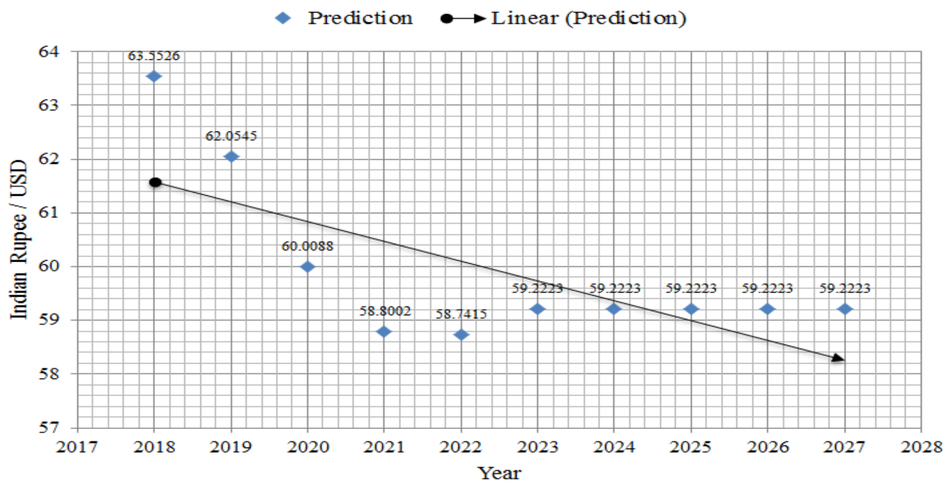

Figure-7. Graphical Presentation of the Out-of-Sample Forecast

Source: Author's Own Computation

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[4] *For 95% confidence intervals, z(0.025) = 1.96*

Table 13 shows the main results of the optimal model, the ARIMA (0, 1, 6) model. Only θ_1, θ_3 *and* θ_4 are significant, indicating the importance of such shocks (shocks experienced 1 year ago, 3 years ago as well as 4 years ago) in explaining exchange rate dynamics in India. Figures 6 & Figure 7 and Table 14 show the predicted Indian Rupee / USD exchange rate over the period 2018 to 2027: the annual Indian Rupee / USD exchange rate is expected to fall (appreciate) over the forecasted period. Our findings are partially consistent with Goyal (2018) who observed that in 2017, the Indian Rupee / USD exchange rate appreciated. Our findings show that major appreciation will not persist into the medium term but only occur over the period 2020 – 2022, after which the Indian Rupee / USD exchange rate will start depreciating again. The Rupee, as argued by Goyal (2018) cannot appreciate substantially unless the Renminbi does so, since China (and not the US) is a major trade competitor and partner.

5. CONCLUSION & POLICY IMPLICATIONS

Exchange rates have long fascinated, challenged and puzzled researchers in international finance (Zorzi *et al.*, 2015). Exchange rate prediction is one of the demanding applications of modern time series forecasting (Nwankwo, 2014). The rates are inherently noisy, non-stationary and deterministically chaotic (Box and Jenkins, 1994). Generating quality forecasts is not an easy task (Mustafa *et al*, 2017). Given the analysis and forecasts of this study, our recommendation is that policy makers in India ought to devalue the Rupee in order to restore and maintain exchange rate stability. Once devaluation is implemented in India, the local manufacturing sector will grow phenomenally and this is likely to be accompanied by inflows of the much awaited foreign capital.

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