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Exchange Rate Volatility under Inflation-Targeting Regime

A time series analysis.

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Abstract

The foreign exchange market is the largest financial market in the world by sheer trading volume. There is a necessity to forecast exchange rates and their volatility not just amongst investors, but also by policy-makers. This report tries to understand some of the features that make exchange rate volatility and the Central Bank's intervention in the forex market, crucial. Furthermore, since India formally adopted Inflation-Targeting in 2015 with targets fixed in January 2016, a statistical analysis on time-series USD-INR exchange rate data in this period gives insights into the role of exchange rates under an Inflation-Targeting regime. We also conduct a univariate time series analysis, by modelling the variance of exchange rate log returns using a GARCH(1,1) model. Making use of this model, rolling predictions of volatility is made.

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Contents

1 Introduction

The largest financial market in the world in terms of sheer trading volume is the foreign exchange market. According to the Bank of International Settlements (BIS) triennial survey, in 2019 the value of all instruments traded at the forex market amounted to 6.6 trillion US dollars. [BIS Survey, 2019]

Forecasting foreign exchange rates are not only important for investors, but also for policy makers. It is found in [BIS Survey, 2019] that the US dollar (USD) is the most traded currency. It is also noteworthy that USD-INR trade corresponds to about 1.7% of total currency pairs traded daily. This accounts for an average daily trade of the Rupee to the value of 110 billion USD. Therefore, forecasting of the exchange rates is of immense importance to monetary policy objective set by the Reserve Bank of India. The fact that India recently adopted an Inflation-Targeting regime since 2016, adds further reasoning to this task.

1.1 Objective

This report carries out a time series analysis on forecasting the volatility of the USD-INR exchange rate, since the adoption of Inflation-Targeting. We make use of standard statistical models for conditional volatility such as ARCH and GARCH models and attempt to fit historical data to a suitable model. Further, using this we attempt to predict the volatility of the Rupee for the future.

Firstly, following this introduction, we briefly review the methods of monetary policy intervention in the foreign exchange market carried out by RBI. Further, we discuss the events that led to the adoption of Inflation-Targeting in India in 2016. In the subsequent sections we perform a literature survey on Exchange Rate Volatility models and carry out a univariate time series analysis.

This research carries out a univariate analysis of modeling exchange rate volatility. It employs statistical tests in the determination of volatility of log returns on exchange rate data. This stand-out feature of this report is the analysis of the data pertaining to the Inflation-Targeting economy. In Section 2, we discuss some general aspects of Central Bank's Intervention channels and some particular episodes of volatility and the methods employed by RBI in curbing the said volatility. Section 3 is an analysis of the role that exchange rate plays under an Inflation-Targeting economy; and the particular case with India. In Section 4, a literature review is undertaken and the case and lessons from several countries is summarized. Sections 5 and 6 deal with the time-series analysis of the chosen data, where the model is constructed and statistically tested. In the final section the results are summarized and concluded.

2 Exchange Rate Volatility in India

2.1 Central Bank's Intervention

Liberalization of the '90s allowed foreign capital inflows into India in the form of private capital flows i.e., Foreign Direct Investment (FDI) and Portfolio Investment. Domestic Companies started raising foreign capital through Global Depository Receipts and American Depository Receipts. The movement towards full capital account convertibility resulted in a surge in forex inflows, as well as adding uncertainties to the financial markets. It also increased the speculation in the forex market. The RBI therefore intervenes to curb such excessive fluctuations and correct misalignments. Although there is much debate over the efficacy of Central Bank intervention, much of the contention is about whether it leads to change in trend growth. In the regime of removing volatility in the short-term there has been some evidence in favour of the Central Bank's intervention. [Behera et al., 2012] We shall now elaborate on the different types of intervention channels employed by the Central Bank.

Types of Intervention

There are two types of intervention in the forex market. They are referred to as sterilized and non-sterilized interventions. Direct intervention is defined as the purchase of foreign currency assets by the Central Bank to influence exchange rate. There are other reasons for purchase and sale of foreign assets by the Central Bank. If these interventions lead to increase in monetary base they are called non-sterilized interventions. If, however, the authorities simultaneously (with short time-lag) take steps to offset the effects of change in foreign asset holdings on monetary base then it is called sterilized intervention. Note that non-sterilized intervention affects exchange rate because of the changes in stock of the monetary base. The effect of sterilized intervention on exchange rate is much debated; However it is certain that sterilized interventions leave the monetary base unchanged.

Sterilized Intervention

Since the objective here is focussed on sterilized interventions, we shall list the three major possible channels through which such interventions occur:

1. **Portfolio Balance Approach**: In this approach, domestic and foreign assets are assumed to be imperfect substitutes. The premise is that investors allocate portfolios to balance their risk against expected rate of return and the Central Bank intervenes by selling foreign currency assets, thereby leading to excess supply of foreign currency and excess demand for domestic currency assets. In order to return to equilibrium, agents need to be compensated by a higher expected return on foreign currency assets. This could take the form of widening interest rate differentials and appreciation of domestic currency.

2. **Signalling Channel**: This method assumes information asymmetry between market participants and the Central Bank. The premise here is that intervention causes private agents to alter their exchange rate expectations. By buying foreign currency for domestic currency in forex, the Central Bank might signal an expansionary monetary policy. (due to increase in money supply). The market participants will then expect an easy monetary policy and would revise their expectations of future exchange rate. The would also reassess their expectations on future spot rates, but only if Central Bank's forex operations are perceived to be credible.

3. **Noise Trading Channel**: This channel can be operated even when the intervention is carried out discreetly. There is no need to provide a signal to market participants, nor does is it large enough to alter relative supply of domestic and foreign currency assets. This method induces noise traders to buy or to sell currency. The Central Bank can manipulate the exchange rate by entering in a relatively thin market and on a minute-by minute basis. Note that the exchange rate is determined by marginal demand and supply flow in forex market.

Opinion is divided on the effectiveness of Central Bank intervention of stabilizing exchange rate. There are three different channels of response as enlisted above. These responses reduce exchange rate volatility by stopping speculative attacks on the currency. But response could also increase market uncertainty and encourage speculative attack on the currency only to cause much of the problem discussed here.

RBI intervenes secretly through select public-sector banks. It corrects demand-supply mismatch in the forex market. The Public sector banks would undertake deals in inter-bank market & RBI provides cover at the end of each day. RBI intervention is secret and is partially sterilized. Thus, the effectiveness of RBI intervention is unclear.

2.2 Major Volatility Episodes

We now review the major episodes of volatility in the Indian Foreign Exchange Market in the period 1993-2013 and the response by RBI. Volatility of exchange rate, which is the amount of uncertainty or risk involved with size of changes in the Rupee's exchange rate, is computed by the RBI through the standard deviations of daily foreign exchange market returns and are subsequently annualized. A complete account of all the major volatility episodes is presented in [Prakash, 2012]. We shall now summarize these major episodes of exchange rate volatility in India.

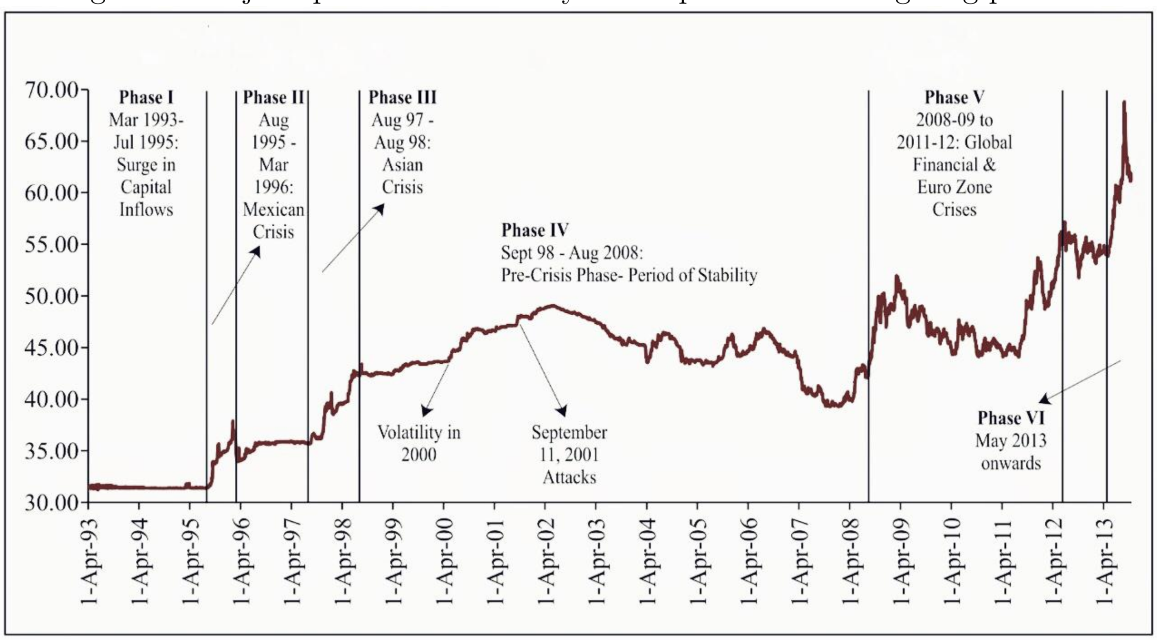
Adoption of Market-determined Exchange Rates

We noted earlier that the Forex Markets facilitate cross border trade, investment and financial transactions. In a market determined exchange rate system – excessive exchange rates volatility, out of line with economic fundamentals can impose real costs on the economy through its effects on international trade and investment. Furthermore, the pressures from foreign exchange markets could complicate the conduct of monetary policy. Thus, an adoption market-determined exchange rate in 1993 in India had heightened volatility. Since then there has been several incidents of high volatility. In Figure 1, the exchange rates of USD-INR is plotted and the period between liberalization and adoption of inflation-targeting is split into five major phases as will be explained below.

The exchange rate policy of RBI was:

- Maintaining orderly conditions in the foreign exchange market.
- Preventing the emergence of destabilising and self-fulfilling speculative activities, and
- Allowing the exchange rate to reflect the macroeconomic fundamentals.

Figure 1: Major Episodes of volatility in the pre-inflation-targeting period.



Post exchange rate unification period. (March 1993 to July 1995)

- Backdrop: Surge in capital inflows due to liberalization in capita account. Move towards market determined exchange rate system.

- Actions: To maintain external competitiveness of exports and stability of the rupee, RBI intervened in spot market, purchased dollars and thereafter conducted open market operations to partially sterilize the expansionary impact on domestic liquidity.

- Outcome: India's forex reserves increased from \$6.4B to \$20.8 billion – representing 7-month import cover – period of prolonged stability in the range Rs.31.37 and Rs.31.65 per 1 US dollar.

Impact of Mexican Crisis (August 1995 to March 1996)

- Backdrop: Contagion of the Mexican currency crisis – sharp devaluation of Mexican peso in Dec 1994 on account of inappropriate policies, large CAD and weak macro-economic fundamentals, leading to sharp slowdown in capital inflows, and certain endogenous factors – accentuated the demand for dollar. The rupee had depreciated to Rs.36.48 per US dollar.

- Action: Rupee was overvalued in REER terms (REER – real effective exchange rate); imposition of interest surcharge on import finance, ease of CRR requirement, tightening export credit etc.

- Outcome: Stability in the range of Rs.34.28 to Rs.35.79 per US dollar.

Impact of East-Asian Crisis (August 1997 to August 1998)

- Backdrop: Challenges to exchange rate management due to the contagion effect of the South-East Asian crisis, the economic sanction imposed by many industrialized nations after the nuclear explosion in Pokhran (India) in May 1998 and the downgrading of the sovereign rating of India by certain international rating agencies.

- Action: RBI intervenes in spot, swap and forward markets to manage expectations and bring forward premia down – had sold billions of USD – to the tune of \$3.1B. RBI's forward liabilities increased – but came down subsequently upon normalcy.

- Stability returned and expectations of the market participants about further depreciation in the exchange rate of rupee were contained and also reversed to a certain extent.

Global Financial Crisis (2008-09 to 2011-12)

- Backdrop: Collapse of Lehman brothers and other investment banks. Fed bailing out AIG and its quantitative easing, operation twist, forward guidance etc. Large withdrawals of funds from the equity markets by the FIIs, reflecting the credit squeeze and global deleveraging that resulted in large capital outflows during September-October 2008, with concomitant pressures in the foreign exchange market across the globe, including India.
- Action: RBI sold US dollar through agent banks. Rupee dollar swap facility for Indian banks was introduced for comforting Indian banks in managing short term foreign funding requirements. RBI also continued Special Market Operations (SMO) to meet forex requirements of OMCs. which are liquidity neutral operations.

3 Inflation-Targeting in India

India adopted Inflation-Targeting, formally, in the 2016. In this section, we shall discuss first the reasons for emerging market economies to adopt Inflation-Targeting(IT). An IMF paper elucidates six main reasons for the enhanced role of exchange rates in Inflation-Targeting EMEs, which are summarized here. Further we shall look at the backdrop of Indian Monetary Policy that led to this decision. In addition, the study by [Mohan & Ray, 2018] investigates the reasons that led to India's adoption of IT.

3.1 Role of Exchange Rate in Inflation-Targeting economies

Emerging economies that are inflation-targeting often have less flexible exchange rates and have frequent foreign exchange interventions. When emerging economies that are more vulnerable to exchange rate fluctuations intervene in the forex market, it causes confusion about the Central Bank's commitment to the set inflation target. In inflation-targeting (IT) emerging market economies (EMEs) there is an explicit but limited support for role of exchange rates. The economy structure and shocks exposed dictate this role in policy rules. Systematic, transparent and market-based policy implementation was found to reduce policy conflicts. This approach towards exchange rate also helps EMEs move towards IT.

Enhanced role in IT-EMEs

The reasons for an enhanced role of exchange rate in an inflation-targeting emerging economy are as follows.

1. There exists a pass-through from exchange-rate to inflation and therefore, price stability. Thus for emerging economies, the lower credibility of policy owes its origin to this factor.

2. EMEs often use exchange rate to mitigate the impact on output of short-term currency movements.

3. Managing exchange rate helps in financial stability, especially against the impact of potential depreciation on balance sheets with currency mismatches.

4. It also helps avoid the adverse consequences for external stability of a sudden stop in capital inflows.

5. Exchange rate management is necessary in undeveloped domestic financial markets that reduce exchange rate flexibility by amplifying shocks in exchange rate and therefore hindering policy implementation.

6. High degree of policy credibility frees up exchange rates, allowing it to float and hence enhances policy implementation. This is necessary for adopting a fully inflation-targeting anchor.

Appropriate Role for the Exchange Rate in the Monetary Policy Rule

For improving macroeconomic performance of an economy certain policy rule trade-offs have to be undertaken. It is seen that inflation/output volatility is higher for emerging economies than for advanced economies. Thus advanced economies have little to gain from incorporating exchange rate explicitly in the policy function, especially in response to demand shocks, while the converse is true for emerging economies.

However it must be noted that while emerging economies might benefit from incorporating exchange rate in their policy function, too much emphasis on it also might prove detrimental. Inclusion of exchange rate in policy function helps mitigate impact of risk-premium shocks and cost-push shocks by dampening interest rate and exchange rate volatility.

Role of Forex Intervention in Inflation-Targeting

In emerging economies, establishing strong policy implementation under inflation targeting can be a difficult task. Under IT, interest rate is the main monetary policy instrument. If forex interventions are done in a systematic and transparent manner, then it can help reduce the confusion regarding the inflation target. Transparency should be with respect to policy objectives, operational procedures and ex post evaluation; this significantly reduces the confusion regarding inflation target. A better signalling of monetary policy comes when the domestic money markets are significantly improved. The development of domestic money market encourages using domestic monetary instruments for policy implementation rather than relying heavily on the forex intervention. Further, a strengthened domestic money market also aids in the sterilization of foreign exchange interventions.

Role of Exchange rate during the transition to IT

There are certain emerging economies with a flexible exchange rate regime, but not a full-fledged inflation-targeting framework. These are referred to as emerging economies with other anchors. In such economies the exchange rates are actively managed by forex interventions, consequently however, the monetary policy implementations tends to be more ad hoc with less basis on the market and more focus on the forex intervention. For such EMEs with other anchors is that the exchange rate channels are more stronger and also more uncertain than IT EMEs because they are financially less developed and more dollarized, thus having less overall credibility. In order to transition to IT, such EMEs must establish a more systematic, consistent and market based role for exchange rates. This can be achieved by:

- Giving exchange rate a larger weight in the the interest rate reaction function or using the exchange rate as the operating policy target during the transition.
- The choice of operating policy target depends upon the degree of development of domestic money markets.
- Over time, the weights of exchange rate in the interest rate reaction function can be reduced, in gradually transitioning to inflation-targeting.

3.2 Monetary Policy

A summary of monetary policy of India through the years if first taken up here. The major watershed moments are:

- Credit Planning till mid 1980s. Credit was channelled at cheap administered rated for growth. Inflation due to structural shocks such as drought, flood, oil price changes.
- Monetary targeting first adopted in mid 1980s. Monetary targeting was adopted for growth in nominal GDP after accounting for tolerable inflation. RBI introduced money market instruments, and deregulated interest rates in existing money market instruments. Cash Reserve Ratio (CRR) was the prime monetary policy tool, owing to poor money-market and predominance of RBI credit to the central government.
- Monetary policy became operationally independent in April 1997 when automatic monetisation by ad hoc treasury bill creation was done away with.
- Multiple indicators approach adopted by RBI in April 1998, where apart from broad money, other macroeconomic variables such as interest rates, rates of return in different markets (money, capital, govt. securities etc.), currency, credit data, fiscal position, trade, capital flows, inflation rate, exchange rate etc, are used along with output data for policy formulation.

- Liquidity Adjustment Facility (LAF) set up in 2000 enabling RBI to use repo and reverse repo rates as key policy signalling rates. Multiple indicators approach and monetary operations through LAF has constituted the operating framework of Indian Monetary policy until 2013.

In the period between 2009-13, RBI practised a hands-off approach in its capital account management and forex interventions, that is there was no announced change in Indian Exchange rate policy. Following the taper tantrum episode in 2013, RBI finally changed its intervention strategy. During this, the capital outflows from India accelerated and various factors were attributed to the widening of India's current account deficit, such as 1. Sluggish growth since 2009, that affects Indian exports 2. Elevation in international commodity prices, also supported by accomodative monetary policies in advanced economies and 3. Domestic supply and policy constraints leading to increase in imports.

Monetary policy between Nov 1997 to Sep 2013 was called the multiple indicators approach. Under this, inflation amongst several other variables were key indicators. Instead of a formal inflation target, RBI set an outlook for inflation in its monetary policy statement. In 2015 it was pointed out by the Committee for Financial Sector Reforms that:

> *The RBI should formally have a single objective, to stay close to a low inflation number, or within a range, in the medium term, and move steadily to a single instrument, the short term interest rate (repo and reverse repo) to achieve it.*

India formally adopted Inflation-Targeting, and a Monetary Policy Framework Agreement (MPFA) was signed between GoI and RBI on Feb 25, 2015. The target was set to bring down inflation below 6% by Jan 2016, 4 % for that financial year and all other years with a band of +/- 2 percent.

Why hadn't RBI adopted Inflation-Targeting earlier?

The reasons to this are as follows:

1. Unlike many other emerging economies, India has had a record of moderate inflation, with double-digits being the undesirable exception.

2. Inflation-targeting requires efficiency in monetary transmission which happens through the operation of efficient financial markets and the absence of interest rate distortions. India still requires further development in the money market, forex and corporate and govt. debt markets. Also, administered interest rates exist too.

3. Inflationary pressures often occur due to significant exogeneous supply shocks such as energy and food price sources. Therefore targeting a theoretical core inflation rate that excludes a portion of any inflation index in a low income economy is useless.

4. Until recently India did not have a pan-India consumer price index (CPI).

4 Literature Review

The effectiveness of Central Bank intervention in curbing excess exchange rate volatility is topic of much debate. Primarily, evidences from different sources seem to prove that in some cases intervention reduced volatility, while in other cases has infact caused greater exchange rate volatilty, and in some others, the effect is unclear.

Several countries, especially emerging market economies (EMEs), over the years have adopted an inflation-targeting regime, having set their short-term interest rate as an operating target, to anchor expectations of inflation. Under an inflation-targeting (IT) regime, utmost importance is given to the operating target of inflation – that is maintaining price stability. Under such, the objective of exchange rate stability is only secondary.

In [Cabral et al., 2020], it was found that the exchange rate was significance in the policy function of non-IT countries. Since foreign exchange (forex) interventions can be viewed as a signaling mechanism to market participants, the central bank's role in intervention should not conflict their stated inflation-targeting objectives. In this aspect, [Castillo, 2014], while finding that the Bank employs two different instruments to carry forward its objectives: which are 1. Inflation target, and 2. Upper limit on nominal exchange rate volatility, also observed that the Bank must exercise caution while using both the above instruments simultaneously, in order to avoid sending conflicting signals to the market participants – hence, endangering their inflation target.

From the studies by, [Mishkin, 2008, Filardo & Siklos, 2016] we know that there can be a high degree of pass through from exchange rate swings to rate of inflation. Hence central banks, especially those of EMEs cannot afford to abstain from forex interventions. EMEs often state that the interventions are for the purpose of curbing excessive volatility alone and not for changing the level of exchange rates.

A research gap identified is that the evidence on the effectiveness of forex interventions by IT regime EMEs is mixed. Inflation-targeting implies a fully floating exchange rate regime. This warrants central bank intervention. However, in EMEs this cannot be performed without compromising the existing IT monetary policy. Deviations affect the Bank's credibility.

From [Berganza & Broto, 2012], we know that a flexible IT, with managed-floating exchange rates, the forex interventions are effective in reducing volatility over non-IT countries. This was based on a panel data involving 37 countries (EMEs). Credibility is not undermined if the Central bank communicated its primary commitment towards IT and explains or highlights the reasons for particular interventions stemming from a need to stabilize shocks.

From [Caselli & Roitman, 2019], we know that there exists nonlinearities and asymmetries in pass- through of exchange rate fluctuations to prices. When the exchange rate depreciates, it is found that the pass-through to prices becomes non-linear.

Table 1: Country-wise Literature

Country	**Work**	**Insights**
India	Ghosh et al (2016)	1. Policy reaction function estimated. 2. Whether Discretionary monetary policy or Inflation-targeting preferred depends on the volatility of the shock with respect to the bank's time inconsistency problem. 3. Under imperfect capital mobility, sterilized intervention with inflation targeting is effective.
Uganda	Katusiime and Agbola (2018)	1. Found mixed impact of forex interventions on exchange rate volatility. 2. Inflation targeting used to curb temporary shocks in exchange rate. 3. From the model, evidence was found that increase in order flow reduced volatility, but the increase in interbank and operating target rate increased volatility.
Czech	Disyatat and Galati (2007)	1. Central bank intervention had a weak but significant impact on the spot rate and the risk reversal. 2. No evidence that intervention had an influence on short-term exchange rate volatility. 3. Authorities appeared to intervene mainly in response to an acceleration of the speed of koruna appreciation.

Guatemala	Catalan-Herrera (2016)	1. Central Bank reaction function estimated using a friction model. 2. Evidence found in terms of threshold effects in reaction functions, which mean that intervention dampened exchange rate volatility. 3. It had no effect of the level of exchange rate. 4. Central bank intervened to deviations from short-term trends.
Panel data of 37 countries	Berganza and Broto (2012)	1. For EMEs the question is whether to implement a strict IT - which means that the exchange rate is fully flexible. Or to apply a flexible IT, which means a managed-floating exchange rate by forex interventions.

5 Time Series Analysis

A time series $\{y_t\}$ is a sequence of observations of a variable y_i where i indexes time. When the observations of a time series are recorded at successive, equally-spaced points in time, it is called a *discrete time series.* [Brockwell & Davis, 2016]. We shall now briefly establish concepts and models in time series analysis that can be found in standard textbooks such as [Tsay, 2010, Cryer & Chan, 2008, Enders, 2008, Nielsen, 2019].

Stationarity

In order to perform time series analysis, it is important to check if the classical linear regression model (CLRM) assumptions hold. The fundamental assumption when it comes to time-series data is that of stationarity. A time series $\{y_t\}$ is said to be strictly stationary if its joint distribution does not change when shifted in time. That is, the distribution of terms $\{y_t, y_{t+1}, y_{t+2}, ...\}$ and $\{y_{i+t}, y_{i+t+1}, y_{i+t+2}, ...\}$ have the same distribution. Since this cannot be expected of all time series data, we usually use a weaker form of stationarity, which is when the mean of $\{y_t\}$ and the covariance between $\{y_t\}$ and $\{y_t - k\}$ are time invariant. k is any arbitrary integer. Thus we can now define weak stationarity as follows:

Definition. A time series is said to be weakly stationary if:

- $E[y_t] = \mu$
- $Cov(y_t, y_{t-k}) = \gamma_k$
- $Var(y_t, y_{t-k}) = \sigma_k^2$ (equivalent to above)

where μ is a constant and γ_k depends only on the lag length k. Hence, the first two moments of the distribution is of interest while examining the stationarity of a time-series process.

Autocorrelations

The Autocorrelation function (ACF) fundamentally measures the self-correlation of time-series data. The idea is that the value of the exchange rate at some point in time may have a correlation with the value in another point of time. It is fairly obvious to assume that in time series data of macroeconomic variables, since current values depend on previous values, a significant level of self-correlation is present.

Definition. Autocorrelation, or serial correlation, is the correlation of a signal with a delayed copy of itself as a function of the delay. Simply put, it is the similarity between observations as a function of the time lag between them.

For instance, one may observe that the value of exchange rate in the month of April might be correlated with that of the month of August. In such a case, one can make predictions of exchange rate in the month of August based on the values in April.

AR model

The autoregressive (AR) model is used when the output variable depends linearly on its past value in addition to an innovation term (or disturbance term) ϵ_t, that incorporates everything else new in the series at time t which the past values fail to explain. A p^{th} order autoregressive process $\{y_t\}$ is expressed as follows.

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{1}$$

Note that ϵ_t is assumed to be independent of all lags in the series. The number of significant lags can be visualized by the PACF correlogram. If there are p significant lags (lags that cut above the error bands in the correlogram), then a AR(p) model is imminent for estimation. Note however, that several of these lag terms might be insignificant, in which case, it makes sense to employ a simpler model.

MA model

The moving average (MA) model is expressed as a weighted linear combination of present and past white noise terms. The intuition is that, in this model, one predicts future values, by taking in account of a fraction of the error in the past values. The MA(q) model is expressed as follows:

$$y_t = \mu + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{2}$$

ARMA model

If a series has traits from both autoregressive and moving average processes, it constitutes an ARMA model, given by:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \qquad (3)$$

5.1 Modeling Exchange Rate returns

In our analysis we shall be using exchange rate returns rather than actual values. The reasons would be obvious in subsequent sections. If y_t denotes the exchange rates, then the exchange rate returns are defined as:

$$r_t = \left(\frac{y_t - y_{t-1}}{y_t} \right) \qquad (4)$$

Now, if we have a large number of periods (say n periods) corresponding to a time interval, then the total return is simply the sum of the individual period's returns. Thus, we have:

$$r_t = \sum_{i=1}^{n} r_i = \sum_{i=1}^{n} \left(\frac{y_i - y_{i-1}}{y_i} \right) \qquad (5)$$

Note here that, although the above expression points to a discrete time series, the variable y_t could infact be continuous. Hence, the limiting case of this variable as $\Delta t \to 0$ is $\Delta y \to dy$, and one can replace the summation by an integral. Thus,

$$r_t = \ln \left(\frac{y_t}{y_{t-1}} \right) \qquad (6)$$

Since the value of natural logarithms tend to be extremely small, we shall multiply it by a factor of hundred and use the following definition of exchange rate returns.

$$r_t = 100 \times \ln \left(\frac{y_t}{y_{t-1}} \right) \qquad (7)$$

GARCH(1,1) model

Bollerslev(1986) extended Engle's ARCH model so as to obtain the Generalized Autoregressive Conditional Heteroscedasticity Model. Conditional Heteroscedasticity models have been used in econometric analysis to typically estimate and forecast the volatility of asset returns and stock prices. As noted in the literature review section, there is ample support for the use of these models in exchange rate volatility forecasting also.

A complete forecasting ARCH or GARCH model has three components. They are:

- a mean equation, such as a constant mean or an AR process.
- a variance equation, modeling the volatility using GARCH, and,
- a distribution for standardized residuals.

We specify the basic GARCH(1,1) model as follows:

$$\begin{aligned} r_t &= \mu + \epsilon_t \\ \epsilon_t &= \sigma_t \omega_t \\ \sigma_t^2 &= \omega + \alpha \epsilon_t^2 + \beta \sigma_{t-1}^2 \end{aligned} \tag{8}$$

6 Data and Methodology

We shall now perform a univariate time series analysis to forecast the volatility of the exchange rate using a GARCH model. The data for this is obtained from the Reserve Bank of India website and the Federal Reserve Economic Data portal. The particular time series chosen here is the USD-INR exchange rate, which gives the equivalent value of one dollar in Rupees.

The analysis is carried out in two datasets:

- USD-INR daily series - period 2016-2020 using GARCH.
- USD-INR monthly series - period 1990-2020 using GARCH.

6.1 Preprocessing time-series data

First, we carry out forecasting using an ARMA model. The daily exchange rate data of USD-INR in the period January 2016 to June 2020 is taken up for this study. This spans a total number of 1173 trading days. This period was chosen so, because the first inflation-targeting objective was set from January of 2016. The analysis was carried out on Python, and the outputs and inferences are presented here.

Exploratory Data Analysis

We first import the relevant packages on python and perform an exploratory data analysis. The summary statistics of the data is shown below in Table 2.

The exchange rate data has a mean of 68.45. The kurtosis value is less than 3.0, implying a platykurtic nature. Platykurtosis measures the extremity of the data of a probability distribution. A normal bell-shaped distribution is mesokurtic. A

Table 2: Summary statistics of the time-series data

```
count       1643.000000
mean        68.481222
std         03.265543
min         63.369900
25%         66.226000
50%         67.995500
75%         70.969700
max         76.936400
kurtosis   -0.3971000535624869
skewness    0.5334319860507775
```

distribution that has less extreme values than the normal distribution is considered platykurtic. Thus the platykurtic distribution has lighter tails than a normal distribution with few values at the extreme ends of the curve. A leptokurtic distribution has more extreme data than the normal curve.

Plotting Exchange Rates

There are periods of high volatility. Although the Rupee value seems to have depreciated vis-a-vis the US Dollar, we are unable determine stationarity visually and require a statistical test such as Augmented Dickey Fuller Test.

Figure 2: USD-INR exchange rates

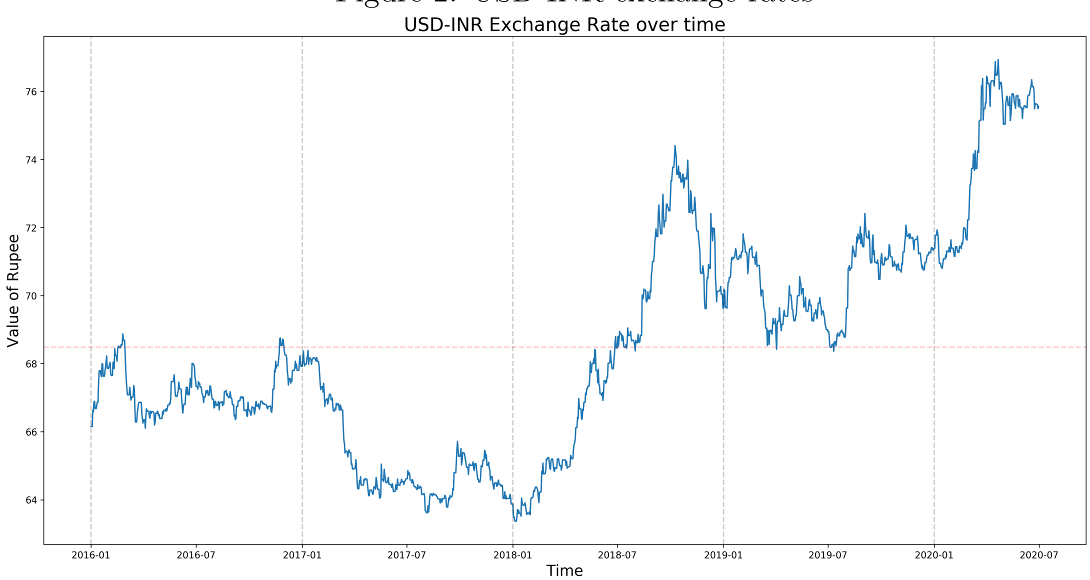
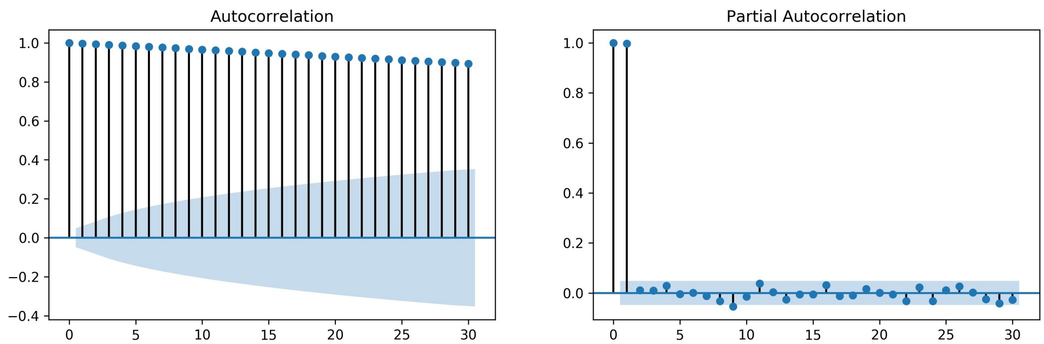


Figure 3: ACF anf PACF



In Figure 2, the vertical dashed gray lines indicate the beginning of each year. The horizontal red line is the mean Rupee value for the entire period. Clearly, the time series data falls below the mean in the period 2016-17 and rises much above the mean in 2019-20. This increasing trend in the mean Rupee value owing to currency depreciation means that the data cannot be stationary.

ACF and PACF

The ACF is decaying exponentially and the PACF exhibits a damped sinosoidal pattern as seen in Figure 3. From the PACF of the first lag is significant in the autoregregressive process. From the ACF plot, the lags fall insignificant beyond a large number lags. The autocorrelations are significant for a large number of lags (about 115) because the autocorrelation of lags 2 and above are perhaps, merely a propagation of the autocorrelation at lag 1. This again is confirmed by the PACF plot as shown.

Tests for Stationarity

It seems that the series exhibits both AR(p) and MA(q) terms. But to be certain one has to conduct tests for stationarity on the data using statistical tests such as the Augmented Dickey Fuller test or the Kwiatkowski-Phillips-Schmidt-Shin (KPSS). There are three types of stationarity:

- Strict Stationary: Satisfies the mathematical conditions for strict stationarity.
- Trend Stationary: Series that has no unit root but exhibits a trend. Once the trend is removed, the resulting series will be strict stationary. The KPSS test

classifies a series as stationary on the absence of unit root. This means that the series can be strict stationary or trend stationary.

- Difference Stationary: A time series that can be made strict stationary by differencing falls under difference stationary. ADF test is also known as a difference stationarity test.

We could conduct both the ADF and the KPSS tests. Based on the result of these, there are 4 possible outcomes.

- Case 1: Both tests conclude that the series is not stationary
- Case 2: Both tests conclude that the series is stationary series is stationary.
- Case 3: KPSS gives stationary and ADF gives not stationary result → trend stationary, remove the trend to make series strict stationary.
- Case 4: KPSS gives not stationary and ADF gives stationary result → difference stationary, use differencing to make series stationary.

Augmented Dickey Fuller (ADF) Test

The hypotheses at 5 percent significance level are:

- H_0: The time series is not stationary.
- H_1: The time series is stationary.

Our objective is to reject the null hypothesis when the p-value is less that 0.05 and ensure stationarity of the time series data.

Table 3: Results of Dickey-Fuller Test

```
Test Statistic                     -0.427478
p-value                             0.905409
#Lags Used                          0.000000
Number of Observations Used      1642.000000
Critical Value (1%)                -3.434339
Critical Value (5%)                -2.863302
Critical Value (10%)               -2.567708
```

Since p-value is greater that 0.05 in Table 3, we cannot reject the null hypothesis. The exchange rate time series is in fact non-stationary. This calls for a transformation that would make the data stationary. One could calculate the differences or obtain the logarithmic returns of the exchange rate data. The reason one uses returns rather than actual exchange rate values is that returns have more suitable statistical properties than rates [Campell et al., 1997]. Logarithmic returns (continuously compounded returns) are used frequently, which we adopt here.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test is also used to test for stationarity of time-series data. The null hypothesis for the KPSS test and the ADF test are opposites. The hypotheses at 5 percent significance level are:

- H_0: The time series is trend stationary.
- H_1: The time series a unit root (series is not stationary).

Table 4: Results of the KPSS test

```
KPSS Statistic: 3.8643306549809835
p-value: 0.01
num lags: 25
Critial Values:
 10% : 0.347
 5% : 0.463
 2.5% : 0.574
 1% : 0.739
Result: The series is not stationary
```

Again from Table 4 we observe that the exchange rate value series is non-stationary.

6.2 GARCH(1,1) Model

The data is first transformed to the log returns as defined below.

$$r_t = 100 \times \ln\left(\frac{y_t}{y_{t-1}}\right) \tag{9}$$

The base GARCH model fitted here is:

$$\begin{aligned} r_t &= \mu + \epsilon_t \\ \epsilon_t &= \sigma_t \omega_t \\ \sigma_t^2 &= \omega + \alpha\epsilon_t^2 + \beta\sigma_{t-1}^2 \end{aligned} \tag{10}$$

Here, r_t is the log returns, μ is the conditional mean and ϵ_t is the disturbance term. The first equation above is called the mean equation. The third equation is the GARCH model where ω is white noise. Note that we assume a zero mean process in doing so. The reason for this is because of the property of financial log-returns series to have mean close to zero. [Piotr, 2005]

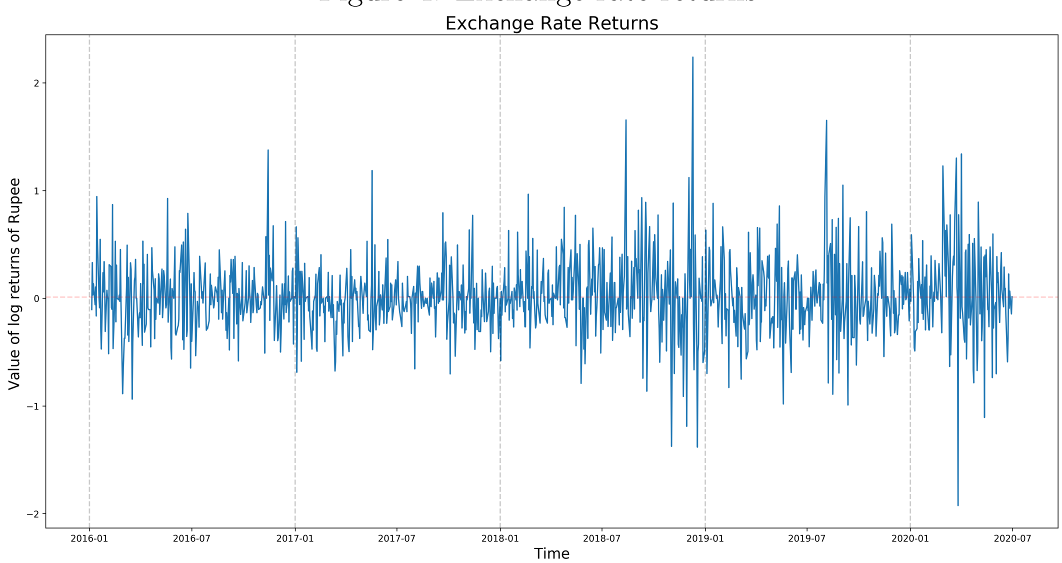
Properties of log returns series

There are four important properties satisfied by most financial log-return series, be it exchange rates or stock returns.

1. The sample mean of the series id close to zero.
2. The marginal distribution is roughly symmetric or slightly symmetric, has a peak at zero, and is heavily tailed.
3. The sample autocorrelations of the series are small at almost all lags, but the sample autocorrelations of the absolute values and squares of the series are significant for a large number of lags.
4. Volatility is clustered, i.e. days of either large of small movements are followed by days of similar characteristics.

Plotting Exchange Returns

Figure 4: Exchange rate returns

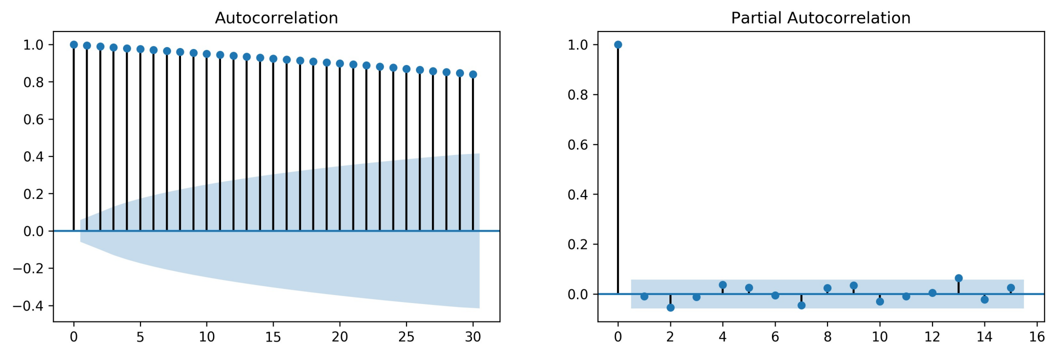


The plot of exchange rate log returns in Figure 4 indicates that the data appears to be stationary. We also see that the mean is zero. As is evident from the picture there are clear peaks of volatility and there is also evidence to believe volatility clustering occuring.

ACF and PACF

The ACF for returnsin Figure 5 shows a decay to zero. The PACF for returns show a significant autocorrelation at lag 2. One could attempt to fit an AR(2) model. As is convention with a GARCH process, one first fits the data into an autoregressive model and then assume the conditional heteroscedaticity in the data and explain for volatility by assuming that the variance of the lags afffect the current variances. This is clearly the reason for the phenomenon of volatility clustering.

Figure 5: ACF and PACF of log returns



Tests for stationarity

We again conduct stationarity checks on log returns data using ADF and KPPS tests. Both the test confirm stationarity as shown in the results in Table 5.

Table 5: Tests for stationarity on log returns

```
Results of Dickey-Fuller Test:

Test Statistic                    -25.596547
p-value                             0.000000
#Lags Used                          1.000000
Number of Observations Used      1169.000000
Critical Value (1%)                -3.435956
Critical Value (5%)                -2.864016
Critical Value (10%)               -2.568088

Results of KPSS Test:
```

```
KPSS Statistic: 0.04804458082927966
p-value: 0.1
num lags: 23
Critial Values:
   10% : 0.119
   5% : 0.146
   2.5% : 0.176
   1% : 0.216
Result: The series is stationary
```

Fitting the GARCH(1,1) model

Upon testing it was found that it was indeed the GARCH(1,1) model that had the fulfilled the least scores on AIC, BIC and HQIC tests. The results of the constant mean GARCH model are shown in Table 6.

Table 6: Results of the GARCH(1,1) fit.

```
Constant Mean - GARCH Model Results
==================================================================
Dep. Variable:            DEXINUS   R-squared:              -0.000
Mean Model:         Constant Mean   Adj. R-squared:         -0.000
Vol Model:                  GARCH   Log-Likelihood:       -382.809
Distribution:              Normal   AIC:                   773.617
Method:        Maximum Likelihood   BIC:                   793.880
No. Observations:            1171
Df Residuals:                1167
Df Model:                       4

                           Mean Model
==================================================================
         coef    std err       t      P>|t|     95.0% Conf. Int.
------------------------------------------------------------------
mu   6.9476e-03  8.996e-03   0.772   0.440  [-1.068e-02,2.458e-02]
                       Volatility Model
==================================================================
            coef    std err     t      P>|t|      95.0% Conf. Int.
------------------------------------------------------------------
omega 6.0606e-03  3.005e-03  2.017  4.370e-02 [1.714e-04,1.195e-02]
alpha[1]  0.0791  3.199e-02  2.473  1.341e-02  [1.640e-02,  0.142]
beta[1]   0.8724  4.599e-02  18.971  2.958e-80   [  0.782,  0.963]
==================================================================
```

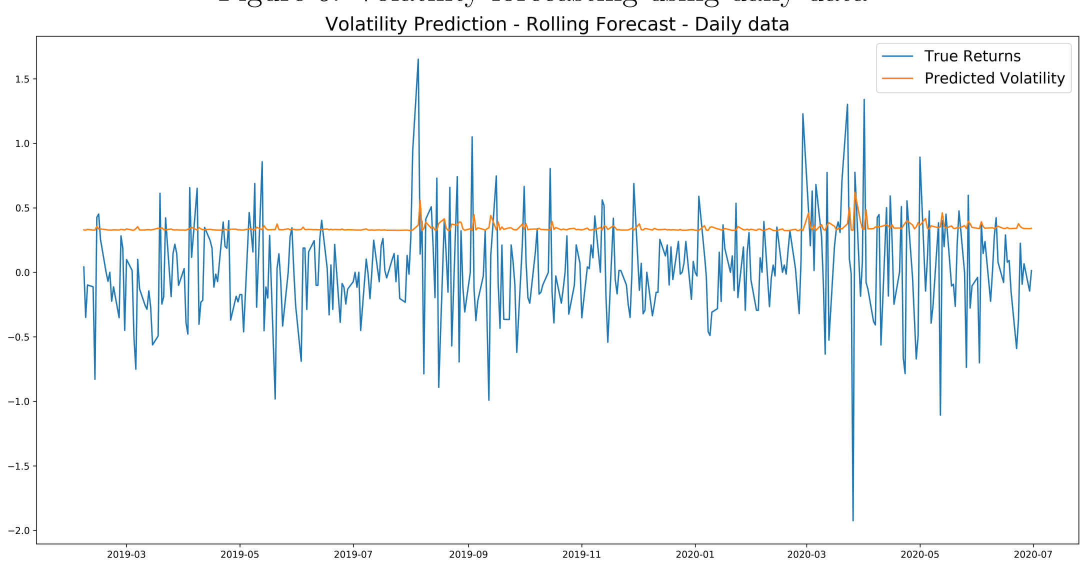
Thus the coefficient parameters ω, α and β turned out to be significant in the volatility model. However, in terms of the mean model, the μ value turned to be insignificant. Thus our volatility model is given by:

$$\sigma_t^2 = 0.0791\epsilon_{t-1}^2 + 0.8724\sigma_{t-1}^2 \tag{11}$$

6.3 Predictions using the model

We conducted the predictions of volatility using this model The results showed significant peaks in volatility when compared to the actual data. We also repeated this process for monthly data of USD-INR in the period from 1990-2010. In that model too we observed that the volatility was captured to a great extent by the GARCH(1,1) process. Figures 6 and 7, depict the volatility corresponding to the periods 2016-2020 (inflation-targeting) and 1990-2020 (liberalization), respectively.

Figure 6: Volatility forecasting using daily data

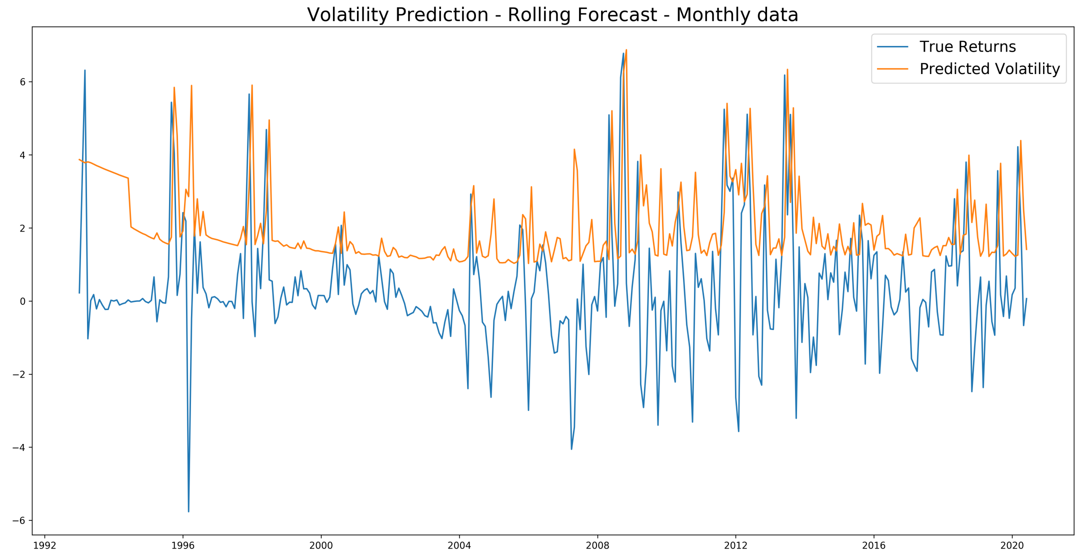


We also note from above that the GARCH process predicts variances only the positive axis and not in the negative side. The asymmetric effects of real economic shocks could also be specified in a more elaborate model specification and is scope for further work in this arena.

6.4 Model Validity checking

The validity of the GARCH model is checked by exploring the features of the residuals. The following test are conducted in the regard.

Figure 7: Volatility forecasting using monthly data



- The standardized residuals from the GARCH model should approach normal distribution. We use the Shapiro-Wilk test and Jarque-Bera normality test. Histogram of the residuals is also a good visual tool to check normality.

- The standardized squared residuals from the GARCH model should not be autocorrelated. Use Ljung-box Q-statistic for this purpose.

- The ARCH LM test on the residuals can also be conducted to check for remaining ARCH effects in the residuals.

Figure 8: Normality of residuals

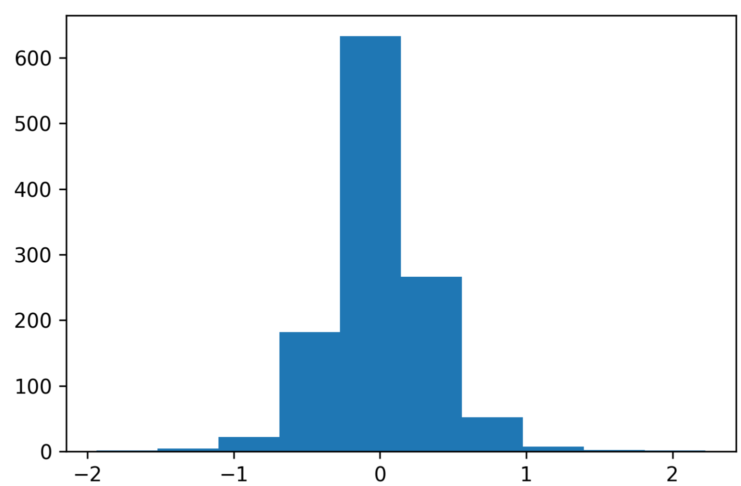


Table 7: Test of Normality of Residuals

```
              resid
count   1170.000000
mean      -0.001297
std        0.351215
min       -1.937799
25%       -0.192577
50%       -0.012707
75%        0.183446
max        2.225825
kurtosis  [3.73378267]
skewness  [0.39525826]
```

These tests conducted confirm the near-normality of the residuals of the model as is clear from the above histogram of the residuals in Figure 8. Also note that compared to the normal, it has a stronger peak, more rapid decay, and heavier tails. The skewness near zero and kurtosis is slightly higher than 3, which are typical of log returns data as can be seen in Table 7.

7 Conclusions

This project explored methods employed in time-series analysis. The study of exchange rates, Central Bank intervention in foreign exchange market and their cumulative role in India under an Inflation-Targeting regime was undertaken. The major episodes of exchange rate volatility in India were studied and the possible reasons were understood. Using univariate time-series analysis, a GARCH(1,1) model that predicts the volatility of the exchange rates was fitted to the data. The using a method of rolling predictions, the GARCH-fit variances were forecast. The model was also validated using tests for normality of residuals.

It was observed that there exists three main kinds of sterilized intervention channels undertaken by the Central Bank - Portfolio Balance, Signalling and Noise Trading Approaches. We had also seen the multiple modes of intervention by RBI in numerous volatility episodes post 1990. This study was centered on the exchange-rate volatility during the Inflation-Targeting regime, which India adopted since 2016. We had emphasized the enhanced role of Exchange rates in an Inflation-Targeting EME. The reasons for this were that the exchange rates has: high pass-through to inflation, impacting in short-term currency movements, helpful in maintaining financial stability and in avoiding adverse consequences for external stability in case abrupt stop in capital inflows. Further, in countries transitioning to Inflation-Targeting, a systematic, consistent and market-based role of exchange rate is helpful for the overall credibility of monetary policy.

The time-series analysis resulted in non-stationarity for USD-INR exchange rate data. This was also tested using ADF and KPSS tests. However, this issue was avoided by transforming the data into log returns. The modeling of log returns also enabled us to fit the data into a GARCH(1,1) model with a constant mean equation. Further, the validity of the model was checked using tests for normality of residuals. The properties of log-returns series such as having a sample mean close to zero, almost symmetric marginal distribution, volatility clustering were all observed and explained by the model presented here.

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