Report on

FORECASTING USD/INR EXCHANGE RATE USING SINGLE EXPONENTIAL SMOOTHING METHOD

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CERTIFICATE

This is to certify that the dissertation report titled **"Forecasting USD/INR exchange rate using Single Exponential Smoothing Method"** is a bonafide work carried out by **Ms. L.Saranya** of **MBA 2015-17** and submitted to Delhi School of Management, Delhi Technological University, Bawana Road, Delhi-42 in partial fulfillment of the requirement for the award of the Degree of Masters of Business Administration.

Signature of Guide **Signature of Head (DSM)**

Seal of Head

Place:

Date:

DECLARATION

I, **L.Saranya**, student of **MBA 2015-17** of Delhi School of Management, Delhi Technological University, Bawana Road, Delhi – 42, hereby declare that the dissertation report **"Forecasting USD/INR exchange rate using Single Exponential Smoothing Method"** submitted in partial fulfillment of Degree of Masters of Business Administration is the original work conducted by me.

The information and data given in the report is authentic to the best of my knowledge.

This report is not being submitted to any other University, for award of any other Degree, Diploma or Fellowship.

Place: **L.Saranya**

Date:

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ABSTRACT

Exchange rate forecasts are necessary to evaluate the foreign denominated cash flows involved in international transactions. Thus, exchange rate forecasting is very important to evaluate the benefits and risks attached to the international business environment.

The aim of this study is to forecast USD/INR exchange rate for Jan 2017- March 2017 using historic data for ten years from Jan 2007- Dec 2016 by time series analysis. The method used is Simple Exponential Smoothing method.

Firstly, suitable data series is identified for applying exponential smoothing method by converting the data set into a stationary time series.

Eviews 9 is used to apply exponential smoothing method to the data. The accuracy of this forecast is done using indicators like Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

After testing the model by forecasting values of year 2016, the model will be used to forecast the values of the first quarter of 2017.

This study is purely based on technical analysis. Any deviations from the forecasted value may be attributed to fundamental factors that may influence the exchange rate like any changes in the current political system, changes in fiscal/monetary policies, GDP, inflation rate etc. In this study, few of the factors could be identified for the forecasted period and are explained in the analysis section.

Table of Contents

1.INTRODUCTION

Money helps to simplify the dealings done amongst a group of individuals in a commercial setup by being a medium of exchange in itself. Be that as it may, exchanges between individuals who live in various nations are more entangled due to the presence of various mediums through which trade is done.

According to Economic Times, "An exchange rate describes the price of one currency in terms of another". Along these lines, estimating this rate of exchange is crucial for all the organizations which have businesses spread across various nations or firms that are in a need to raise long term or short term reserves from worldwide markets additionally for the organizations which have restricted their whole business in their domestic market only, on the grounds that a change in foreign exchange rate can change. As stated in the article titled 'Forecasting Exchange Rate: A Univariate Out-of-Sample Approach' that "Forecasting exchange rate is an important input to different corporate choices like currency for invoicing, pricing decision, borrowing and lending decisions and management of exposures and hedging strategies".

1.1 Significance of forecasting exchange rates

Numerous treasurers don't estimate foreign exchange rates formally, most know about patterns in the remote trade showcase, especially for those monetary standards that affect their organizations. One purpose behind this is the treasurer's duty is for the most part to hedge foreign exchange exposures as per the already concurred treasury approach. By and large, the treasury approach is very particular concerning how a specific introduction ought to be overseen. This implies, on an everyday premise, a treasurer may have almost no compelling reason to figure a specific exchange rate. Also, according to treasurytoday.com, "in light of the fact that exposures will be dealt with, the treasurer will know about the patterns in the business sectors, and there are some strong arguments which suggest that treasurers and finance directors should be more aware of currency forecasts and how they are calculated".

Business decisions

Forecasting the exchange rates may be fruitful whilst the crucial decisions of business are being made, especially when a firm is entering into new markets where natural hedges are unavailable, at the least to start with. Organizations will need to comprehend the economics each of long-term capital expenditure and of shorter-time period contracts. The role of treasurers will be crucial to evaluate the forthcoming necessities for funding and short-term investments.

Hedging decisions

Likewise, forecasting the rates of currency exchange can be useful when building or evaluating a supporting procedure. Supporting methodologies rely on upon outside variables and additionally the inner prerequisites of a business. Specifically, if an organization determines an exchange rate and then that fixed rate moves in the organization's support, it is presented to the hazard that its rivals can exploit the good rate development.

Volatility

The other reason for forecasting is to distinguish exchange rate volatility. Exchange rate volatility can significantly affect an organization's foreign currency profits. This may not be an issue in the long haul, if the impact is comprehended by financial specialists. Be that as it may, it will influence the hedging strategy of the organization, especially over the shorter term, with the end goal that it might mean a higher percentage of short-term exposures are hedged.

1.2 Approaches to Exchange-Rate Forecast

The two most regularly utilized techniques for forecasting exchange rates are:

- Fundamental Approach − This is strategy that uses rudimentary information identified with a nation, for example, Gross Domestic Product, Inflationary Rates, Productivity, Balance of Trade (BoT), and Level of Unemployment. The

guideline is that the 'true worth' of a cash will in the long run be acknowledged sooner or later of time.

- Technical Approach − In the technical approach, the investor sentiment decides the adjustments in the exchange rate. It makes forecasts by plotting the patterns. Also, according to tutorialpoints.com, "positioning surveys, moving-average trend-seeking trade rules, and Forex dealers' customer-flow data are used in the technical approach".

Models of Exchange-Rate Forecasting

There are many models that can forecast the exchange rates, some of those models have been discussed below in detail.

Purchasing Power Parity Model

The 'Purchasing Power Parity (PPP)' forecasting methodology depends on the 'Law of One Price'. This model expresses that similar products in various nations ought to have indistinguishable costs. For instance, the 'Law of One Price' contends that a chalk in Australia will have an indistinguishable cost from a chalk of equivalent measurements in the U.S. (considering the exchange rate and barring exchange and transporting costs). Meaning that is impossible to purchase shabby product in one nation and offer that same product at a benefit to the other country.

Contingent upon the standard, the PPP approach predicts that the exchange rate will modify by balancing the value changes happening because of inflation.

Relative Economic Strength Model

The 'Relative Economic Strength Model' chooses the orientation of exchange rates by considering the strength of economic improvement in different countries. The idea behind this approach is that a strong economic improvement will attract more speculations from overseas investors. To purchase these interests in a particular country, the investor will buy the country's currency – extending the request and value (thankfulness) of the currency of that particular country.

Also, another variable passing on investors to a country is its interest rates. Higher interest rates will attract larger number of investors, moreover the interest for that currency will extend, which would lead the currency to appreciate.

On the other hand, if the interest rates are low then that will do the inverse and investors will may hesitate from investing in a specific nation. The foreign investors can also acquire the nation's low-estimated currency for subsidizing different speculations. A similar situation was seen when the Japanese Yen had lower interest rates. This is usually referred to as 'Carry Trade Strategy'.

The 'Relative Economic Strength Approach' does not precisely forecast the future values of exchange rates like the 'PPP Approach'. It just advises that whether a currency will acknowledge or devalue.

Econometric Models

It is a model that is utilized to forecast exchange rates by combining every single pertinent component that may influence a specific currency. It interfaces every one of these elements to forecast the exchange rate. The elements are regularly from economic theory; however, any factor can be added to it if required.

'Coursehero.com' in a document titled 'Exchange Rate Forecasts' has given an example that, "a forecaster for a Canadian company has researched factors he thinks would affect the USD/CAD exchange rate. From his research and analysis, he found that the most influential factors are: the interest rate differential (INT), the GDP growth rate differences (GDP), and the income growth rate (IGR) differences."

The econometric model is −

$$\text{USD/CAD (1 year)} = z + a(\text{INT}) + b(\text{GDP}) + c(\text{IGR})$$

Now, also according to 'Coursehero.com', "using this model, the variables mentioned, i.e., INT, GDP, and IGR can be used to generate a forecast. The coefficients used (a, b, and c) will affect the exchange rate and will determine its direction (positive or negative)."

Time Series Model

The time series model is completely technical and does not include any economic theory. The popular time series approach is known as the autoregressive moving average (ARMA) process.

According to 'TutorialsPoint.com', "The rationale is that the past behavior and price patterns can affect the future price behavior and patterns. The data used in this approach is just the time series of data to use the selected parameters to create a workable model".

Forecasting the exchange rate is a vigorous errand and that is the reason many organizations and financial specialists only tend to hedge the risk of currency. Still, a few people have faith in forecasting exchange rates and attempt to discover the variables that influence currency rate developments. For them, the approached said above are a decent indicate begin with.

1.3 Objective

To forecast USD/INR exchange rate for Jan 2017- March 2017 using historic data for ten years from Jan 2007- Dec 2016 using time series analysis.

The method used is Simple Exponential Smoothing method.

The accuracy of the forecast will be found out using two parameters: Mean Absolute Error and Mean Absolute Percentage Error

The above stated objective is conducted in three stages.

Stage 1: Stationarity Test

> The objective is to find out a stationary data series from the given data set historic closing prices of USD/INR) on which time series analysis can be done.

Stage 2: Testing the Model

> The objective is to test the accuracy of the method on the identified time series by forecasting the values of USD/INR for the year 2016 and then comparing it with the actual values.

Stage 3: Forecasting

> To forecast the USD/INR exchange rate for the quarter Jan 2017-March 2017.

This research focuses on the above mentioned objective in three stages.

Some of the researches done in the area of exchange rate forecasting is mentioned in the next section of this study.

2. LITERATURE REVIEW

This section focuses on some of the researches done in the area of exchange rate forecasting using exponential smoothing method. Few of the researches have been listed down.

Exchange rate forecasts are necessary to evaluate the foreign denominated cash flows involved in international transactions. Thus, exchange rate forecasting is very important to evaluate the benefits and risks attached to the international business environment.

'Meese and Rogoff (1983)' compared a number of time series and structural models on the basis of out of sample forecasting accuracy and stated "in the short horizon (less than one year) random walk model outperforms a range of fundamentals based models of exchange rate determination. Meese and Rogoff examined the relationship between real exchange rates and real interest rates over the modern (post 1970) flexible rate period". They concluded that "the exchange rate depends on fundamentals such as relative national money supplies, real incomes, short-term interest rates, expected inflation differentials, and cumulated trade balances". Meese & Rogoff challenged the long held idea that economic fundamentals determine currency values. They stated that "a random walk model was just as good at predicting exchange rates as models based on fundamentals. Economic fundamentals, like trade balances, money supply, national income, and other key variables, are of little use in forecasting exchange rates between countries with roughly similar inflation rates"

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The same author ('Meese and Rogoff, 1983b') in another study stated that "the random walk models do not yield the minimum forecast errors when forecast horizon is extended to periods beyond one year. In the long run, structural models perform more accurately than random models."

A number of authors like 'MacDonald and Taylor, 1993, Chinn and Meese, 1995; Mark, 1995; MacDonald and Marsh, 1997'; state "models whose out-of sample forecasting

performance improves upon a random walk". Later, some researchers (Van Dijk 1998, Kilian 1999 and Berkowitz and Giorgianni 2001) stated "the inference procedures and robustness of results of these studies have to be questioned and although difficult but it is still possible to beat random walk models."

'Făt Codruța Maria and Dezsi Eva (2011)' in their study state that "In this study the behavior of daily exchange rates of the Romanian Leu against the Euro, United States Dollar, British Pound, Japanese Yen, Chinese Renminbi and the Russian Ruble is investigated. Smoothing techniques are generated and compared with each other. These models include the Simple Exponential Smoothing technique, as the Double Exponential Smoothing technique, the Simple Holt-Winters, the Additive Holt-Winters, namely the Autoregressive Integrated Moving Average model. All the results indicate the appreciation of the Romanian Leu against the other currencies. In the case of the first five forecast techniques the results are similar, from the point of view of the forecast coefficients, which points out that the optimal models were found. The exponential smoothing techniques in some cases outperform the ARIMA models, because of the speed with which they adapt to the smallest changes to the market conditions. In addition, the ARIMA models present some difficulties in estimating and validating the model, are more effective in rendering the medium-term trend (in this study, 4 months). So these models show the changes in trend, while the forecasting models based on exponential smoothing techniques are an effective tool for those interested in the evolution of the exchange rate."

'M.K. Newaz (2008)', in his paper wrote that "comparison of different time series models to forecast exchange rate has been made in this study. A survey of literature shows that continuous debate is going on whether exchange rate follows a random walk or it can be modeled; there is also a debate whether one should use structural models or time series models to forecast exchange rate. Paper uses Box-Jenkins methodology for building ARIMA model, exponential smoothing, naïve 1 and naïve 2 models. This paper used the monthly exchange rate data INR/BDT . Sample data for the paper were taken from September 1985 to June 2006, out of which data till December 2002 were used to

build the model while remaining data points were used to do out of sample forecasting and check the forecasting ability of the model. All the data were collected from various issues of International Financial Statistics published by International Monetary Fund. Result of this study shows that ARIMA models provides a better forecasting of exchange rates than exponential smoothing and Naïve models do. Comparison of the MAE, MEAE, MAPE, MSE and RMSE shows that the proposed ARIMA model is the best among all these models."

'Timothy M. Znaczko (2013)' in his research wrote "a variety of foreign exchange forecasting models and compared the future predictions to a random walk mode are compared. The analysis included 124 quarterly observations from 1980 to 2010, as well as four different countries' variables. The countries include the United States, Great Britain, Japan, and Canada. The financial data used was gathered from the Federal Reserve Bank of St Louis. The variables of foreign exchange rate, gross domestic product, and Consumer Price Index included quarterly data ranging from the year 1980 to 2010. The result of this study was that moving average was the best forecast in predicting foreign exchange rates for two of the three currencies used in this study."

'Daniya Tlegenova (2015)' in her paper wrote "yearly exchange rates between USD/KZT, EUR/KZT and SGD/KZT are modelled, and compared the actual data with developed forecasts using time series analysis over the period from 2006 to 2014. The official yearly data of National Bank of the Republic of Kazakhstan was used for this study. The goal of this paper was to apply the ARIMA model for forecasting of yearly exchange rates of USD/KZT, EUR/KZT and SGD/KZT. The accuracy of the forecast is compared with Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). ARIMA technique for forecasting currency exchange rates of Kazakh tenge against three other currencies such as US Dollar (USD), Euro (EUR), and Singapore Dollar (SGD) was applied over the period from 2006 to 2014. Results showed that the MAPE values for all three currencies were the smallest, i.e. the most effective."

However, it was found that very few researches have done in the area of forecasting USD/INR spot exchange rate. Hence, the motivation of this study is to forecast USD/INR exchange rate and calculate the accuracy of the forecast by comparing it with the actual exchange rate.

3. METHODOLOGY

3.1 Data Set

The data set of ten years (daily data) is used in this study, assuming that it can cover one business cycle and capture the volatilities in the market appropriately. When long period of data set is chosen, there are less chances of getting skewed results.

The data set used is USD/INR exchange rate for the duration 01 Jan 2007 – 31 March 2017. This time series data is 5 day a week. So, 250 data points for a year. So, the total number of data points used for analysis is 2651. 9

The data has been obtained from the website www.investing.com. This website has historic data of the exchange rates. The link for the data is : https://in.investing.com/currencies/usd-inr-historical-data

To fulfill the objective of this study, time-series forecasting technique is used and the method used is simple exponential smoothing. Assumption is that there is no trend or seasonality. Since this is technical analysis, so, fundamental factors are not taken into consideration.

3.2 Time Series Forecasting

A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Forecasting is a method that is used extensively in time series analysis to predict a response variable, such as monthly profits, stock performance, or unemployment figures, for a specified period of time. Forecasts are based on patterns in existing data. One can use a variety of time series methods, such as trend analysis, decomposition, or single exponential smoothing, to model patterns in the data and extrapolate those patterns to the future.

Stationarity

To perform forecasting, most techniques require the stationarity conditions to be satisfied.

A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. Most statistical forecasting methods are based on the assumption that the time series can be rendered approximately stationary (i.e., "stationarized") through the use of mathematical transformations. A stationarized series is relatively easy to predict: you simply predict that its statistical properties will be the same in the future as they have been in the past. The predictions for the stationarized series can then be "untransformed," by reversing whatever mathematical transformations were previously used, to obtain predictions for the original series. Thus, finding the sequence of transformations needed to stationarize a time series often provides important clues in the search for an appropriate forecasting model.

Another reason for trying to stationarize a time series is to be able to obtain meaningful sample statistics such as means, variances, and correlations with other variables. Such statistics are useful as descriptors of future behavior only if the series is stationary. For example, if the series is consistently increasing over time, the sample mean and variance will grow with the size of the sample, and they will always underestimate the mean and variance in future periods. And if the mean and variance of a series are not well-defined, then neither are its correlations with other variables.

Most business and economic time series are far from stationary when expressed in their original units of measurement, and even after deflation or seasonal adjustment they will typically still exhibit trends, cycles, random-walking, and other non-stationary behavior. If the series has a stable long-run trend and tends to revert to the trend line following a disturbance, it may be possible to stationarize it by de-trending (e.g., by fitting a trend line and subtracting it out prior to fitting a model, or else by including the time index as an independent variable in a regression), perhaps in conjunction with logging or deflating. Such a series is said to be trend-stationary. However, sometimes even de-trending is not sufficient to make the series stationary, in which case it may be necessary to transform it into a series of period-to-period and/or season-to-

season differences. If the mean, variance, and autocorrelations of the original series are not constant in time, even after detrending, perhaps the statistics of the changes in the series between periods or between seasons will be constant. Such a series is said to be difference-stationary. (Sometimes it can be hard to tell the difference between a series that is trend-stationary and one that is difference-stationary, and a so-called unit root test may be used to get a more definitive answer

Making Time Series Stationary

To check a whether a time series is stationary or not a test known as Breakpoint Unit Root Test is used. This test has a null hypothesis that

Ho: Series has a unit root

If a series has unit root test then it a non-stationary series. To check the hypothesis, p-value is seen i.e. if p-value is less than 0.05 then hypothesis is rejected and time series is stationary, where as if p-value is greater than 0.05 then hypothesis is accepted and the time series is non-stationary.

One way to make a time series stationary is to compute the differences between consecutive observations. This is known as differencing. Transformations such as logarithms can help to stabilize the variance of a time series. Differencing can help stabilize the mean of a time series.

- Random walk model

The differenced series is the change between consecutive observations in the original series, and can be written as

$$y'_t = y_t - y_{t-1}$$

The differenced series will have only $T-1$ values since it is not possible to calculate a difference $y'1$ for the first observation.

Once the series is stationary, one can run time series analysis to perform forecasting.

3.3 Exponential smoothing

This is a very popular scheme to produce a smoothed Time Series. Whereas in Single Moving Averages the past observations are weighted equally, Exponential Smoothing assigns exponentially decreasing weights as the observation get older.
Exponential smoothing schemes weight past observations using exponentially decreasing weights

In other words, recent observations are given relatively more weight in forecasting than the older observations.

In the case of moving averages, the weights assigned to the observations are the same and are equal to 1/N. In exponential smoothing, however, there are one or more smoothing parameters to be determined (or estimated) and these choices determine the weights assigned to the observations.

Single Exponential Smoothing

This smoothing scheme begins by setting S_2 to y_1, where S_i stands for smoothed observation or EWMA, and y stands for the original observation. The subscripts refer to the time periods, $1,2,\ldots,n$. For the third period, $S_3=\alpha y_2+(1-\alpha)S_2$; and so on. There is no S_1; the smoothed series starts with the smoothed version of the second observation.

For any time period t, the smoothed value S_t is found by computing

$$S_t=\alpha y_{t-1}+(1-\alpha)S_{t-1} \qquad 0<\alpha\leq 1$$

This is the basic equation of exponential smoothing and the constant or parameter α is called the smoothing constant.

There is an alternative approach to exponential smoothing that replaces y_{t-1} in the basic equation with y_t, the current observation.

When applied recursively to each successive observation in the series, each new smoothed value (forecast) is computed as the weighted average of the current observation and the previous smoothed observation; the previous smoothed observation was computed in turn from the previous observed value and the smoothed value before the previous observation, and so on. Thus, in effect, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depending on the value of parameter alpha. If it is equal
to 1 (one) then the previous observations are ignored entirely; if it is equal to 0 (zero), then the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value (which in turn is computed from the smoothed observation before it, and so on; thus all smoothed values will be equal to the initial smoothed value S0). In-between values will produce intermediate results.

Advantages and Disadvantages of Simple exponential Smoothing:

Advantages

1. It is easy to apply. Only three pieces of data are required for exponential smoothing methods. One, it needs the forecast for the most recent time period. Two, it needs the actual value for that time period. And three, it needs the value of the smoothing constant, a weighting factor that reflects the weight given to the most recent data values.

2. If we use the moving averages method to forecast, we need to have M past values. This is cumbersome if there are many items for which forecasting is required. Because exponential smoothing relies on only two pieces of data (the last period's actual value and the forecasted value for the same period), it minimizes the data storage requirements.

3. It produces accurate forecasts. An exponential smoothing method produces a forecast for one period ahead. Using the trend projection technique, forecasts for more periods ahead can then be generated. The forecast is considered

accurate as it accounts for the difference between actual projections and what actually occurred.

4. It gives more significance to recent observations. Observed data is the sum of two or more components, one being the random error which is the difference between the observed value and the true value. In a smoothing technique, the random variation is neglected. As such, it's much more easier to see the underlying phenomenon.

Disadvantages

1. It produces forecasts that lag behind the actual trend. The lag is a side effect of the smoothing process. There's a reason this method has "smoothing" in its name because it neglects the ups and downs associated with random variation. As such, seeing this on a graph shows you a smoother line or curve. But ignoring the random variation also allows you to see the underlying phenomenon, which helps when presenting data and making a forecast of future values.

2. It cannot handle trends well**.** Exponential smoothing is best used for forecasts that are short-term and in the absence of seasonal or cyclical variations. As a result, forecasts aren't accurate when data with cyclical or seasonal variations are present. As such, this kind of averaging won't work well if there is a trend in the series.

3. Methods like this are only accurate when a reasonable amount of continuity can between the past and future can be assumed. As such, it's best suited for short-term forecasting as it assumes future patterns and trends will look like current patterns and trends. While this kind of assumption may sound reasonable in the short term, it creates problems the further the forecast goes.

4. Exponential smoothing will fail to account for the dynamic changes at work in the real world, and the forecast will constantly require updating to respond new information

3.4 Project Stages

The data analysis is done in three stages:

Stage 1: Stationarity Test

Before applying the exponential smoothing method, stationarity of time series is checked using Augmented Dicky Fuller Unit root test in Eviews 9. The p value will be analyzed to find out whether the time series is stationary or not to obtain meaningful results.

Suitable data series is identified for applying exponential smoothing method.

Stage 2: Testing the Model

Forecast for the period 1 Jan 2016 – 31 Dec 2016 is done using the sample 1 Jan 2007 – 31 Dec 2015.

Eviews 9 is used to apply exponential smoothing method to the data.

The accuracy of this forecast is done using indicators like Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

The accuracy of this forecast can be calculated using MAPE. Also, standard deviation of the actual data will be compared with the MAE.

By the end of stage 2, it can be concluded whether meaningful forecast can be obtained by this method by comparing actual values of year 2016 with the forecasted values.

Stage 3: Forecasting

Now, forecast for the period 1 January 2017 – 31 March 2017 is made using exponential smoothing method and the forecasted value is compared with the actual value.

The return series is calculated using the closing prices from 01 Jan 2007- 31 Dec 2016.

Exponential smoothing is applied on the return series to obtain the forecasted return series.

Forecast of closing prices of exchange rate is made using the forecasted return series.

Again, to evaluate the accuracy of this forecast, Mean Absolute Error and Mean Absolute Percentage Error will be calculated. This can be indicative of the accuracy of the process.

4. DATA ANALYSIS

The data analysis has been performed in three stages on the data set.

4.1 Stage 1: Stationarity Test

In the first stage, stationarity of time series is checked using Augmented Dicky Fuller Unit root test in Eviews 9. The p value is be analyzed to find out whether the time series is stationary or not to obtain meaningful results. Suitable data series is identified for applying exponential smoothing method.

Stationarity test is carried out on the closing price and absolute return series.

Result of stationarity test on closing prices

Table. 4.1.1

Null Hypothesis: EXCHRATE_ACTUAL has a unit root			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.562827	0.8762
Test critical values:	1% level	-3.432607	
	5% level	-2.862423	
	10% level	-2.567285	
Dependent Variable: D(EXCHRATE_ACTUAL)			
Sample (adjusted): 1/08/2007 3/31/2017			
Included observations: 2670 after adjustments			

Fig . 4.1.1

This is the graphical representation of the movement of USD/INR between Jan 2007 to Mar 2017

Inference

The absolute t value is 0.56 which is less than absolute test critical value. Therefore null hypothesis may be accepted. Also, p value is 0.8762 which is greater than 0.005. This also indicates that null hypothesis may be accepted.

Therefore Unit root test is carried out again.

Testing for root in 1st difference

Table 4.1.2

Null Hypothesis: D(EXCHRATE_ACTUAL) has a unit root			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-25.35378	0.0000
Test critical values:	1% level	-3.432607	
	5% level	-2.862423	
	10% level	-2.567285	
Dependent Variable: D(EXCHRATE_ACTUAL,2)			
Sample (adjusted): 1/08/2007 3/31/2017			
Included observations: 2670 after adjustments			

Inference

Here, t absolute value of statistic is greater than the absolute critical value. Hence null hypothesis is rejected. The first difference of exchange rate has a unit root, this is rejected. Also, p value is 0.000 which is lesser than 0.005. This also indicates that null hypothesis is rejected. It can be concluded that the data is stationary.

First difference of exchange rate is the return series.

Further, unit root test is applied on the relative return series. Results are as below.

Table 4.1.3

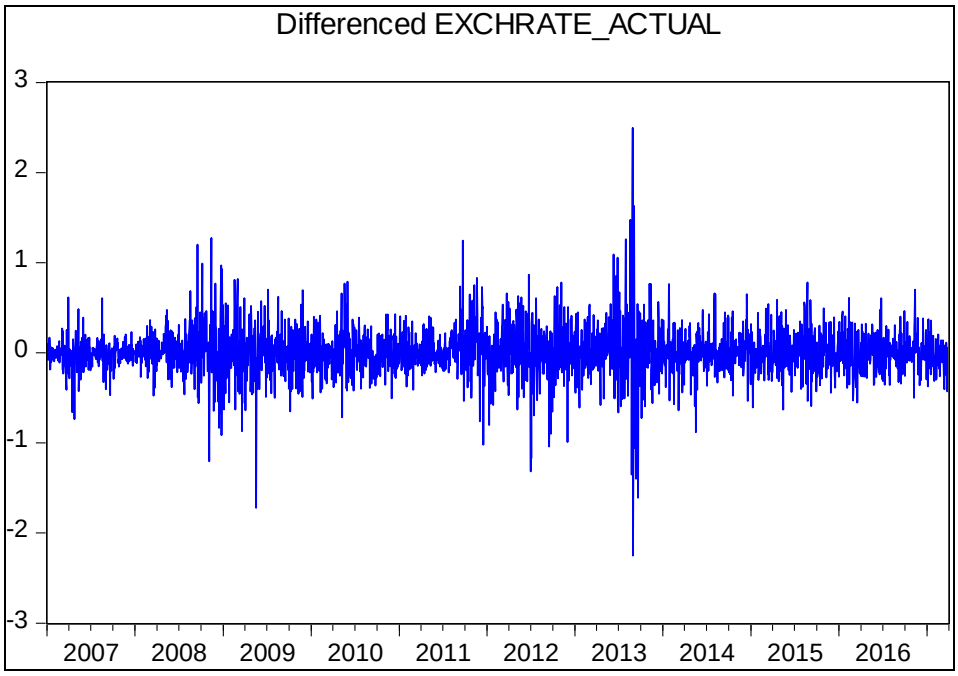
Null Hypothesis: D(RELATIVE_RET) has a unit root			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.62898	0.0000
Test critical values:	1% level	-3.432617	
	5% level	-2.862427	
	10% level	-2.567287	
Dependent Variable: D(RELATIVE_RET,2)			
Sample (adjusted): 1/23/2007 3/31/2017			
Included observations: 2659 after adjustments			

Inference

Here, t absolute value of statistic is greater than the absolute critical value. Hence null hypothesis is rejected. The first difference of exchange rate has a unit root, this is rejected. Also, p value is 0.000 which is lesser than 0.005. This also indicates that null hypothesis is rejected. It can be concluded that the data is stationary.

Therefore, the return series can be used for time series analysis.

Fig. 4.1.2



This is the graphical representation of the % change in USD/INR between Jan 2007 to Mar 2017.

Inference:

The data series identified is the return series which is stationary. So, further tests will be applied on the relative return series.

4.2 Stage 2: Testing the model

In stage 2, the model is be tested by making forecast for the period 1 Jan 2016 – 31 Dec 2016 using the sample 1 Jan 2007 – 31 Dec 2015. By the end of stage 2, it is concluded whether meaningful forecast can be obtained by this method by comparing actual values of year 2016 with the forecasted values.

Exponential smoothing test is run on the sample 1 Jan 2007 – 31 Dec 2015, to obtain the return series for the year 2016.

The exponential smoothing test is run on the return series to generate the relative return series for the year 2016. Using the return series, price is forecasted for the year 2016.

Alpha = 0.01

Table 4.2.1

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
1/1/2016	66.235	-0.000688736			
1/4/2016	66.579	0.001197753	66.314	0.265	0.398
1/5/2016	66.481	0.000292976	66.599	0.118	0.177
1/6/2016	66.698	8.79E-07	66.481	0.217	0.325
1/7/2016	66.891	-1.44E-05	66.697	0.194	0.290
1/8/2016	66.847	-0.000691551	66.845	0.002	0.003
1/11/2016	66.76	0.001194938	66.927	0.167	0.250
1/12/2016	66.946	0.000290162	66.779	0.167	0.249
1/13/2016	66.917	-1.94E-06	66.946	0.029	0.043
1/14/2016	67.316	-1.72E-05	66.916	0.400	0.594
1/15/2016	67.775	-0.000694366	67.269	0.506	0.746
1/18/2016	67.661	0.001192124	67.856	0.195	0.288
1/19/2016	67.734	0.000287347	67.680	0.054	0.079
1/20/2016	67.958	-4.75E-06	67.734	0.224	0.330
1/21/2016	67.799	-2.00E-05	67.957	0.158	0.233
1/22/2016	67.549	-0.00069718	67.752	0.203	0.300
1/25/2016	67.755	0.001189309	67.629	0.126	0.185

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
1/26/2016	67.739	0.000284533	67.774	0.035	0.052
1/27/2016	68.144	-7.56E-06	67.738	0.406	0.595
1/28/2016	68.053	-2.28E-05	68.142	0.089	0.131
1/29/2016	67.878	-0.000699995	68.005	0.127	0.188
2/1/2016	67.835	0.001186495	67.959	0.124	0.182
2/2/2016	67.975	0.000281718	67.854	0.121	0.178
2/3/2016	67.934	-1.04E-05	67.974	0.040	0.059
2/4/2016	67.544	-2.56E-05	67.932	0.388	0.575
2/5/2016	67.81	-0.000702809	67.497	0.313	0.462
2/8/2016	68.034	0.00118368	67.890	0.144	0.211
2/9/2016	67.901	0.000278903	68.053	0.152	0.224
2/10/2016	67.861	-1.32E-05	67.900	0.039	0.058
2/11/2016	68.471	-2.85E-05	67.859	0.612	0.894
2/12/2016	68.118	-0.000705624	68.423	0.305	0.447
2/15/2016	68.131	0.001180866	68.198	0.067	0.099
2/16/2016	68.474	0.000276089	68.150	0.324	0.473
2/17/2016	68.329	-1.60E-05	68.473	0.144	0.211
2/18/2016	68.542	-3.13E-05	68.327	0.215	0.314
2/19/2016	68.545	-7.08E-04	68.493	0.052	0.075
2/22/2016	68.533	0.001178051	68.626	0.093	0.135
2/23/2016	68.561	0.000273274	68.552	0.009	0.014
2/24/2016	68.431	-1.88E-05	68.560	0.129	0.188
2/25/2016	68.768	-3.41E-05	68.429	0.339	0.493
2/26/2016	68.737	-0.000711253	68.719	0.018	0.026
2/29/2016	68.208	0.001175237	68.818	0.610	0.894
3/1/2016	67.753	0.00027046	68.226	0.473	0.699
3/2/2016	67.395	-2.16E-05	67.752	0.357	0.529
3/3/2016	67.122	-3.69E-05	67.393	0.271	0.403
3/4/2016	66.938	-0.000714067	67.074	0.136	0.203
3/7/2016	66.989	0.001172422	67.016	0.027	0.041
3/8/2016	67.313	0.000267645	67.007	0.306	0.455
3/9/2016	67.128	-2.45E-05	67.311	0.183	0.273
3/10/2016	67.302	-3.97E-05	67.125	0.177	0.262
3/11/2016	66.921	-0.000716882	67.254	0.333	0.497
3/14/2016	67.138	0.001169608	66.999	0.139	0.207
3/15/2016	67.372	0.000264831	67.156	0.216	0.321
3/16/2016	67.173	-2.73E-05	67.370	0.197	0.294
3/17/2016	66.619	-4.25E-05	67.170	0.551	0.827
3/18/2016	66.384	-0.000719696	66.571	0.187	0.282

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
3/21/2016	66.5	0.001166793	66.461	0.039	0.058
3/22/2016	66.755	0.000262016	66.517	0.238	0.356
3/23/2016	66.93	-3.01E-05	66.753	0.177	0.264
3/24/2016	66.916	-4.53E-05	66.927	0.011	0.016
3/25/2016	66.829	-0.000722511	66.868	0.039	0.058
3/28/2016	66.608	0.001163979	66.907	0.299	0.449
3/29/2016	66.375	0.000259202	66.625	0.250	0.377
3/30/2016	66.375	-3.29E-05	66.373	0.002	0.003
3/31/2016	66.255	-4.82E-05	66.372	0.117	0.176
4/1/2016	66.365	-0.000725325	66.207	0.158	0.238
4/4/2016	66.106	0.001161164	66.442	0.336	0.508
4/5/2016	66.422	0.000256387	66.123	0.299	0.450
4/6/2016	66.517	-3.57E-05	66.420	0.097	0.146
4/7/2016	66.757	-5.10E-05	66.514	0.243	0.365
4/8/2016	66.551	-0.00072814	66.708	0.157	0.236
4/11/2016	66.287	0.00115835	66.628	0.341	0.515
4/12/2016	66.283	2.54E-04	66.304	0.021	0.031
4/13/2016	66.496	-3.85E-05	66.280	0.216	0.324
4/14/2016	66.597	-5.38E-05	66.492	0.105	0.157
4/15/2016	66.66	-0.000730954	66.548	0.112	0.168
4/18/2016	66.416	0.001155535	66.737	0.321	0.483
4/19/2016	66.15	0.000250758	66.433	0.283	0.427
4/20/2016	66.166	-4.13E-05	66.147	0.019	0.028
4/21/2016	66.489	-5.66E-05	66.162	0.327	0.491
4/22/2016	66.66	-0.000733769	66.440	0.220	0.330
4/25/2016	66.685	0.001152721	66.737	0.052	0.078
4/26/2016	66.404	0.000247944	66.702	0.298	0.448
4/27/2016	66.362	-4.42E-05	66.401	0.039	0.059
4/28/2016	66.401	-5.94E-05	66.358	0.043	0.065
4/29/2016	66.425	-0.000736583	66.352	0.073	0.110
5/2/2016	66.346	0.001149906	66.501	0.155	0.234
5/3/2016	66.558	0.000245129	66.362	0.196	0.294
5/4/2016	66.627	-4.70E-05	66.555	0.072	0.108
5/5/2016	66.558	-6.22E-05	66.623	0.065	0.097
5/6/2016	66.6	-0.000739398	66.509	0.091	0.137
5/9/2016	66.752	0.001147092	66.676	0.076	0.113
5/10/2016	66.631	0.000242315	66.768	0.137	0.206
5/11/2016	66.561	-4.98E-05	66.628	0.067	0.100
5/12/2016	66.757	-6.50E-05	66.557	0.200	0.300

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
5/13/2016	66.855	-0.000742212	66.707	0.148	0.221
5/16/2016	66.844	0.001144277	66.932	0.088	0.131
5/17/2016	66.825	0.0002395	66.860	0.035	0.052
5/18/2016	67.14	-5.26E-05	66.821	0.319	0.474
5/19/2016	67.436	-6.79E-05	67.135	0.301	0.446
5/20/2016	67.408	-0.000745027	67.386	0.022	0.033
5/23/2016	67.409	1.14E-03	67.485	0.076	0.113
5/24/2016	67.63	0.000236686	67.425	0.205	0.303
5/25/2016	67.273	-5.54E-05	67.626	0.353	0.525
5/26/2016	66.927	-7.07E-05	67.268	0.341	0.510
5/27/2016	67.031	-0.000747841	66.877	0.154	0.230
5/30/2016	67.171	0.001138648	67.107	0.064	0.095
5/31/2016	67.209	0.000233871	67.187	0.022	0.033
6/1/2016	67.434	-5.82E-05	67.205	0.229	0.339
6/2/2016	67.268	-7.35E-05	67.429	0.161	0.239
6/3/2016	67	-0.000750656	67.218	0.218	0.325
6/6/2016	66.79	0.001135833	67.076	0.286	0.428
6/7/2016	66.658	0.000231057	66.805	0.147	0.221
6/8/2016	66.5	-6.10E-05	66.654	0.154	0.231
6/9/2016	66.753	-7.63E-05	66.495	0.258	0.387
6/10/2016	66.952	-0.00075347	66.703	0.249	0.372
6/13/2016	67.187	0.001133019	67.028	0.159	0.237
6/14/2016	67.292	0.000228242	67.202	0.090	0.133
6/15/2016	67.079	-6.39E-05	67.288	0.209	0.311
6/16/2016	67.315	-7.91E-05	67.074	0.241	0.358
6/17/2016	67.074	-0.000756285	67.264	0.190	0.283
6/20/2016	67.551	0.001130204	67.150	0.401	0.594
6/21/2016	67.624	0.000225428	67.566	0.058	0.085
6/22/2016	67.449	-6.67E-05	67.619	0.170	0.253
6/23/2016	67.279	-8.19E-05	67.443	0.164	0.244
6/24/2016	67.885	-0.000759099	67.228	0.657	0.968
6/27/2016	67.914	0.00112739	67.962	0.048	0.070
6/28/2016	67.715	0.000222613	67.929	0.214	0.316
6/29/2016	67.422	-6.95E-05	67.710	0.288	0.428
6/30/2016	67.504	-8.47E-05	67.416	0.088	0.130
7/1/2016	67.19	-0.000761914	67.453	0.263	0.391
7/4/2016	67.265	0.001124575	67.266	0.001	0.001
7/5/2016	67.434	0.000219799	67.280	0.154	0.229
7/6/2016	67.411	-7.23E-05	67.429	0.018	0.027

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
7/7/2016	67.495	-8.76E-05	67.405	0.090	0.133
7/8/2016	67.139	-0.000764729	67.443	0.304	0.453
7/11/2016	67.138	1.12E-03	67.214	0.076	0.114
7/12/2016	66.975	0.000216984	67.153	0.178	0.265
7/13/2016	67.016	-7.51E-05	66.970	0.046	0.069
7/14/2016	66.843	-9.04E-05	67.010	0.167	0.250
7/15/2016	67.141	-0.000767543	66.792	0.349	0.520
7/18/2016	67.137	1.12E-03	67.216	0.079	0.118
7/19/2016	67.204	0.000214169	67.151	0.053	0.078
7/20/2016	67.163	-7.79E-05	67.199	0.036	0.053
7/21/2016	67.153	-9.32E-05	67.157	0.004	0.006
7/22/2016	67.154	-7.70E-04	67.101	0.053	0.079
7/25/2016	67.412	0.001116132	67.229	0.183	0.272
7/26/2016	67.321	0.000211355	67.426	0.105	0.156
7/27/2016	67.072	-8.07E-05	67.316	0.244	0.363
7/28/2016	67.014	-9.60E-05	67.066	0.052	0.077
7/29/2016	66.655	-0.000773172	66.962	0.307	0.461
8/1/2016	66.764	0.001113317	66.729	0.035	0.052
8/2/2016	66.682	0.00020854	66.778	0.096	0.144
8/3/2016	66.767	-8.36E-05	66.676	0.091	0.136
8/4/2016	66.84	-9.88E-05	66.760	0.080	0.119
8/5/2016	66.842	-7.76E-04	66.788	0.054	0.081
8/8/2016	66.81	0.001110503	66.916	0.106	0.159
8/9/2016	66.774	0.000205726	66.824	0.050	0.074
8/10/2016	66.765	-8.64E-05	66.768	0.003	0.005
8/11/2016	66.75	-0.000101634	66.758	0.008	0.012
8/12/2016	66.908	-0.000778801	66.698	0.210	0.314
8/15/2016	66.853	0.001107688	66.982	0.129	0.193
8/16/2016	66.87	0.000202911	66.867	0.003	0.005
8/17/2016	66.893	-8.92E-05	66.864	0.029	0.043
8/18/2016	66.83	-0.000104449	66.886	0.056	0.084
8/19/2016	67.137	-0.000781616	66.778	0.359	0.535
8/22/2016	67.202	0.001104874	67.211	0.009	0.014
8/23/2016	67.122	0.000200097	67.215	0.093	0.139
8/24/2016	67.167	-9.20E-05	67.116	0.051	0.076
8/25/2016	67.016	-0.000107263	67.160	0.144	0.215
8/26/2016	67.136	-0.00078443	66.963	0.173	0.257
8/29/2016	67.113	0.001102059	67.210	0.097	0.145
8/30/2016	67.144	0.000197282	67.126	0.018	0.026

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
8/31/2016	66.973	-9.48E-05	67.138	0.165	0.246
9/1/2016	66.801	-0.000110078	66.966	0.165	0.246
9/2/2016	66.795	-7.87E-04	66.748	0.047	0.070
9/5/2016	66.47	0.001099245	66.868	0.398	0.599
9/6/2016	66.28	0.000194468	66.483	0.203	0.306
9/7/2016	66.478	-9.76E-05	66.274	0.204	0.308
9/8/2016	66.631	-0.000112892	66.470	0.161	0.241
9/9/2016	66.895	-0.000790059	66.578	0.317	0.473
9/12/2016	66.738	0.00109643	66.968	0.230	0.345
9/13/2016	67.14	0.000191653	66.751	0.389	0.580
9/14/2016	66.798	-0.000100444	67.133	0.335	0.502
9/15/2016	66.86	-0.000115707	66.790	0.070	0.104
9/16/2016	67.075	-0.000792874	66.807	0.268	0.400
9/19/2016	66.98	0.001093616	67.148	0.168	0.251
9/20/2016	66.985	1.89E-04	66.993	0.008	0.011
9/21/2016	66.744	-0.000103259	66.978	0.234	0.351
9/22/2016	66.633	-0.000118521	66.736	0.103	0.155
9/23/2016	66.707	-0.000795688	66.580	0.127	0.190
9/26/2016	66.613	0.001090801	66.780	0.167	0.250
9/27/2016	66.425	0.000186024	66.625	0.200	0.302
9/28/2016	66.349	-0.000106073	66.418	0.069	0.104
9/29/2016	66.812	-0.000121336	66.341	0.471	0.705
9/30/2016	66.556	-0.000798503	66.759	0.203	0.304
10/3/2016	66.546	0.001087987	66.628	0.082	0.124
10/4/2016	66.609	0.00018321	66.558	0.051	0.076
10/5/2016	66.572	-0.000108888	66.602	0.030	0.045
10/6/2016	66.697	-0.00012415	66.564	0.133	0.200
10/7/2016	66.602	-0.000801317	66.644	0.042	0.062
10/10/2016	66.492	0.001085172	66.674	0.182	0.274
10/11/2016	66.834	0.000180395	66.504	0.330	0.494
10/12/2016	66.812	-0.000111702	66.827	0.015	0.022
10/13/2016	66.794	-0.000126965	66.804	0.010	0.014
10/14/2016	66.717	-0.000804132	66.740	0.023	0.035
10/17/2016	66.789	0.001082358	66.789	0.000	0.000
10/18/2016	66.733	0.000177581	66.801	0.068	0.102
10/19/2016	66.645	-0.000114517	66.725	0.080	0.121
10/20/2016	66.83	-0.000129779	66.636	0.194	0.290
10/21/2016	66.926	-0.000806946	66.776	0.150	0.224
10/24/2016	66.845	0.001079543	66.998	0.153	0.229

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
10/25/2016	66.806	0.000174766	66.857	0.051	0.076
10/26/2016	66.863	-0.000117331	66.798	0.065	0.097
10/27/2016	66.881	-0.000132594	66.854	0.027	0.040
10/28/2016	66.778	-0.000809761	66.827	0.049	0.073
10/31/2016	66.686	0.001076729	66.850	0.164	0.246
11/1/2016	66.696	0.000171952	66.697	0.001	0.002
11/2/2016	66.762	-0.000120146	66.688	0.074	0.111
11/3/2016	66.668	-0.000135409	66.753	0.085	0.127
11/4/2016	66.796	-0.000812575	66.614	0.182	0.273
11/7/2016	66.745	0.001073914	66.868	0.123	0.184
11/8/2016	66.246	0.000169137	66.756	0.510	0.770
11/9/2016	66.515	-0.00012296	66.238	0.277	0.417
11/10/2016	66.865	-0.000138223	66.506	0.359	0.537
11/11/2016	67.565	-0.00081539	66.810	0.755	1.117
11/14/2016	67.785	0.001071099	67.637	0.148	0.218
11/15/2016	67.786	1.66E-04	67.796	0.010	0.015
11/16/2016	67.999	-0.000125775	67.777	0.222	0.326
11/17/2016	68.023	-0.000141038	67.989	0.034	0.049
11/18/2016	68.191	-0.000818204	67.967	0.224	0.328
11/21/2016	68.228	0.001068285	68.264	0.036	0.053
11/22/2016	68.396	0.000163508	68.239	0.157	0.229
11/23/2016	68.784	-0.000128589	68.387	0.397	0.577
11/24/2016	68.761	-0.000143852	68.774	0.013	0.019
11/25/2016	68.519	-0.000821019	68.705	0.186	0.271
11/28/2016	68.579	0.00106547	68.592	0.013	0.019
11/29/2016	68.615	0.000160694	68.590	0.025	0.036
11/30/2016	68.598	-0.000131404	68.606	0.008	0.012
12/1/2016	68.236	-0.000146667	68.588	0.352	0.516
12/2/2016	68.031	-0.000823833	68.180	0.149	0.219
12/5/2016	68.025	1.06E-03	68.103	0.078	0.115
12/6/2016	67.742	0.000157879	68.036	0.294	0.434
12/7/2016	67.438	-0.000134218	67.733	0.295	0.437
12/8/2016	67.546	-0.000149481	67.428	0.118	0.175
12/9/2016	67.47	-0.000826648	67.490	0.020	0.030
12/12/2016	67.431	0.001059841	67.542	0.111	0.164
12/13/2016	67.411	0.000155065	67.441	0.030	0.045
12/14/2016	67.475	-0.000137033	67.402	0.073	0.109
12/15/2016	67.857	-0.000152296	67.465	0.392	0.578
12/16/2016	67.855	-8.29E-04	67.801	0.054	0.080

Date	Closing Price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
12/19/2016	67.844	0.001057027	67.927	0.083	0.122
12/20/2016	67.917	0.00015225	67.854	0.063	0.092
12/21/2016	67.837	-0.000139847	67.908	0.071	0.104
12/22/2016	67.848	-0.00015511	67.826	0.022	0.032
12/23/2016	67.837	-0.000832277	67.792	0.045	0.067
12/26/2016	67.76	0.001054212	67.909	0.149	0.219
12/27/2016	67.978	0.000149436	67.770	0.208	0.306
12/28/2016	68.233	-0.000142662	67.968	0.265	0.388
12/29/2016	67.936	-0.000157925	68.222	0.286	0.421
12/30/2016	67.955	-0.000835092	67.879	0.076	0.111

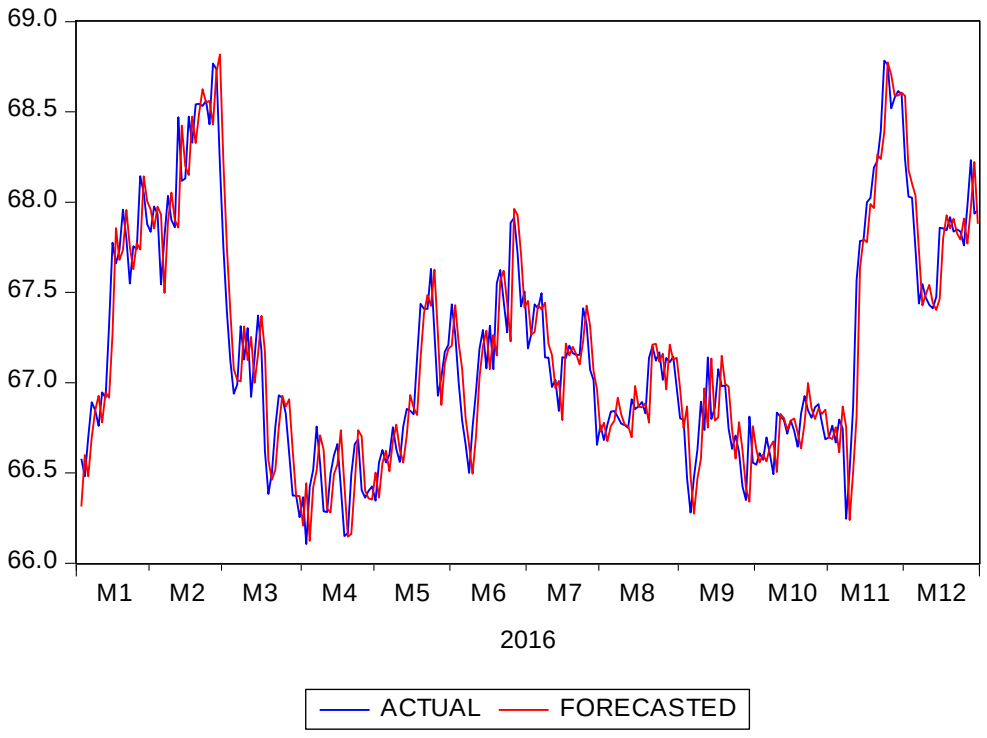
MAE	MAPE
0.164	0.244

Inference

Mean Absolute Error is 0.16 and Mean Absolute Percentage Error is 0.24%.

These results indicate that the model is 99.76% accurate.

Fig 4.2.1



Inference:

Standard deviation of the actual values is 0.622 and Mean Absolute Error is 0.16.

Mean absolute percentage error is 0.24. This suggests that the model is 99.76% accurate.

The same model will now be applied to forecast the values for the first quarter of 2017.

4.3 Stage 3: Forecasting

In stage 3, forecast for the period 1 January 2017 – 31 March 2017 is made using exponential smoothing method and the forecasted value is compared with the actual value.

Now, the same model is used to forecast return series for Jan 2017-March 2017.

Table 4.3.1

Date	Closing price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
12/30/2016	67.955				
1/2/2017	68.145	0.00066932	68.000	0.145	0.212
1/3/2017	68.26	-0.00012903	68.136	0.124	0.181
1/4/2017	67.886	-0.00041543	68.232	0.346	0.509
1/5/2017	67.743	-0.00036194	67.861	0.118	0.175
1/6/2017	68.115	-0.00102102	67.674	0.441	0.648
1/9/2017	68.1	0.00066697	68.160	0.060	0.089
1/10/2017	68.327	-0.00013138	68.091	0.236	0.345
1/11/2017	68.312	-0.00041778	68.298	0.014	0.020
1/12/2017	68.141	-0.00036429	68.287	0.146	0.214
1/13/2017	68.18	-0.00102337	68.071	0.109	0.159
1/16/2017	68.103	0.00066462	68.225	0.122	0.180
1/17/2017	67.862	-0.00013373	68.094	0.232	0.342
1/18/2017	68.22	-0.00042012	67.833	0.387	0.567
1/19/2017	68.1	-0.00036664	68.195	0.095	0.139
1/20/2017	68.075	-0.00102572	68.030	0.045	0.066
1/23/2017	68.051	0.00066227	68.120	0.069	0.102
1/24/2017	68.138	-0.00013608	68.042	0.096	0.141

Date	Closing price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
1/25/2017	67.988	-0.00042247	68.109	0.121	0.178
1/26/2017	68.176	-0.00036899	67.963	0.213	0.313
1/27/2017	68.105	-0.00102807	68.106	0.001	0.001
1/30/2017	67.829	0.00065992	68.150	0.321	0.473
1/31/2017	67.515	-0.00013843	67.820	0.305	0.451
2/1/2017	67.415	-0.00042482	67.486	0.071	0.106
2/2/2017	67.21	-0.00037134	67.390	0.180	0.268
2/3/2017	67.184	-0.00103042	67.141	0.043	0.064
2/6/2017	67.195	0.00065757	67.228	0.033	0.049
2/7/2017	67.35	-0.00014078	67.186	0.164	0.244
2/8/2017	67.05	-0.00042717	67.321	0.271	0.405
2/9/2017	66.765	-0.00037369	67.025	0.260	0.389
2/10/2017	66.854	-0.00103277	66.696	0.158	0.236
2/13/2017	66.975	0.00065522	66.898	0.077	0.115
2/14/2017	66.835	-0.00014313	66.965	0.130	0.195
2/15/2017	66.875	-0.00042952	66.806	0.069	0.103
2/16/2017	67.08	-0.00037604	66.850	0.230	0.343
2/17/2017	67.08	-0.00103512	67.011	0.069	0.104
2/20/2017	66.905	0.00065287	67.124	0.219	0.327
2/21/2017	66.985	-0.00014548	66.895	0.090	0.134
2/22/2017	66.95	-0.00043187	66.956	0.006	0.009
2/23/2017	66.69	-0.00037838	66.925	0.235	0.352
2/24/2017	66.645	-0.00103747	66.621	0.024	0.036
2/27/2017	66.7	0.00065052	66.688	0.012	0.017

Date	Closing price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
2/28/2017	66.725	-0.00014783	66.690	0.035	0.052
3/1/2017	66.865	-0.00043422	66.696	0.169	0.253
3/2/2017	66.785	-0.00038073	66.840	0.055	0.082
3/3/2017	66.78	-1.04E-03	66.716	0.064	0.097
3/6/2017	66.675	0.00064817	66.823	0.148	0.222
3/7/2017	66.625	-0.00015018	66.665	0.040	0.060
3/8/2017	66.765	-0.00043657	66.596	0.169	0.253
3/9/2017	66.69	-0.00038308	66.739	0.049	0.074
3/10/2017	66.555	-0.00104217	66.620	0.065	0.098
3/13/2017	66.18	0.00064582	66.598	0.418	0.632
3/14/2017	65.775	-0.00015253	66.170	0.395	0.600
3/15/2017	65.63	-0.00043892	65.746	0.116	0.177
3/16/2017	65.385	-0.00038543	65.605	0.220	0.336
3/17/2017	65.475	-0.00104452	65.317	0.158	0.242
3/20/2017	65.345	0.00064347	65.517	0.172	0.263
3/21/2017	65.344	-1.55E-04	65.335	0.009	0.014
3/22/2017	65.455	-0.00044127	65.315	0.140	0.214
3/23/2017	65.455	-0.00038778	65.430	0.025	0.039
3/24/2017	65.425	-0.00104687	65.386	0.039	0.059
3/27/2017	64.995	0.00064113	65.467	0.472	0.726
3/28/2017	65.045	-0.00015723	64.985	0.060	0.093
3/29/2017	64.875	-0.00044362	65.016	0.141	0.218
3/30/2017	64.86	-0.00039013	64.850	0.010	0.016
3/31/2017	64.86	-0.00104922	64.792	0.068	0.105

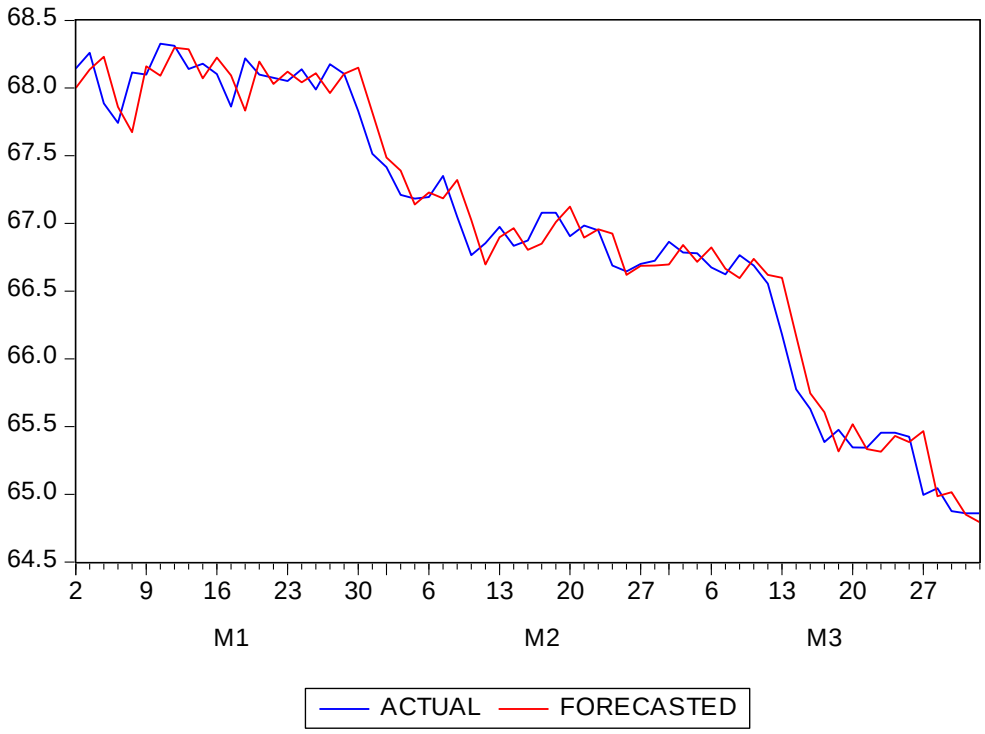
Date	Closing price	Forecasted return (relative)	Forecasted Price	Absolute error	Absolute percentage error
				MAE	MAPE
				0.143	0.214

Inference

Standard deviation for the actual values is 1.039 and the Mean absolute error is coming out to be 0.143.

Mean absolute percentage error is 0.21. This suggests that the model is 99.79% accurate.

Fig. 4.3.1



4.4 Discussion and Analysis

From the empirical studies, it is evident that the model was 99.76% accurate in the testing stage and forecast for the period Jan 01, 2017-March 31, 2017 is 99.79% accurate. However, 0.21% variation is quite significant in USD/INR exchange rate. The variation may be attributed to other macroeconomic fundamental factors. This also suggests that exponential smoothing method may give higher accuracy for forecast for shorter duration.

The deviation in exchange rate from the forecasted value can be attributed to factors that cannot be absorbed by Technical analysis. Fundamental analysis will have to be used to capture the other factors like Political scenario, bank reforms etc.

Explanation for the deviation from forecasted values can be attributed to the following macro factors.

Rupee depreciation

The rupee performed a bit better than most of its regional peers in 2016, weakening just over 2 percent. But, capital outflows intensified toward the end of 2016 after Donald Trump won the US presidential election and Prime Minister Narendra Modi announced the end of high-value bank notes.

Since Trump's election victory, markets have realigned over expectations his administration will bring in sweeping tax cuts, infrastructure projects and deregulation.

The 10-year US Treasury yield has rallied more than 25 percent since the election, hitting a two-year high of 2.641 percent on December 15.

The Federal Reserve also raised the federal funds rate last month for the first time in a year. The central bank signaled a faster pace of rate increases this year based on expectations for fiscal stimulus.

PM Modi's demonetization drive has hampered both industrial and services output, with a private survey this week showing factory activity and services took a hit last month, lending credence to worries that it would dent growth

Rupee appreciation

In this fiscal year or most part of 2016, most of time rupee's behaviour was different from what the other emerging markets currencies were behaving like and this was primarily due to the region. Indian economy is showing growth (despite demonetization) estimated growth is 6.9% for FY17. The government estimate still is at 7.1%. This was a big sized economy which was growing.

Looking at other factors like inflation coming down -- though in between it will keep on fluctuating. There are capital inflows though on the portfolio side there were outflows even for FCNR (B) redemptions in last quarter of previous calendar year. But the inflows in the form of FDI were coming in. All in all, this gives relative strength to the Indian currency and that is why it behaved the way it has behaved in most part of this fiscal.

Now the recent strengthening of rupee vis-à-vis dollar is based on the assessment that the kind of political outcome especially in the state of Uttar Pradesh, most of the people are betting on or are of the view that the reform process will continue and looking at the way the ruling coalition in general and BJP in particular had political gain people are writing about 2019. Those who are tracking the economy believe the chances of the same coalition coming back to power in 2019 is bright.

RBI in its sixth Bi - Monthly Monetary Policy review kept its benchmark repo rate unchanged at 6.25 percent. Other important rates were also kept at the same levels; reverse repo rate at 5.75 percent, marginal standing facility and bank rate at 6.75 per cent. The rationale behind this neutral stance could be attributed to the stubborn core inflation rate, implantation of 7th Central Pay Commission, transitory effects of demonetization and looming uncertainty in the global arena. The RBI governor expects inflation rate to linger in the range of 4 to 4.5 percent in the first half of the financial year and thereon to move towards 5 percent with risks evenly balanced around this projected path. Due to all the above factors, USDINR spot appreciated.

The rupee retreated from the lows of Rs 68/USD last seen in the year 2016 to claim the tag of Asia's third-best performing currency in the first three months of the year 2017.

The Indian rupee appreciated more than 3 percent against US Dollar so far in the year to Rs 65.45/USD which was closer to a 17-month high of 65.36, a level which was last seen on October 30, 2015.

The appreciation of the rupee is likely to continue in near term as the rupee is reasonably well placed on inflation differential, current account deficit, and foreign direct investment (FDI) flow.

On the political front, BJP-led government coming in power with a sweeping victory in country's largest state Uttar Pradesh has provided strength to rupee on the back of stable government along with the hope of more bold reforms coming in future, suggest experts.

The Reserve Bank of India's (RBI) neutral stance on policy rates has signalled rupee to trade higher against the dollar. The dollar index, which measures the greenback against a basket of six major currencies, dipped below the 100 level for the first time since Feb. 7 on Wednesday.

After strong GDP data and stable December quarter earnings from India Inc., foreign institutional investors (FII) who had turned net seller in the Indian debt as well as equity markets post demonetisation have now become net buyers.

The rupee appreciation will bring pain for the export-oriented sectors like information technology, pharma, reality, and Tourism. However, somebody loss is somebody gains, so import oriented sectors like power and metal sectors are in the list of beneficiary sectors from rupee appreciation.

5.CONCLUSION AND LIMITATIONS

From the empirical studies, it is evident that the model was 99.76% accurate in the testing stage and forecast for the period Jan 01, 2017-March 31, 2017 is 99.79% accurate. However, 0.21% variation is quite significant in USD/INR exchange rate. The variation may be attributed to other macroeconomic fundamental factors. This also suggests that exponential smoothing method may give higher accuracy for forecast for shorter duration.

This study has some limitations. It is assumed that there is zero seasonality and cyclicity in this study. Hence, single exponential smoothing method is applied. It is also assumed that there is reasonable amount of continuity between the past and the future exchange rates

The forecast lags behind as the trend is captured only when there is a movement in the actual exchange rates. This is clearly visible from Fig 4.3.1. This is so because the volatility is captured by the process only after it has occurred. Any change in volatility cannot be predicted by this method until it is reflected in the actual exchange rate movement.

This study is purely based on technical analysis. Any deviations from the forecasted value may be attributed to fundamental factors that may influence the exchange rate like any changes in the current political system, changes in fiscal/monetary policies, GDP, inflation rate etc.

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