ECON F342
APPLIED ECONOMETRICS:

EXCHANGE RATE
INR with respect to USD

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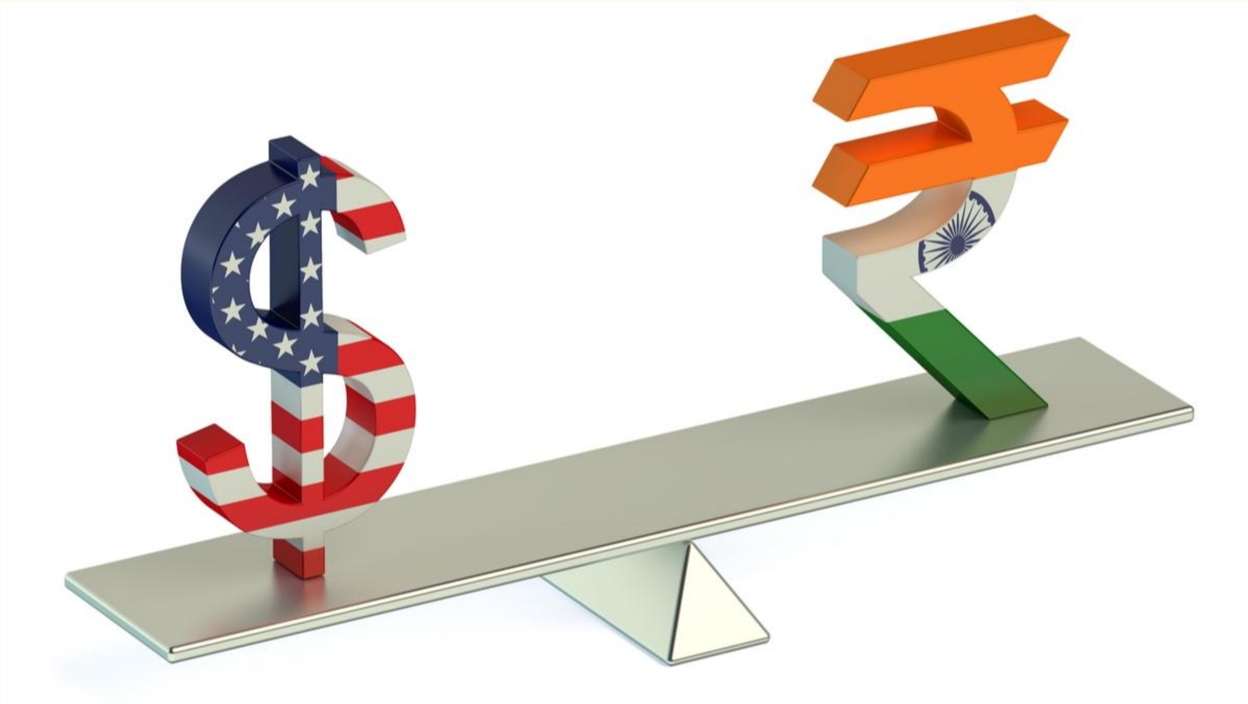


The report consists of two parts, first one consists of an ARIMA analysis of the Exchange Rate of 1 USD in INR in INDIA. Whereas in the second part using the data from the first part we have aimed to identify the trade as one of the determinants of Exchange Rate in India by building a FDL model.

PART 1:

In this section we use annual time series data on the Indian Currency Rupee to the US currency Dollars from 1960 to 2019, and fit the model and forecast the Exchange Rate of INR with respect to the USD using the ARIMA technique.
Our first diagnostic test concluded that the R is an I(1) variable. From the results we derived, we followed that an ARIMA model (2,1,0) is suitable for our variable.
The further tests show that the model is stable and hence we proceeded with the forecasting of the Indian Rupee to USD Exchange Rate. The forecasting was done to predict the Exchange Rates for the next 5 years, that is, from 2020-2024 and we found that our results are significant.

The main policy analysis we derive from the results of this part is that the Monetary Policy authority of India, the Reserve Bank of India should devalue the Rupee to have the required Exchange Rate stability and to facilitate the Exports, promoting the Local Business.

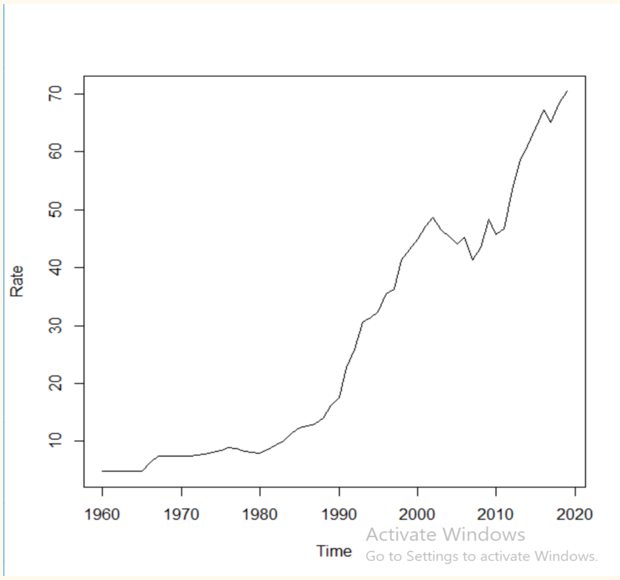
INTRODUCTION:

The Forex market is the largest market in the world with Exchange Rate being the most important variable and is the focus of the eye of every country and Central Bank around the globe. The Exchange Rate influences every individual directly and indirectly ranging from the participants of the foreign Exchange Market to exporters, importers, Business activities, Tourist attractiveness, Bankers and investors. (Dua and Ranjan, 2011).

For floating exchange rates it becomes extremely important that proper forecasting is available for proper research and subsequent decision making. (Hu, 1999)

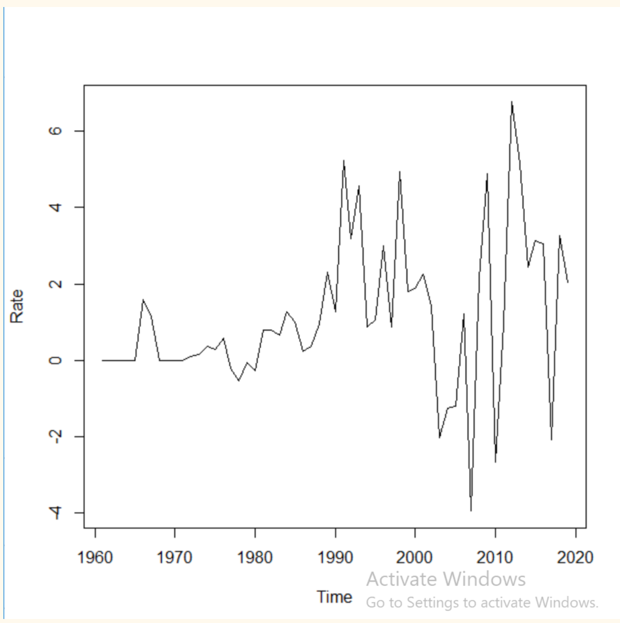
<u>Our expectations from the topic were to contribute in policy formulation through appropriate forecasting.</u>

METHODOLOGY:



We will first plot the data for the exchange rate using the plot.ts() command in R:

This plot indicates that the data might be non-stationary



Therefore we will take the first difference of the data using diff() command in R and plot it

The plot above shows some evidence for stationary data.

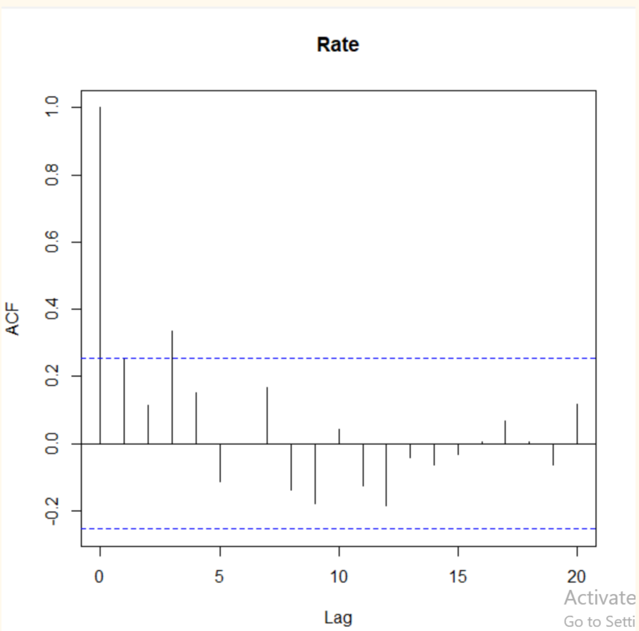
```
> stationary.test(data.ts)
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag  ADF p.value
[1,]   0 4.63   0.990
[2,]   1 3.01   0.990
[3,]   2 2.61   0.990
[4,]   3 1.39   0.956
```

To check whether our interpretation is correct we will check for stationarity using stationarity.test() in R. This command uses the Augmented Dickey-Fuller test to check for stationarity by rejecting the null hypothesis of non- stationarity in favour of the alternative hypothesis if the p-value is less than 0.05 for a 95% significance level.

```
> stationary.test(data.diff1)
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag   ADF p.value
[1,]   0 -4.71  0.0100
[2,]   1 -3.19  0.0100
[3,]   2 -1.86  0.0625
[4,]   3 -1.69  0.0878
```

Both the test results are consistent with our interpretation from the plot. Therefore, we were correct to assume that the data becomes stationary after taking the first difference.

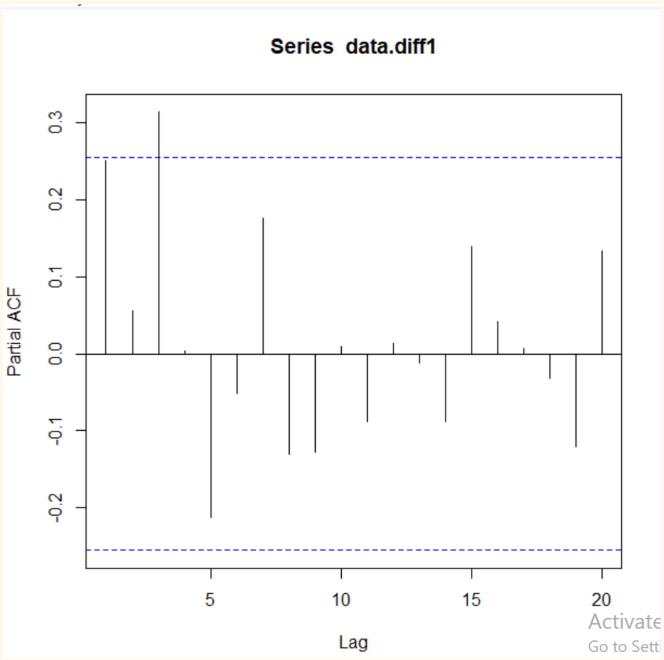
- To select the correct ARIMA model for our data, we will first plot the correlogram and partial correlogram for our data for 20 lags using the acf() and pacf() commands in R.



The ACF plot along with the values above show that the autocorrelation value at the first lag is almost significant (close to 0.255) and the third lag is significant. Such a variation in the values might be due to sampling error or by chance.

```
> acf(data.diff1,lag.max=20,plot=FALSE)

Autocorrelations of series ‘data.diff1’, by lag

     0      1      2      3      4      5      6      7      8      9     10     11     12 
 1.000  0.250  0.115  0.334  0.152 -0.114 -0.003  0.166 -0.139 -0.179  0.041 -0.127 -0.184 
    13     14     15     16     17     18     19     20 
-0.043 -0.065 -0.031  0.005  0.068  0.005 -0.063  0.117 
```

- Similar results can also be derived for the PACF plots and values shown below:




```
> pacf(data.diff1,lag.max=20,plot=FALSE)

Partial autocorrelations of series ‘data.diff1’, by lag

     1      2      3      4      5      6      7      8      9     10     11     12     13 
 0.250  0.056  0.314  0.004 -0.212 -0.051  0.176 -0.130 -0.127  0.009 -0.088  0.013 -0.012 
    14     15     16     17     18     19     20 
-0.087  0.140  0.042  0.006 -0.031 -0.121  0.134 
```

```
> auto.arima(data.diff1)
Series: data.diff1
ARIMA(2,1,0)

Coefficients:
          ar1      ar2
      -0.6120  -0.4967
s.e.   0.1137   0.1161

sigma^2 estimated as 3.836:  log likelihood=-120.64
AIC=247.28   AICc=247.73   BIC=253.46
```

Since we cannot get a fruitful interpretation from the plots, we go for the auto.arima() command in R to get a concrete ARIMA model for our time series data.
From the output beside, we get that an ARIMA model of order (2,1,0) is suitable for our data.

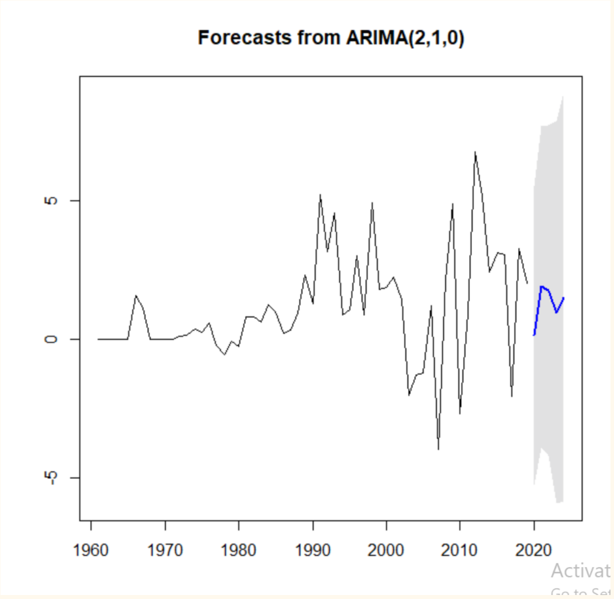
Therefore, we will use the above interpretation to make a predictive model to forecast future values of the time series using the arima() command in R.

```
> arimamodel<-arima(data.diff1,order=c(2,1,0))
> arimamodel

Call:
arima(x = data.diff1, order = c(2, 1, 0))

Coefficients:
          ar1      ar2
      -0.6120  -0.4967
s.e.   0.1137   0.1161

sigma^2 estimated as 3.703:  log likelihood = -120.64,  aic = 247.28
```

We then forecast future values for 5 years at a 99.5% prediction level using the forecast() command in R.

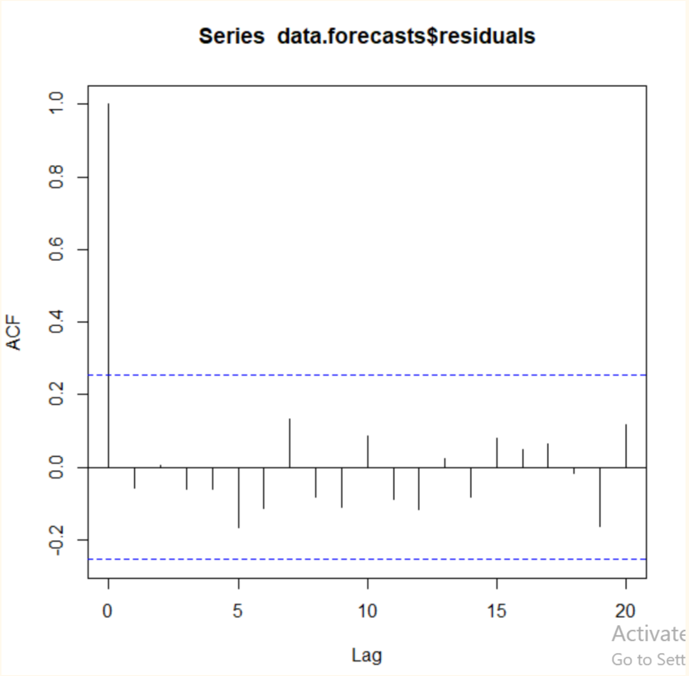
```
> data.forecasts<- forecast(arimamodel,h=5,level=c(99.5))
> data.forecasts
     Point Forecast   Lo 99.5  Hi 99.5
2020      0.1345739 -5.267318 5.536466
2021      1.9095994 -3.884635 7.703834
2022      1.7652211 -4.204280 7.734722
2023      0.9718680 -5.938949 7.882685
2024      1.5291255 -5.839779 8.898030
```

We plot the future values using the plot() command in R.



To check whether the forecasts values are good or not, we will check whether the residuals of the forecasts satisfy the assumptions for our time series data.

We will plot the ACF for the forecast residuals to check whether there is any correlation between successive forecast errors.



We see that the autocorrelation value does not exceed the significance bounds for any lag from 1 to 20, which is consistent with our assumption for time series data.

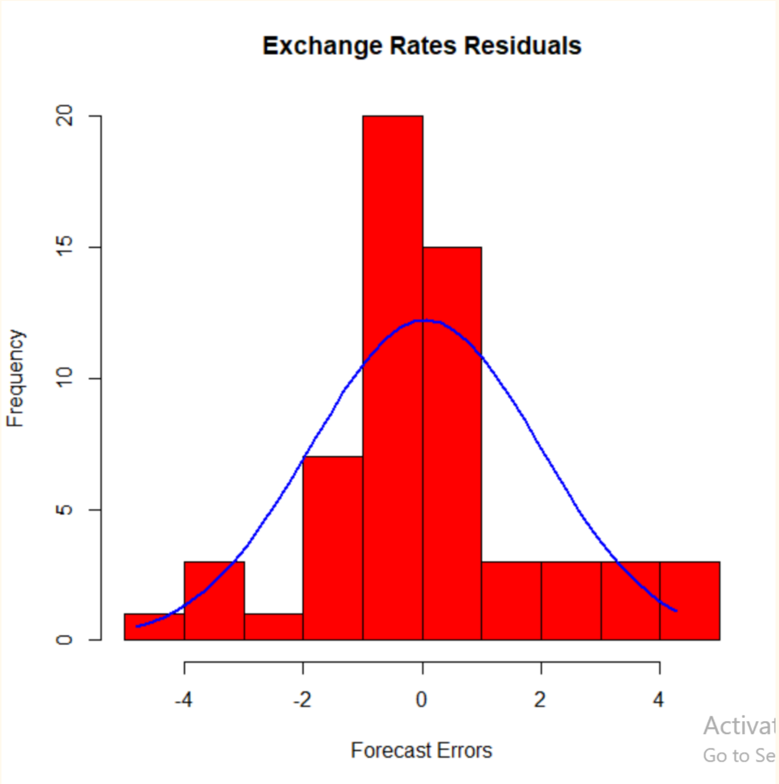
We can check for autocorrelation through the Ljung Box test also, which rejects the null hypothesis of zero autocorrelation in favour of the alternate hypothesis when the p-value is less than 0.05 for a 95% significance level.

We run this test using the Box.test() command in R.

```
> Box.test(data.forecasts$residuals,lag=20,type="Ljung-Box")

        Box-Ljung test

data:  data.forecasts$residuals
X-squared = 13.543, df = 20, p-value = 0.8529
```

As indicated by the test results above, we see that the p-value for the same is 0.85 which tells us that we should not reject the null hypothesis, and therefore conclude that there is no autocorrelation.

Both the tests are consistent with our chosen ARIMA model.
We also plot a histogram overlaid with a normal distribution curve for the forecast residuals to check whether the forecast residuals of our chosen ARIMA model are normally distributed with zero mean and constant variance.



The above plot satisfies the assumption for time series data, therefore verifying the ARIMA model that we chose, since the histogram shows that the forecast residuals are roughly normally distributed with zero mean and a roughly constant variance.

Since both the assumptions are satisfied by our ARIMA model, we can say that that the ARIMA(2,1,0) does seem to provide an adequate predictive model for the Real Exchanges Rates for INR with respect to USD.

PART 2: ARDL/FDL MODEL

Our objective is to analyse the Trade Volume as one of the determinants of the exchange rate in India and check for the statistical significance for the same using a Finite Distributed Lags(FDL) Model. Our fitted Exchange rate was found to be very close to the actual behavior exhibited by the Exchange Rate, therefore we contributed that the variable with the certain lags can be taken as the lead indicator of exchange rate.

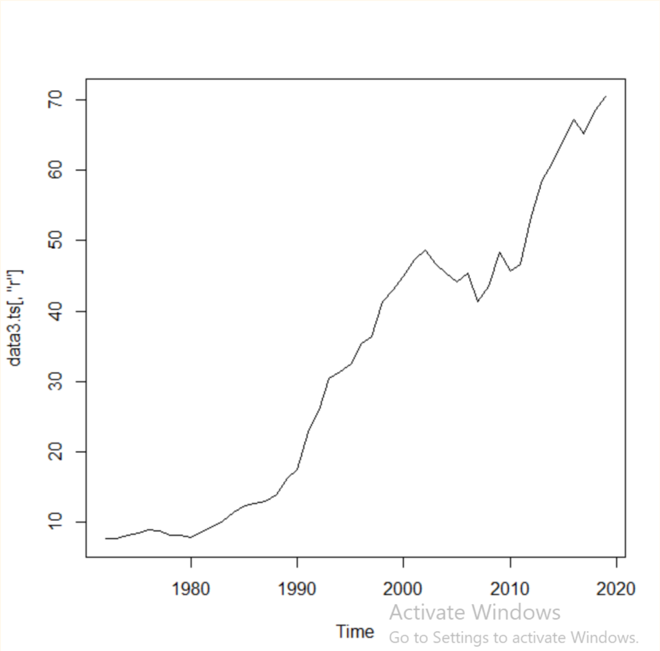
The result that we can conclude from our selected variables is that the appreciation of the Rupee should not always be seen as conveying that the there is a decline in the trade competitiveness of the country, as factors affecting the exchange rate are sometimes self contradictory and there is a little certainty that only single factor contribution is sufficient to describe the behavior of Exchange Rates. In theoretical literature we can say that in the appreciation of the Rupee, some of the factors contributing may be attributed to greater growth, which concludes in the improvement of competitiveness.

Findings from different studies can prove the importance of correct exchange rates, as (Aguirre and Calderon, 2005) founded that the growth of economy is hurt when there is a overvaluation or undervaluation of Real Exchange Rates, though some amount of small undervaluation can in fact improve the growth and this is what the Reserve Bank of India is targeted again and again of doing.

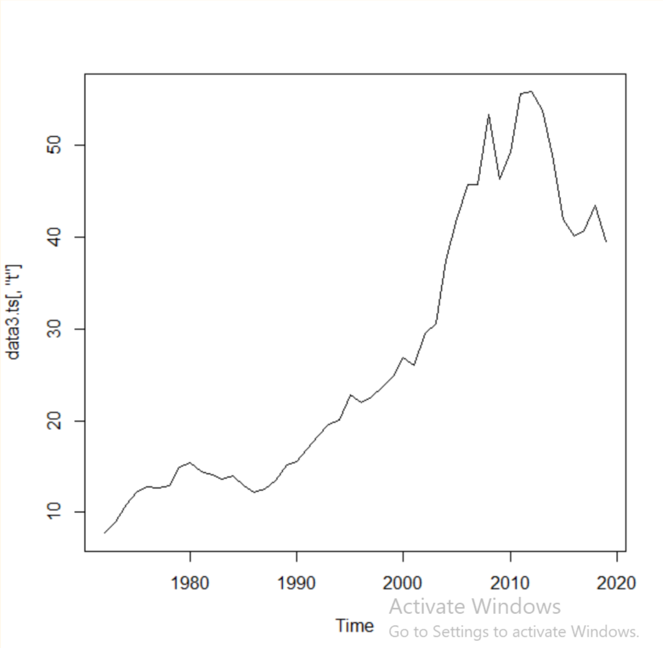
Recently , in March of 2020 the US federal government put India under watchlist for the second time in six months for the Manipulation of the currency and undervaluing it to favor exports and promote growth. This can be attributed to as one of the external factors that the data with the Exchange rate does not come out to be as simple a forecast as we assume it to be theoretically.

THE REASON OF CHOOSING TRADE AS A VARIABLE:

Many major theories developed post 1970s after the collapse of the Bretton Woods System, the world afterwards followed a more integrated approach to the markets and the Globalisation and liberalization added a new debate of trade relations. A country's account balance is matched in terms of net Capital flow, If the current account marks a deficit then capital gets added to the nation, and vice versa. Thus the net foreign asset plays a crucial role, same as when liquidity is required for any commercial company to work, the Foreign assets are required for trade to take place, here instead of targeting the net foreign assets of the country, we have targeted the transactions that happen using these assets as these assets can be arranged as mortgage and mere stock of them won't necessarily define the spot Exchange rate, but may provide stability and a strong future to the currency. Trade can also be used as a proxy for Openness to the external market.



Plot of Exchange Rate over Time:

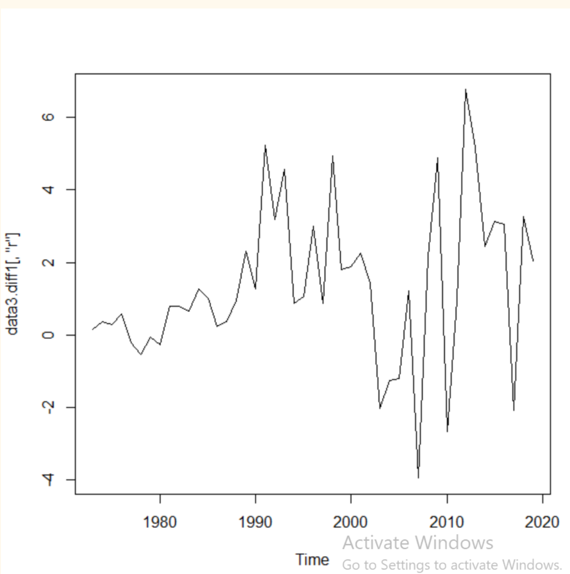


Plot of Total Trade(Volume) as a percentage of GDP

```
> stationary.test(data3.ts[,"t"])
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag   ADF p.value
[1,]   0 0.906   0.899
[2,]   1 0.616   0.816
[3,]   2 0.343   0.737
[4,]   3 0.289   0.722
```

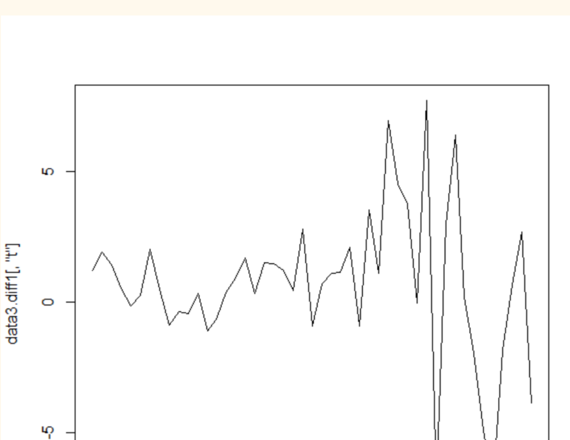
Stationary test of Trade:

Since the p value is greater than 0.05, for 95% significance level, we can conclude that the data is non-stationary.



Plot of first difference of Exchange Rate

(We can see some evidence of stationarity for first difference from the plot)



Plot of first difference of Trade

(we can see some evidence of stationarity for first difference from the plot)

```
> stationary.test(data3.diff1[,"r"])
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag   ADF p.value
[1,]   0 -4.19   0.010
[2,]   1 -2.80   0.010
[3,]   2 -1.62   0.098
[4,]   3 -1.46   0.152
```

Stationary test for First Difference of Exchange Rate: Here the p value is less than the 0.05, for a 95% significance level, therefore we can say that the data is stationary at the first difference.

```
> stationary.test(data3.diff1[,"t"])
Augmented Dickey-Fuller Test
alternative: stationary

Type 1: no drift no trend
     lag   ADF p.value
[1,]   0 -5.60  0.0100
[2,]   1 -3.55  0.0100
[3,]   2 -2.98  0.0100
[4,]   3 -2.50  0.0151
```

Stationary test for First Difference of Trade: Here the p value is less than the 0.05, for a 95% significance level, therefore we can say that the data is stationary at the first difference.

FDL MODELS:

a) 3 lag model:

```
> data2L3.dyn <- dynlm(d(r)~L(d(t), 0:3), data=data3.ts)
> kable(tidy(summary(data2L3.dyn)), digits=4, caption="The `exchange rate` distributed l
ag model with three lags")


Table: The `exchange rate` distributed lag model with three lags

|term           | estimate| std.error| statistic| p.value|
|:--------------|--------:|---------:|---------:|-------:|
|(Intercept)    |   1.5415|    0.3510|    4.3916|  0.0001|
|L(d(t), 0:3)0  |  -0.2327|    0.1125|   -2.0685|  0.0453|
|L(d(t), 0:3)1  |   0.1527|    0.1164|    1.3114|  0.1974|
|L(d(t), 0:3)2  |   0.0198|    0.1172|    0.1694|  0.8664|
|L(d(t), 0:3)3  |  -0.1558|    0.1165|   -1.3377|  0.1887|
```

b) 2 lag model:

```
> data2L2.dyn <- dynlm(d(r)~L(d(t), 0:2), data=data3.ts)
> kable(tidy(summary(data2L2.dyn)), digits=4, caption="The `exchange rate` distributed l
ag model with two lags")


Table: The `exchange rate` distributed lag model with two lags

|term          | estimate| std.error| statistic| p.value|
|:-------------|--------:|---------:|---------:|-------:|
|(Intercept)   |   1.4370|    0.3432|    4.1873|  0.0001|
|L(d(t), 0:2)0 |  -0.2361|    0.1125|   -2.0982|  0.0421|
|L(d(t), 0:2)1 |   0.1270|    0.1151|    1.1035|  0.2762|
|L(d(t), 0:2)2 |   0.0016|    0.1165|    0.0135|  0.9893|
```

Since the models do not show any major difference in terms of significance of coefficients, we will check for the AIC and BIC values for both of them

```
> kable(table, caption="Goodness-of-fit statistics for `exchange rate` models")


Table: Goodness-of-fit statistics for `exchange rate` models

| r.squared| statistic|      AIC|      BIC|
|---------:|---------:|--------:|--------:|
| 0.1144900|  1.767001| 202.1616| 211.1949|
| 0.1535898|  1.769237| 198.6316| 209.3367|
```

Since AIC and BIC are lower for lag 3 therefore we will go for lag 3 model for the given dataset For the 4th lag the BIC value was significantly larger than that of the lag 2 and lag 3 models therefore we rejected that model.

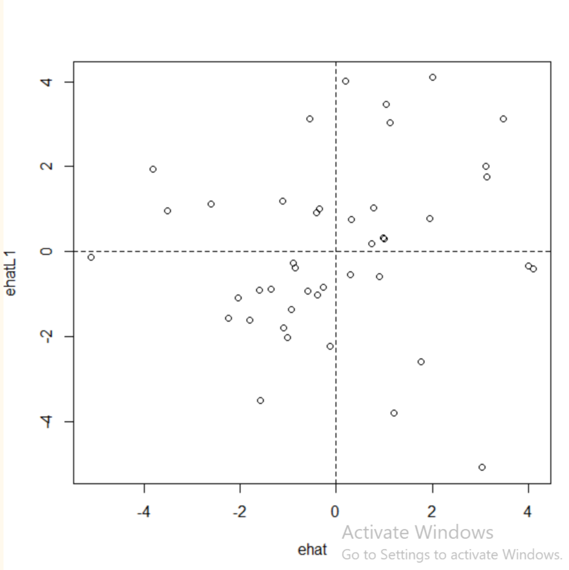
INTERPRETATION : As discussed according to the theory above the result is counterintuitive for some coefficients.

For lag 0, Estimate Value: -0.2327

For a unit change in the difference of trade volume as a % of GDP the difference in the Exchange Rate will decrease by 23.27 % in the current year. As the p-value is less than 0.05, this result is significant at a 95% significance level.
This is further in Accordance with our theory as when the Trade Volume will increase, the country will posses more foreign assets, for example, if the $ that the country is using is

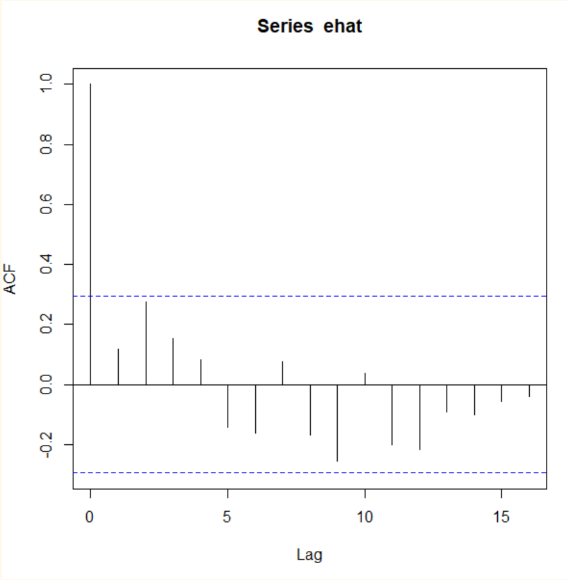
increasing, there will be availability of of $ in the market, this will reduce the demand for the $ in the market and hence rupee will appreciate and the per $ price of the rupee will decrease.
The estimated value at other lags was insignificant.

To check whether the model we have selected is valid or not we will check for serial correlation for residuals of the given model through three methods- Scatter Plot; Correlogram; The results of LM test.



Scatter Plot for residuals of FDL model

Since the plot has points that are randomly distributed, we can say that there is weak or no autocorrelation between the residuals.



Correlogram of residuals of the FDL model

The autocorrelation values do not exceed the significance bounds at any lag from 1 to 15, therefore we can say that there is no significant autocorrelation.

LM Tests of order 3 of F and Chisq types Results Summary:

Table: Breusch-Godfrey test for the Exchange Rates

Method	Statistic	Parameters	p-Value
3, F, 0	0.8066418	1, 38	0.3747706
3, F, NA	0.7823489	1, 37	0.3821356
3, Chisq, 0	5.58051	3	0.1339018
3, Chisq, NA	5.180576	3	0.1590421

We implemented the f-test and the chi- squared test of order 3 for the model. After combining the results we can see that the p value exceeds 0.05 which means that we cannot reject the null hypothesis of zero autocorrelation at a 95% significance level. This means that there is no significant autocorrelation between the residuals.

The above three tests clearly show that there is no autocorrelation between the residuals therefore the model selected is valid.

Now to forecast the future values of the response variable we will first forecast the future values for the independent variable and use those values to forecast the dependent variable.

Forecasts of future values of independent variable using AR(2) model:

Table: Forcasts for the AR(2) growth model

	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2020	39.297	35.694	42.900	33.786	44.808
2021	39.477	34.151	44.803	31.332	47.622
2022	39.702	33.135	46.270	29.658	49.747

After selecting the Point Forecast values from the above table we use the FDL model along with these values to get the future values of the dependent variable.

Forecasts for future values of dependent variable using the independent variable forecasts

```
> forecast(model_dlm,c(39.29706, 39.47681, 39.70231),h=3,level=0.95)
$forecasts
[1] 49.34826 53.46044 49.69637

$call
forecast.dlm(model = model_dlm, x = c(39.29706, 39.47681, 39.70231),
    h = 3, level = 0.95)

attr(,"class")
[1] "forecast.dlm" "dLagM"
```

CONCLUSION:

We have successfully made an ARIMA model of order (2, 1, 0) for the given Exchange Rate Data and forecasted the future values for 5 years for the same using the model. We have tested for auto Correlation of residuals as well as checked for the normal distribution of the residuals using the ACF plot and the box-Ljung test.

We then made a FDL model using the Exchange Rates data and the trade volume as a % of GDP (RBI Database) and checked for serial auto- correlation of the residuals using the scatter plot, ACF plot and LM Test after confirming the results of no- autocorrelation between the residuals we used the FDL model and the forecasted values of the Trade volume to forecast the values of the Exchange rates data for 3 years