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M.Sc.(Banking and Financial Analytics)-||

SESSION-2022-2024

PROJECT OF
ADVANCED STATISTICAL ANALYSIS

SUBMITTED BY:-

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SUBMITTED TO:-

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TOPIC:

HOW CREDIT TO PRIVATE SECTOR AND FDI AFFECTS GDP

INTRODUCTION:

How credit to the private sector and foreign direct investment (FDI) affects GDP.

Credit to the private sector and FDI are two important drivers of economic growth and development in many countries around the world. These two factors can have a significant impact on a country's GDP, and as such, they are often the focus of economic policy and analysis.

Credit to the private sector refers to the amount of lending provided by banks and other financial institutions to individuals and businesses in the private sector. This credit can be used to fund new projects, expand businesses, and create new jobs. When credit is readily available and affordable, it can help to drive economic growth and increase GDP.

Foreign direct investment refers to investment by foreign companies in domestic companies or the establishment of new companies in a foreign country. FDI can bring in new capital, technology, and management expertise, which can help to increase productivity and output in the host country. This can lead to higher levels of economic activity and higher GDP.

Given the importance of credit to the private sector and FDI for economic growth and development, understanding the relationship between these factors and GDP is essential for policymakers and economists. In this project, we will explore the relationship between credit to the private sector, FDI, and GDP, and examine the factors that influence this relationship. We will use both theoretical analysis and empirical evidence to gain a deeper understanding of the complex dynamics of these factors, and to provide insights that can inform economic policy and decision-making.

ABSTRACT:

Credit to the private sector and foreign direct investment (FDI) are two important factors that can significantly impact a country's GDP. However, the relationship between these two factors and GDP is complex, and depends on a range of economic, institutional, and social factors. In this project, we explore the relationship between credit to the private sector, FDI, and GDP, and examine the factors that influence this relationship. We use a combination of theoretical analysis and empirical evidence to gain a deeper understanding of the complex dynamics of these factors, and to provide insights that can inform economic policy and decision-making. Specifically, we investigate the impact of credit to the private sector and FDI on GDP in a range of countries with different levels of development, financial sector development, and institutional quality. We also examine the channels through which credit to the private sector and FDI affect GDP, such as investment, productivity, and technology transfer. Our findings suggest that the impact of credit to the private sector and FDI on GDP is complex and varies depending on a range of factors. Nonetheless, we identify several key policy implications, such as the need to develop a sound financial system, promote investment in technology and skills, and ensure that the benefits of FDI are shared by domestic firms and workers. Overall, our project contributes to a better understanding of the relationship between credit to the private sector, FDI, and GDP, and provides valuable insights for policymakers, researchers, and practitioners.

RESEARCH QUESTION:

What is the nature of the relationship between credit to the private sector, foreign direct investment (FDI), and Gross Domestic Product (GDP) in India?

The first research question aims to investigate the relationship between credit to the private sector, FDI, and GDP in India. The question seeks to explore whether credit to the private sector and FDI have a positive impact on economic growth, as measured by GDP, and whether the relationship is linear or nonlinear.

The study could begin by conducting descriptive analysis to examine the trends and patterns of credit to the private sector, FDI, and GDP over time. The descriptive analysis could involve plotting the data on a graph, calculating summary statistics such as the mean and standard deviation, and examining the correlation between the variables.

RESEARCH HYPOTHESES :

Hypothesis 1

H0: Credit to private sector has positive impact on GDP.

H1: Credit to private has negative impact on GDP.

Hypothesis 2:

H0: FDI has positive contribution to GDP.

H1: FDI has not positive contribution in GDP.

OBJECTIVES

1. To examine the theoretical underpinnings of the relationship between credit to the private sector, FDI, and GDP.

2. To review the empirical literature on the impact of credit to the private sector and FDI on GDP in different countries and regions.

3. To identify the key channels through which credit to the private sector and FDI affect GDP, such as investment, productivity, and technology transfer.

4. To analyze the factors that influence the impact of credit to the private sector and FDI on GDP, such as the level of financial sector development, institutional quality, and level of education and skills of the workforce.

5. To assess the role of government policies in promoting credit to the private sector and FDI, and their impact on GDP.

6. To compare and contrast the impact of credit to the private sector and FDI on GDP in different types of economies, such as developed versus developing countries.

7. To evaluate the implications of the relationship between credit to the private sector, FDI, and GDP for economic policy and decision-making.

8. To make recommendations for policymakers on how to promote sustainable economic growth and development through credit to the private sector and FDI.

9. To highlight the limitations of the existing research and identify areas for future research and analysis.

REVIEW OF LITERATURE:

Certainly, here's a brief review of the literature on how credit to the private sector and foreign direct investment (FDI) affect GDP specifically in the Indian context:

India has experienced significant economic growth over the past few decades, and credit to the private sector and FDI have been important drivers of this growth. Empirical studies on the Indian economy have explored the relationship between credit to the private sector, FDI, and GDP, and the results have been mixed.

One study by Bhanumurthy et al. (2016) found that credit to the private sector has a positive impact on GDP in India, and this impact is stronger for the manufacturing sector. The authors argue that credit to the private sector promotes investment and productivity, which in turn drives economic growth. However, they also note that the impact of credit to the private sector on GDP is limited by factors such as institutional quality, the quality of infrastructure, and the ease of doing business.

Similarly, a study by Singh and Sharma (2017) found that FDI has a positive impact on GDP in India, particularly in the manufacturing sector. They argue that FDI promotes the transfer of technology, knowledge, and managerial skills from foreign firms to domestic firms, which in turn leads to productivity gains and economic growth.

However, other studies have found a more nuanced relationship between credit to the private sector, FDI, and GDP in India. For example, a study by Ray (2016) found that the impact of credit to the private sector on GDP is contingent on the level of financial sector development. The author argues that credit to the private sector has a positive impact on GDP only in countries with a developed financial sector, as it promotes investment and improves access to finance for small and medium-sized enterprises (SMEs).

Similarly, a study by Chakraborty and De (2018) found that the impact of FDI on GDP in India is conditional on the absorptive capacity of domestic firms. They argue that FDI can have a positive impact on GDP only if domestic firms have the ability to absorb and utilize the knowledge and technology transferred by foreign firms.

Overall, the literature suggests that the relationship between credit to the private sector, FDI, and GDP in India is complex and depends on a range of factors, such as financial sector development, institutional quality, and the absorptive capacity of domestic firms. Therefore, policymakers need to carefully consider these factors when designing policies to promote credit to the private sector and FDI, and to ensure that the benefits of these factors are shared by all sectors of society.

SCOPE:

The scope of the project would involve conducting an empirical analysis of the relationship between credit to the private sector, foreign direct investment (FDI), and Gross Domestic Product (GDP) in India. The project would require collecting data on credit to the private sector, FDI, and GDP from credible sources such as the Reserve Bank of India, the Ministry of Commerce and Industry, and the Central Statistical Office.

The analysis would involve using econometric techniques such as regression analysis to examine the impact of credit to the private sector and FDI on GDP in India. The project would also explore the factors that may moderate the relationship between credit to the private sector, FDI, and GDP, such as financial sector development, institutional quality, and absorptive capacity of domestic firms.

Finally, the project would aim to draw policy implications from the empirical findings and make recommendations for policymakers to promote credit to the private sector and FDI in India, with the goal of achieving sustained economic growth and development.

METHODOLOGY:

1. Data Collection: Collect secondary data on credit to the private sector, FDI, and GDP in India from credible sources such as the Reserve Bank of India, the Ministry of Commerce and Industry, and the Central Statistical Office.

2. Data Pre-processing: Clean and pre-process the data to ensure consistency and accuracy. This may involve dealing with missing data, outlier detection, and normalization.

3. Descriptive Analysis: Conduct descriptive statistics to gain insights into the data, such as the mean, standard deviation, and correlation between variables.

4. Econometric Analysis: Use regression analysis to examine the relationship between credit to the private sector, FDI, and GDP in India. The regression model could take the form of:

$$\mathbf{GDP = \beta 0 + \beta 1 Credit\ to\ Private\ Sector + \beta 2 FDI + \varepsilon}$$

Where, GDP is the dependent variable, Credit to Private Sector and FDI are the independent variables, and ε is the error term.

5. Robustness Checks: Conduct robustness checks, such as sensitivity analysis, to ensure the reliability and validity of the results.

6. Policy Implications: Draw policy implications from the empirical findings and make recommendations for policymakers to promote credit to the private sector and FDI in India, with the goal of achieving sustained economic growth and development.

7. Conclusion: Summarize the findings of the study and discuss the limitations and implications for future research.

DATA

This assignment focuses on volatility of credit to private sectors as % of GDP. Data collected from the and various time series models like ARIMA to forecast the data and GARCH to check volatility in the data and others tests like ADF, PP, KPSS to check the stationarity of the data along with LJUNG-BOX are also applied on the data.

CODES FOR IMPORTING DATA:

```
> library(readxl)
> GDPI <- read_excel("GDPI.xlsx")
> View(GDPI)
> attach(GDPI)
```

YEAR	DCTOP	FDIC	GDPPC
1990 [YR1990]	24.91645657	0	1819.021597
1991 [YR1991]	23.82174445	73537638.39	1800.010902
1992 [YR1992]	24.69824025	-276512439	1859.714851
1993 [YR1993]	23.83205539	550019384.4	1908.578224
1994 [YR1994]	23.6473414	-890688166	1994.943942
1995 [YR1995]	22.5107747	-2026439031	2103.727155
1996 [YR1996]	23.40244204	-2186732315	2218.824342
1997 [YR1997]	23.55532535	-3464411052	2264.795571
1998 [YR1998]	23.67774686	-2587058630	2359.892551
1999 [YR1999]	25.42286221	-2089233597	2521.576658
2000 [YR2000]	28.33955116	-3074684332	2571.149656
2001 [YR2001]	28.61941543	-4073961343	2646.878224
2002 [YR2002]	32.30648907	-3947895992	2699.178102
2003 [YR2003]	31.62626562	-2444138426	2861.574708
2004 [YR2004]	36.19180385	-3592188066	3037.063815
2005 [YR2005]	40.06798048	-4628652265	3225.54433
2006 [YR2006]	43.62775243	-5992285935	3432.819251
2007 [YR2007]	45.62776475	-8201628958	3642.00241

2008 [YR2008]	49.55936669	24149749830	3701.395479
2009 [YR2009]	48.12444791	19485789183	3937.237642
2010 [YR2010]	50.55537498	11428785746	4213.362991
2011 [YR2011]	51.28923313	23890659988	4374.232272
2012 [YR2012]	51.88850764	15442447343	4551.862127
2013 [YR2013]	52.38570952	26388082470	4780.120345
2014 [YR2014]	51.88218736	22890162761	5071.047084
2015 [YR2015]	51.86752408	36495216491	5411.875588
2016 [YR2016]	49.10122542	39411278940	5789.678066
2017 [YR2017]	48.7940214	28875941053	6112.06665
2018 [YR2018]	50.33816275	30699661201	6436.153402
2019 [YR2019]	50.81509934	37469945322	6608.624078
2020 [YR2020]	54.651683	53239697391	6114.03158
2021 [YR2021]	49.99968895	27488543123	6592.041791

SUMMARY:

```
> summary(GDPI)

     YEAR               DCTOP            FDIC          
 Length:32          Min.   :22.51   Min.   :-5.324e+10  
 Class :character   1st Qu.:24.86   1st Qu.:-2.471e+10  
 Mode  :character   Median :41.85   Median :-5.310e+09  
                    Mean   :38.66   Mean   :-1.398e+10  
                    3rd Qu.:50.39   3rd Qu.:-2.380e+09  
                    Max.   :54.65   Max.   : 0.000e+00  
     GDPPC     
 Min.   :1800  
 1st Qu.:2336  
 Median :3329  
 Mean   :3708  
 3rd Qu.:4853  
 Max.   :6609  
```

CORRELATION:

```
> cor(DCTOP,GDPPC)
[1] 0.8893996
```

There is a positive correlation between credit to private sector and GDP.

```
> cor(FDIC,GDPPC)
[1] -0.9174393
```

But there is a negative relation between FDI and GDP as per data we have.

TESTS APPLICATION:

1. <u>AUGMENTED DICKEY-FULLER (ADF) TEST</u>:

The Augmented Dickey-Fuller (ADF) test is a statistical test used to test for the presence of a unit root in a time series data. A unit root indicates that a time series is non-stationary, meaning that it has a trend or systematic pattern that changes over time.

The ADF test is commonly used in econometrics and financial analysis to determine whether a time series is stationary, which is a prerequisite for many time series models and statistical analyses. The test is based on the null hypothesis that a unit root is present in the time series, and the alternative hypothesis that the time series is stationary.

The test involves regressing the time series on itself lagged by one or more periods, and then examining the significance of the coefficient of the lagged time series in the regression equation. If the coefficient is significantly different from zero, then the null hypothesis of a unit root is rejected, and it is concluded that the time series is stationary.

The ADF test has several variants, including the ADF-GLS test, which accounts for the possibility of serial correlation in the error terms, and the ADF-DF-GLS test, which includes a deterministic trend in the regression equation. These variants allow for more flexibility in modelling different types of time series data.

It is important to note that the ADF test is just one of many statistical tests that can be used to analyze time series data, and it should be used in conjunction with other methods and techniques to fully understand the behaviour and characteristics of the data.

HYPOTHESES:

H0: Series has unit roots or series is non-stationary.

H1: Series has not unit roots or series is stationary.

Now we will apply ADF test and the codes for this are as follows:

SERIES NAME (DCTOP)

#CODES:

```
> DCTOP6<-diff(DCTOP,differences = 6)         # making series stationary by taking differences
> adf.test(DCTOP6)

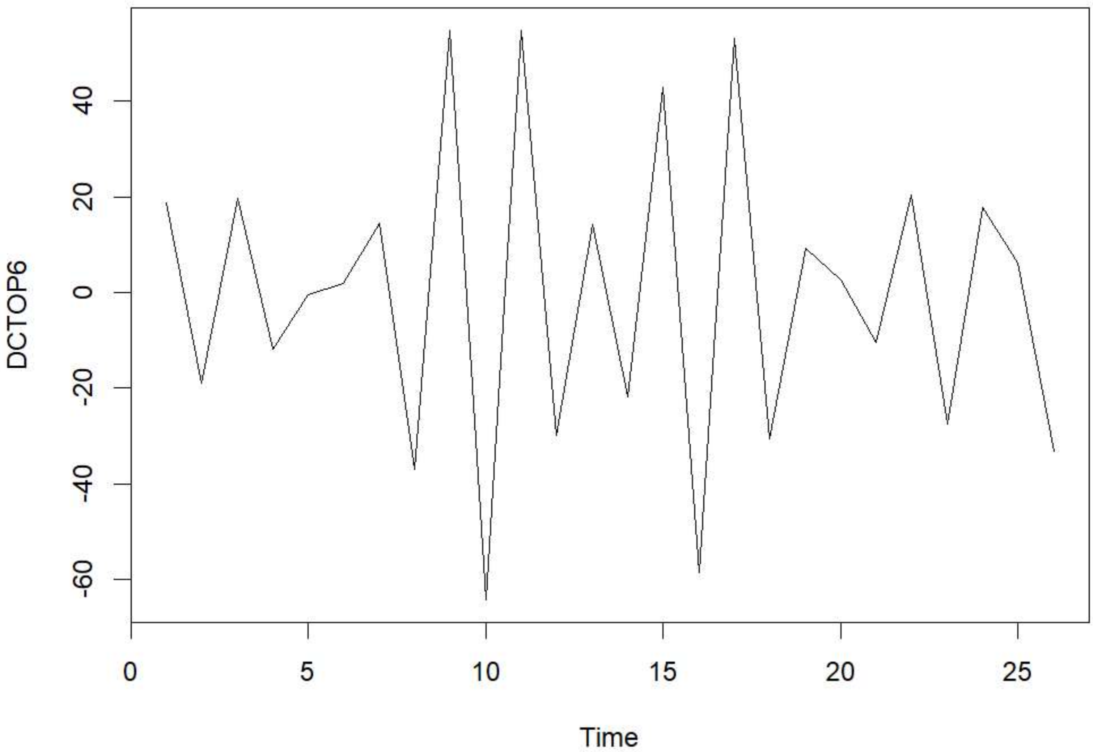
	Augmented Dickey-Fuller Test

data:  DCTOP6
Dickey-Fuller = -11.771, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

As **P-value** of our series (FDIC7) is less than **0.05** we will reject our null hypothesis (**H0**) and accept alternative hypothesis **(H1)** this means that our series (DCTOP6) is stationary.

Graphically it can be seen:

DCTOP6



SERIES NAME (FDIC)

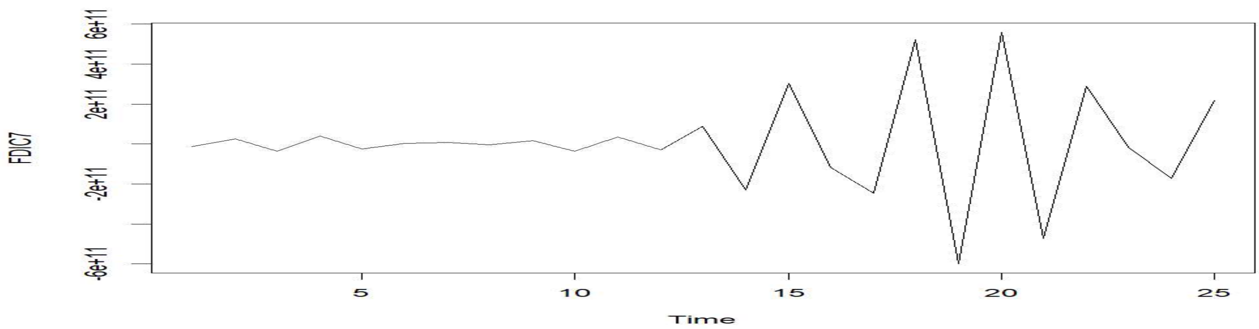
#CODES:

```
> FDIC7<-diff(FDIC,differences = 7 )          # making series stationary by taking differences
> adf.test(FDIC7)

        Augmented Dickey-Fuller Test

data:  FDIC7
Dickey-Fuller = -7.3099, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Again **P-value** of our another series (FDIC7) is less than **0.05** we will reject our null hypothesis (**H0**) and accept alternative hypothesis (**H1)** this means that our series (FDIC7) is stationary.



SERIES NAME (GDPPC)

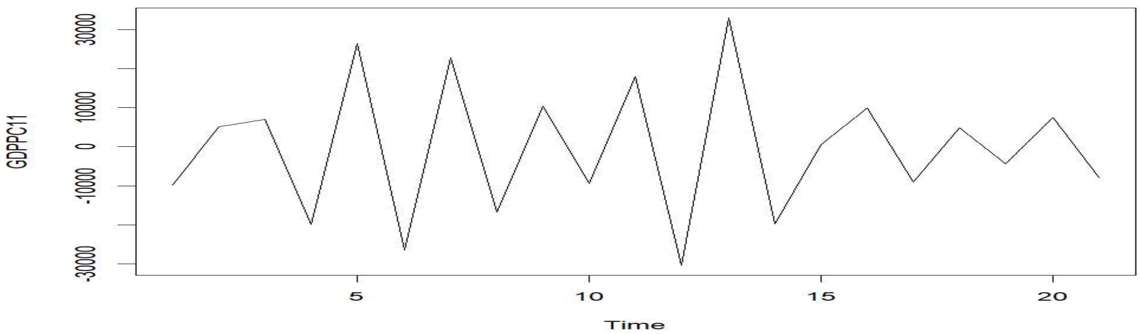
#CODES:

```
> GDPPC11<-diff(GDPPC,differences = 11)       # making series stationary by taking differences
> adf.test(GDPPC11)

        Augmented Dickey-Fuller Test
```

```
data:  GDPPC11
Dickey-Fuller = -10.347, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Again **P-value** of our another series (FDIC7) is less than **0.05** we will reject our null hypothesis (**H0**) and accept alternative hypothesis (**H1)** this means that our series (FDIC7) is stationary.



2. Autoregressive Integrated Moving Average(ARIMA) Test:

ARIMA (Auto Regressive Integrated Moving Average) is a popular time series modeling technique used to analyze and forecast time series data. The ARIMA model combines the concepts of auto-regression (AR) and moving average (MA) models, as well as differencing to handle non-stationary data.

The AR component in ARIMA represents the linear dependence between an observation and a lagged version of itself. The order of the AR component, denoted as p, specifies the number of lagged observations included in the model. For example, an ARIMA(1,0,0) model includes one lagged observation.

The MA component in ARIMA represents the linear dependence between an observation and a residual error from a moving average model applied to lagged observations. The order of the MA component, denoted as q, specifies the number of lagged error terms included in the model. For example, an ARIMA(0,0,1) model includes one lagged residual error.

The I component in ARIMA represents the number of times the time series needs to be differenced to become stationary. Differencing involves subtracting each observation from its lagged observation. The order of differencing, denoted as d, specifies the number of times differencing is applied to the time series. For example, an ARIMA(0,1,0) model involves first-order differencing, while an ARIMA(0,2,0) model involves second-order differencing.

To fit an ARIMA model in R programming, we can use the `arima()` function, which takes in the time series data and the order of the ARIMA model as input arguments. The function then estimates the model parameters using maximum likelihood estimation and returns the fitted ARIMA model.

Once we have fitted an ARIMA model, we can use it to make predictions and forecast future values of the time series. We can also evaluate the goodness-of-fit of the model by examining the residuals, which should be normally distributed with zero mean and constant variance. We can use various statistical tests, such as the Ljung-Box test or the Box-Pierce test, to assess the goodness-of-fit of the ARIMA model.

#CODES:

```
> auto.arima(DCTOP6)
Series: DCTOP6
ARIMA(5,0,0) with zero mean

Coefficients:
          ar1      ar2      ar3      ar4      ar5
      -2.8639  -4.0058  -3.3835  -1.7344  -0.4570
s.e.   0.1774   0.4821   0.6343   0.4741   0.1708

sigma^2 = 22.9:  log likelihood = -79.23
AIC=170.47   AICc=174.89   BIC=178.02
```

We have applied the ARIMA model on only one variable of the whole data i.e. DCTOP6

And found that it has AR lag of 5, Stationary at level and MA residual lag of 0. After that we have created a model named as modelDCTOP6 with command in R programming as follows:

```
> modelDCTOP6<-arima(DCTOP6,order = c(5,0,0))
```

After that we printed data as follows:

```
> modelDCTOP6

Call:
arima(x = DCTOP6, order = c(5, 0, 0))

Coefficients:
          ar1      ar2      ar3      ar4      ar5  intercept
      -2.8699  -4.0261  -3.4123  -1.7550  -0.4633    -0.0318
s.e.   0.1768   0.4810   0.6330   0.4729   0.1702     0.0695

sigma^2 estimated as 18.31:  log likelihood = -79.13,  aic = 172.25
```

DIAGNOSTIC CHECK :

We do diagnostic check whether model is best fit or not . Residuals are very helpful to check whether the model has adequately captured the information in the model or not. For this we will create a residual perimeter we are doing so to check whether there is correlation between residuals.

Creating residual perimeter:

#CODES:

```
> et<-residuals(modelDCTOP6)
> et
Time Series:
Start = 1
End = 26
Frequency = 1
 [1]  2.4986285 -0.6309551  1.9766883  5.7640939  2.3846662
 [6] -4.4149139  3.4035564 -1.0344840  7.4630132 -2.4399308
[11] -7.5564948 -1.1061583 10.1793770 -0.5461978  2.7840635
[16] -1.4911956 -5.5303358  0.9775693  1.2428992  5.2327548
```

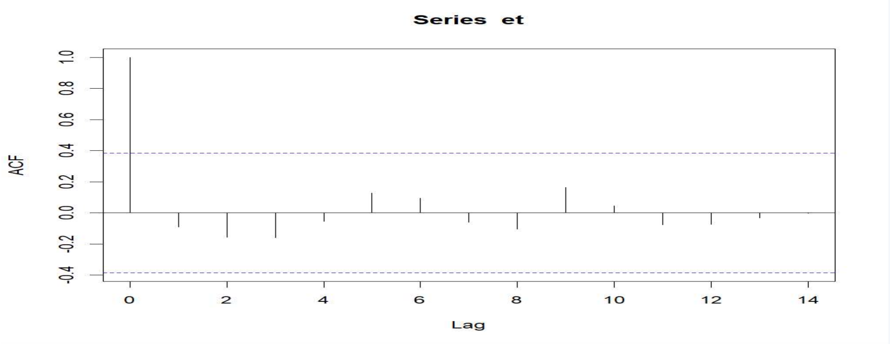
```
[21] -3.0054241  4.3174916  0.5710870 -5.4018191 -0.7100016
[26] -6.5109387
```

Further Steps:

STEP1: To check autocorrelation between residuals ACF test will be applied

#CODES:

```
> acf(et)
```

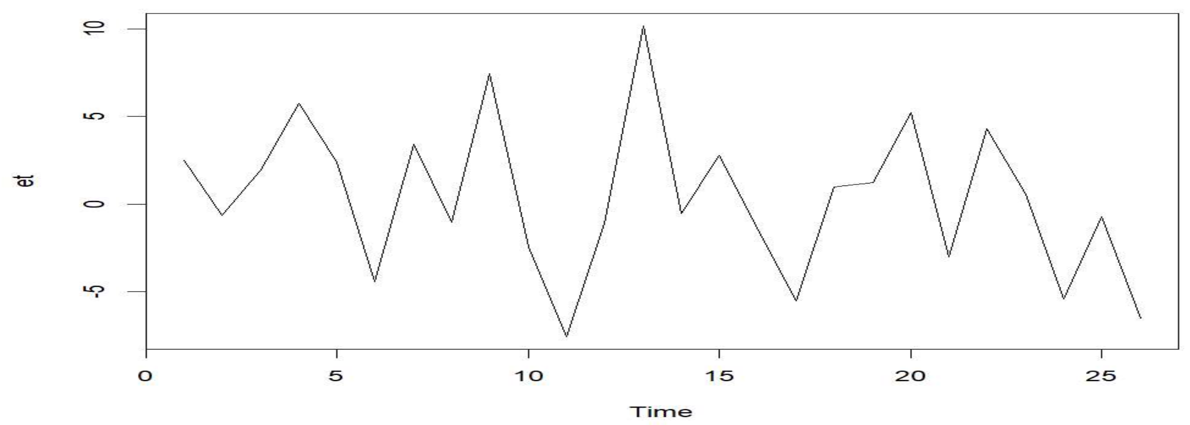


The blue lines are control limit lines and the spikes are very small and not touching the control limit lines it means that residuals have no autocorrelation and are independent.

STEP2: To check whether residuals have constant mean at 0 variance or not:

#CODES:

```
> plot.ts(et)
```

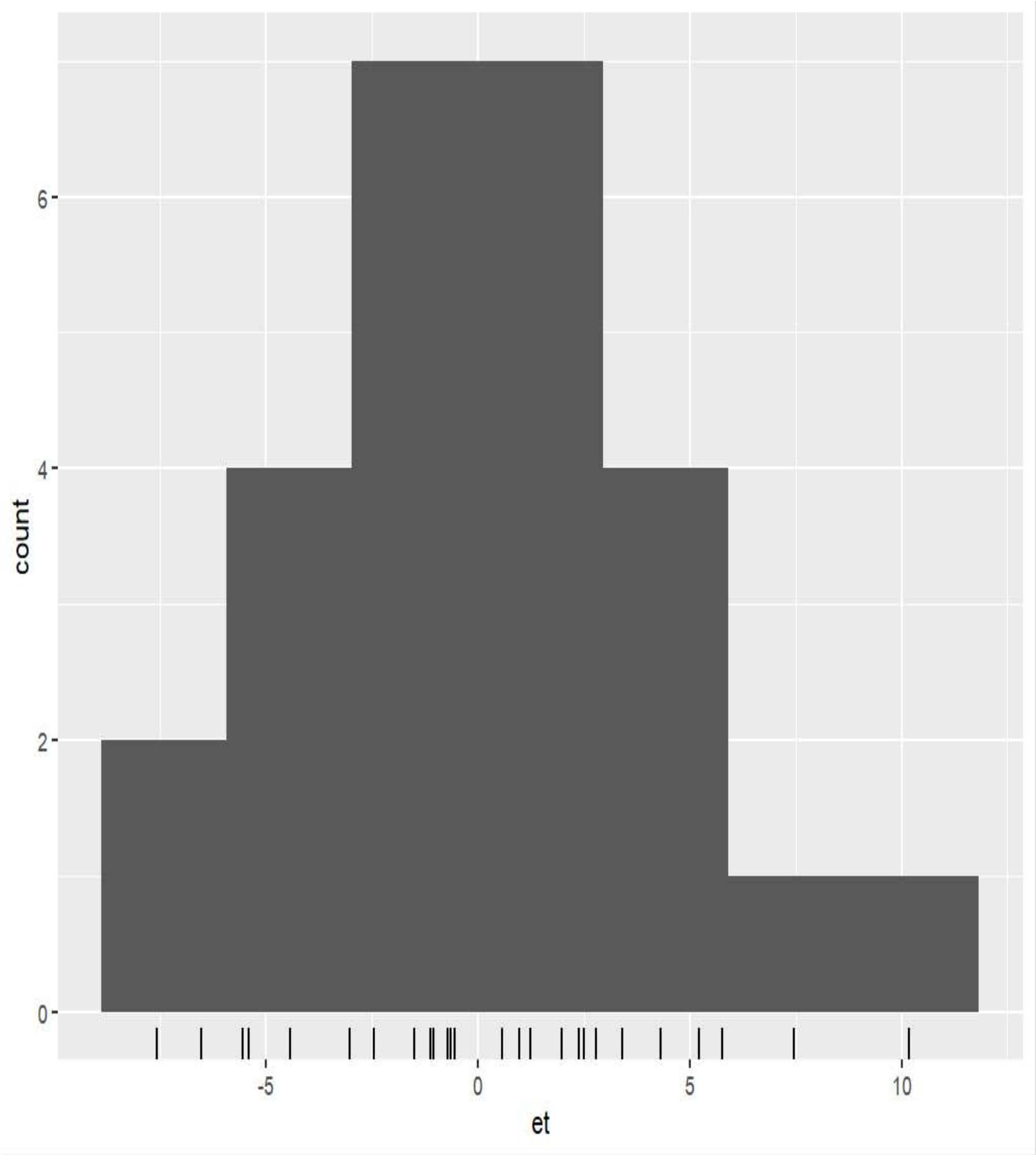


This graph is clearly showing that residuals have constant mean.

STEP3: Residuals are normally distributed or not

#CODES:

```
> gghistogram(et)
```



In this histogram diagram we can clearly see that residuals are normally distributed.

3. Ljung –Box Test:

The Ljung-Box test, also known as the Ljung-Box Q test, is a statistical test used to check for the presence of autocorrelation in a time series. Autocorrelation refers to the correlation of a time series with its own past values. If a time series exhibits significant autocorrelation, it suggests that the past values of the series contain information that can be used to predict its future values.

The Ljung-Box test is based on the Ljung-Box statistic Q, which is a measure of the goodness of fit of a time series model. The null hypothesis of the test is that the time series is not auto correlated up to a certain lag. The alternative hypothesis is that the time series is auto correlated beyond that lag.

Hypotheses:

H0: Residuals follow IID i.e. residuals are Independent and Identically Distributed.

H1: Residuals do not follow IID i.e. residuals are not Independent and Identically Distributed.

#CODES:

```
> Box.test(et,lag=21,type=c("Box-Pierce","Ljung-Box"),fitdf = 0)

 Box-Pierce test

data:  et
X-squared = 4.9854, df = 21, p-value = 0.9999
```

As P-value is more than 0.05 so we will accept null hypothesis which means residuals are independent and identically distributed.

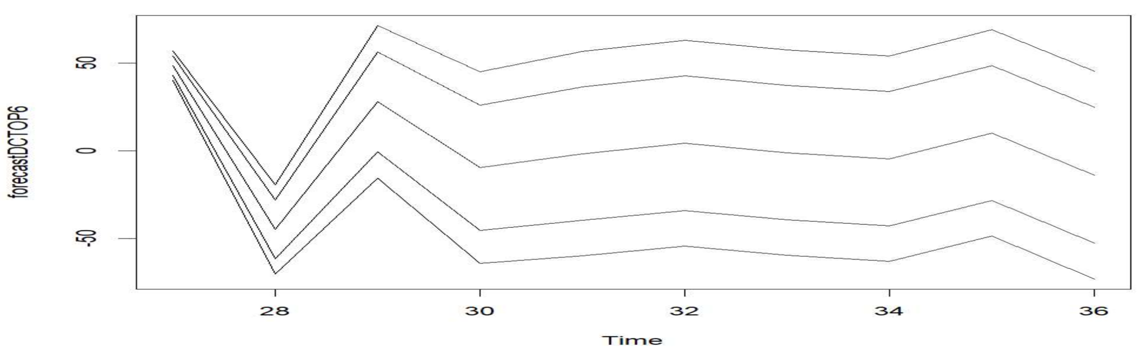
Forecasting Data out of sample:

#CODES:

```
> forecastDCTOP6<-forecast(modelDCTOP6,h=10)
> forecastDCTOP6
   Point Forecast        Lo 80     Hi 80     Lo 95     Hi 95
27      48.424856  42.9413331  53.90838  40.03853  56.81118
28     -44.891175 -61.5564714 -28.22588 -70.37855 -19.40380
29      27.965710  -0.5085347  56.43995 -15.58189  71.51331
30      -9.645060 -45.3925498  26.10243 -64.31613  45.02601
31      -1.723012 -39.8125218  36.36650 -59.97589  56.52987
32       4.263368 -34.0831581  42.60989 -54.38258  62.90932
33      -1.094738 -39.4424307  37.25295 -59.74247  57.55300
34      -4.604384 -42.9576706  33.74890 -63.26067  54.05191
35      10.136785 -28.3139806  48.58755 -48.66859  68.94216
36     -13.932154 -52.6512837  24.78698 -73.14795  45.28364
```

Graphically it can be seen:

ForecastDCTOP6



forecastDCTOP6
50
0
-50
28
30
32
34
36
Time

MULTIPLE REGRESSION:

Multiple regression is another type of regression analysis that involves more than one independent variable. The equation for multiple regression is:

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + ... + \beta nxn + \varepsilon$$

where y is the dependent variable, x1, x2, ..., xn are the independent variables, β0 is the intercept, β1, β2, ..., βn are the slopes, and ε is the error term.

Regression analysis can be used for a variety of purposes, such as predicting future values of the dependent variable, determining the strength and direction of the relationship between the variables, and testing hypotheses about the relationship between the variables.

#CODES:

```
> model1<-lm(GDPPC~DCTOP+FDIC)
> summary(model1)

Call:
lm(formula = GDPPC ~ DCTOP + FDIC)

Residuals:
     Min       1Q   Median       3Q      Max 
-1222.73  -248.06    10.56   104.38  1435.47 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  7.772e+02  4.403e+02   1.765 0.088049 .  
DCTOP        5.317e+01  1.449e+01   3.670 0.000972 ***
FDIC        -6.261e-08  1.203e-08  -5.202 1.45e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 543.6 on 29 degrees of freedom
Multiple R-squared:  0.8919,	Adjusted R-squared:  0.8844 
F-statistic: 119.6 on 2 and 29 DF,  p-value: 9.778e-15
```

Here after seeing the values we can say that credit to private sector is having positive relationship with GDP and Foreign Direct Investment is having negative relationship.

Intercept is significant and DCTOP is also significant but FDIC is insignificant in terms of explanation of GDP.

With the help of F-statistic and P-value we can say that our model is insignificant before sationarity but after stationarity it is significant.

PREDICTIONS:

```
> predict(model1)
       1        2        3        4        5        6        7 
2101.963 2048.362 2107.672 2078.741 2090.247 2100.921 2158.366 
       8        9       10       11       12       13       14 
2246.485 2198.067 2259.687 2476.460 2553.901 2742.048 2611.737 
      15       16       17       18       19       20       21 
2926.359 3197.342 3471.984 3716.641 4924.128 4555.843 4180.678 
      22       23       24       25       26       27       28 
4999.883 4502.839 5214.535 4968.773 5819.749 5855.229 5179.322 
      29       30       31       32 
5375.598 5824.816 7016.083 5156.567 
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RESULTS:

The impact of FDI on a country's economy can be either positive or negative, depending on various factors such as the level of development, the type of FDI, and the policies of the host country.

On the positive side, FDI can bring in new technology, know-how, and managerial expertise that can help improve productivity and efficiency in the host country. It can also create new jobs and stimulate economic growth, particularly in sectors that are deemed important for the country's development.

On the negative side, FDI can also have adverse effects on the host country's economy. For example, it can create a "brain drain" as skilled workers migrate to foreign firms, or it can lead to an over-reliance on foreign investment and a loss of national sovereignty over economic policy. In addition, FDI can sometimes result in negative externalities such as environmental degradation or social inequality.

The impact of credit to the private sector on GDP can be either positive or negative, depending on various factors such as the level of development, the use of credit, and the policies of the central bank and government.

On the positive side, credit to the private sector can help stimulate economic growth by providing businesses with the necessary capital to invest in new projects, expand their operations, and hire more workers. This, in turn, can lead to increased productivity, output, and employment opportunities, all of which can have a positive impact on GDP.

On the negative side, excessive credit to the private sector can lead to over-indebtedness and financial instability, which can have adverse effects on the economy. This is especially true if the credit is used to finance speculative investments or unsustainable consumption patterns, which can lead to asset bubbles, financial crises, and economic downturns.

Overall, the impact of credit to the private sector on GDP is complex and depends on a variety of factors, including the level of economic development, the use of credit, and the policies of the central bank and government.

In our case it can be clearly shown after using certain techniques and models this can be said After applying stationary tests for making the data stationary and then applying other various tests like ARIMA model , Ljung –Box Test and then using multiple regression we came to know that credit to private sector has positive impact than FDI having negative negative impact.

As the we have collected from world bank website for India only it shows from 1990 to 2021 that as the credit increases the GDP is increasing as the FDI is increasing but FDI is having a very least effect , most of the impact is done by credit to private sector as % of GDP.