

**INDIAN INSTITUTE OF TECHNOLOGY**  
**(INDIAN SCHOOL OF MINES) DHANBAD**

**MANAGEMENT STUDIES DEPARTMENT**



**“FINANCIAL ECONOMETRICS ASSIGNMENT”**

**Group - 2**

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**Course: Financial Econometrics**

**Course Instructor: Prof. Aparna Krishna**

# **Financial Econometrics Assignment**

## **Question 1**

### **INTRODUCTION**

The time series under consideration is the Gross Domestic Product (GDP).

The time series analysis utilizes numeric time variables, spanning from the year 1970 to 1991, divided into quarterly intervals. This dataset comprises 88 data points, each representing a quarter, for a total of 22 years with four quarters each.

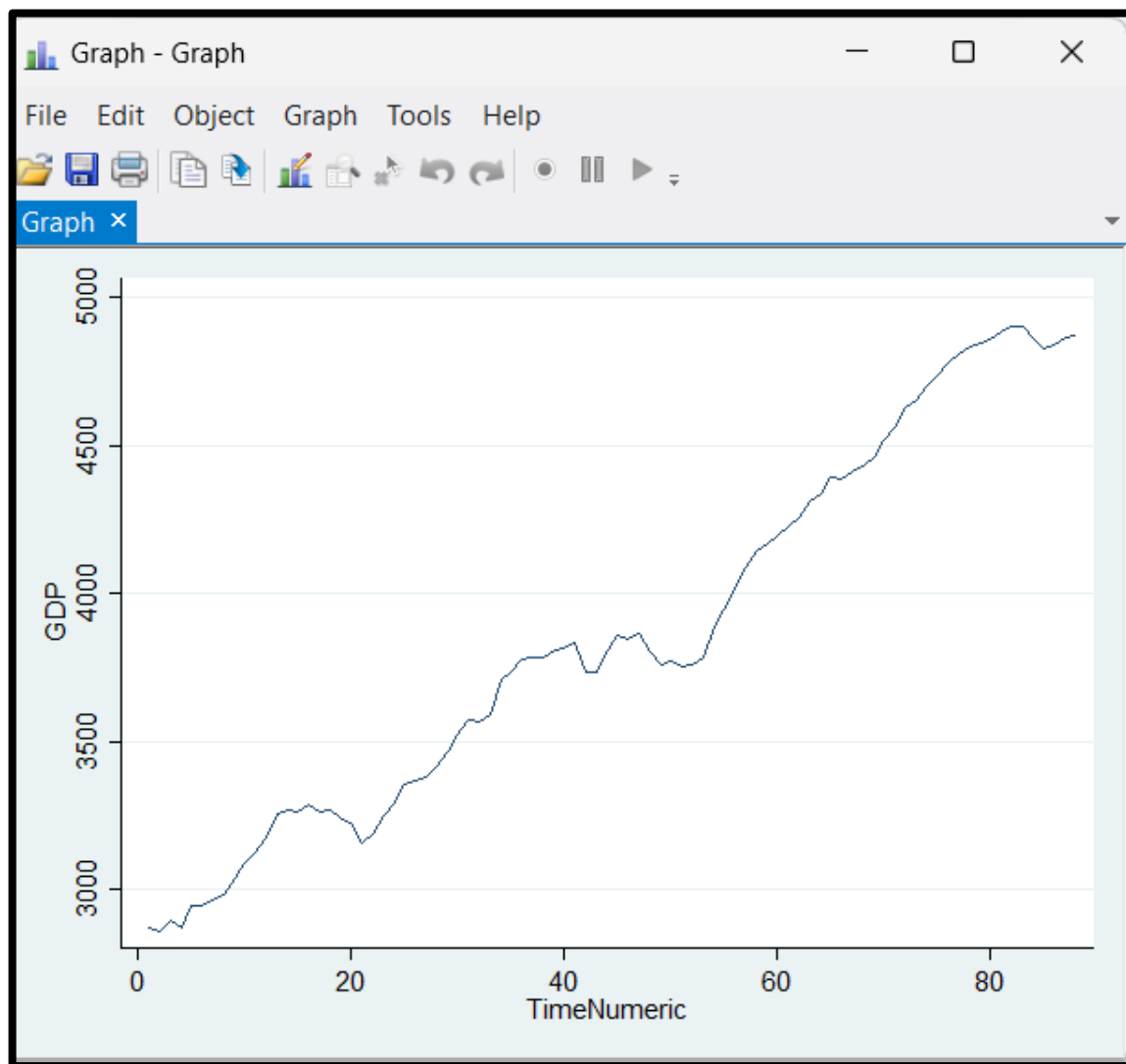
### **IDENTIFICATION**

**The Time variable used** in the dataset by us is represented by the index of observation. Eg- the first observation has time period 1, the second observation has time period 2, and so on.

**Creating a time series plot**

**Stata command used** : `tsline GDP`

**Output** :



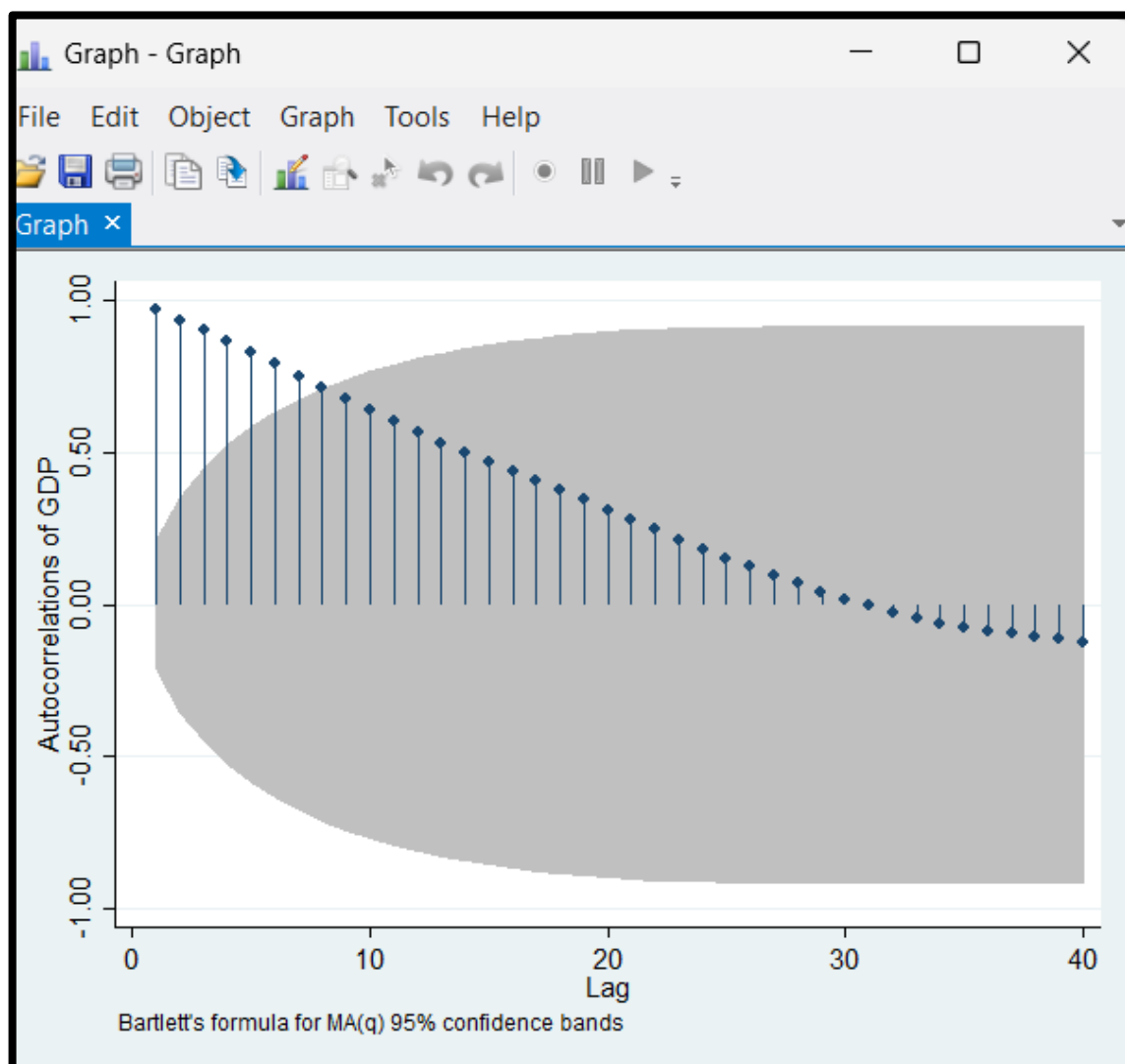
### Interpretation:

The visual representation obtained from plotting the GDP time series indicates an increasing trend over time. Furthermore, the mean and variance of the data exhibit non-stationarity, suggesting that the time series plot lacks stationarity.

### Analyzing autocorrelation Patterns in GDP Data

**Stata command used:** ac GDP

**Output :**



#### Interpretation:

- **Autocorrelations of GDP:** The blue spikes represent the autocorrelation coefficients for the GDP variable at different lags. Autocorrelation measures the correlation of a time series with its own past values.
- **Lag:** The x-axis shows the lag, which is the number of time periods separating the past values from the current value. The graph shows lags up to 40.
- **Confidence Bands:** The grey shaded area represents the 95% confidence bands according to Bartlett's formula for an MA(q) process. If the blue spikes fall within this area, the autocorrelation is not statistically significant at that lag.
- **Decreasing Spikes:** The fact that the spikes decrease as the lag increases suggests that the immediate past values have more influence on the current value than the distant past values.

#### Analysis of GDP Time Series Stationarity Using the Dickey-Fuller Test

The Dickey-Fuller test was conducted with the inclusion of a trend component to account for possible deterministic trends in the GDP data. The test statistic, critical values, and p-value were computed to assess the null hypothesis that the GDP series has a unit root.



The Dickey-Fuller test was applied to the first-differenced GDP data with a trend component. The test statistic, critical values, and p-value were evaluated to determine the presence of a unit root in the differenced series.

**Stata Command used :** `dfuller d.GDP , trend regress`

**Output:**

. dfuller D.GDP, trend regress					
Dickey-Fuller test for unit root			Number of obs	=	86
	Test Statistic	1% Critical Value	Interpolated Dickey-Fuller		
			5% Critical Value	10% Critical Value	
Z(t)	-6.588	-4.071	-3.464	-3.158	
MacKinnon approximate p-value for Z(t) = 0.0000					
D2.GDP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
D.GDP					
L1.	-.6824587	.1035842	-6.59	0.000	-.8884835    -.476434
_trend	-.0282464	.1497305	-0.19	0.851	-.3260544    .2695615
_cons	17.22668	7.841891	2.20	0.031	1.629475    32.82389

## Results

The test statistic for the differenced data is -6.588, which is significantly lower than the critical values at the 1%, 5%, and 10% significance levels of -4.071, -3.464, and -3.158, respectively. The MacKinnon approximate p-value is 0.0000, indicating strong evidence against the null hypothesis.

## Interpretation

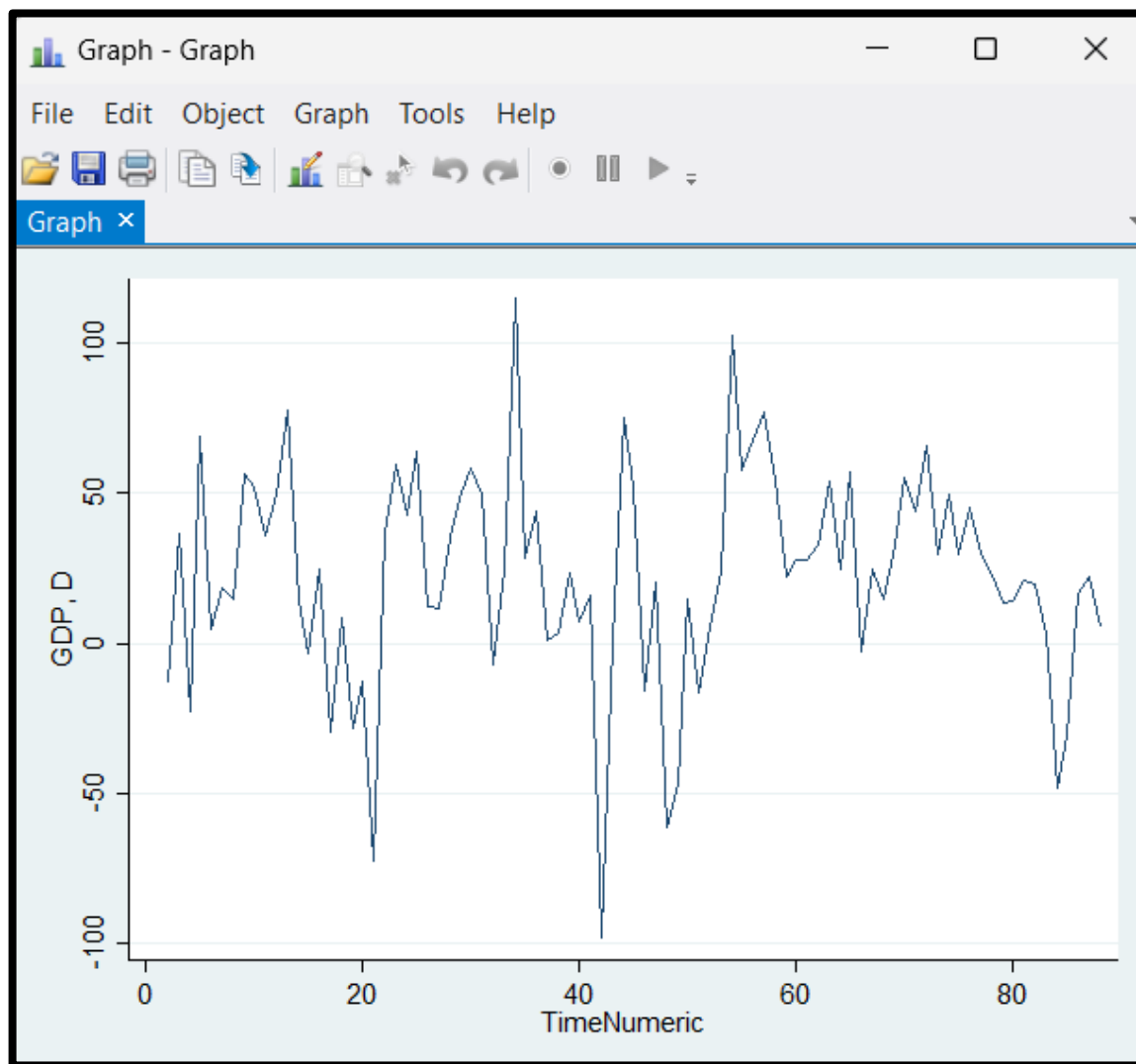
The test statistic being well below the critical values and the p-value being effectively zero suggest that the null hypothesis of a unit root can be rejected for the first-differenced GDP data. This implies that the differencing process has successfully rendered the time series stationary.

## Conclusion

The Dickey-Fuller test results for the first-differenced GDP data indicate that the series is now stationary. The lag 1 of the differenced series is statistically significant, with a p-value of 0.000, confirming its importance in the differenced model..

## Time Series Analysis of GDP Growth

**Stata command used :** `tsline d.GDP`

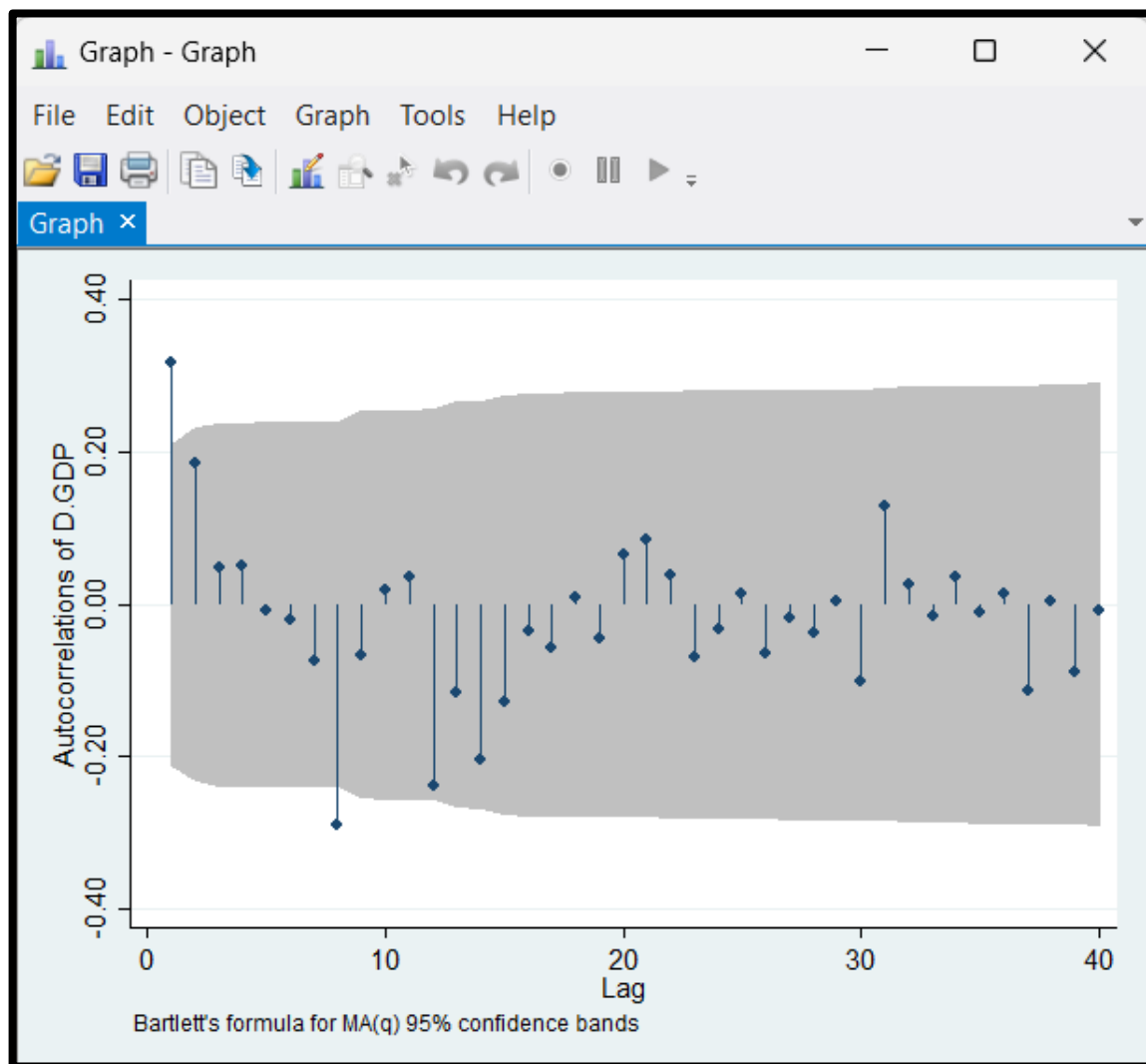


### Conclusion:

The mean of the first difference of GDP appears to fluctuate around mean. The variance of the first difference of GDP doesn't show too much fluctuations. There doesn't appear to be a unit root (i.e., a non-stationary behavior) in the first difference of GDP.

### Degree of ACF and PACF

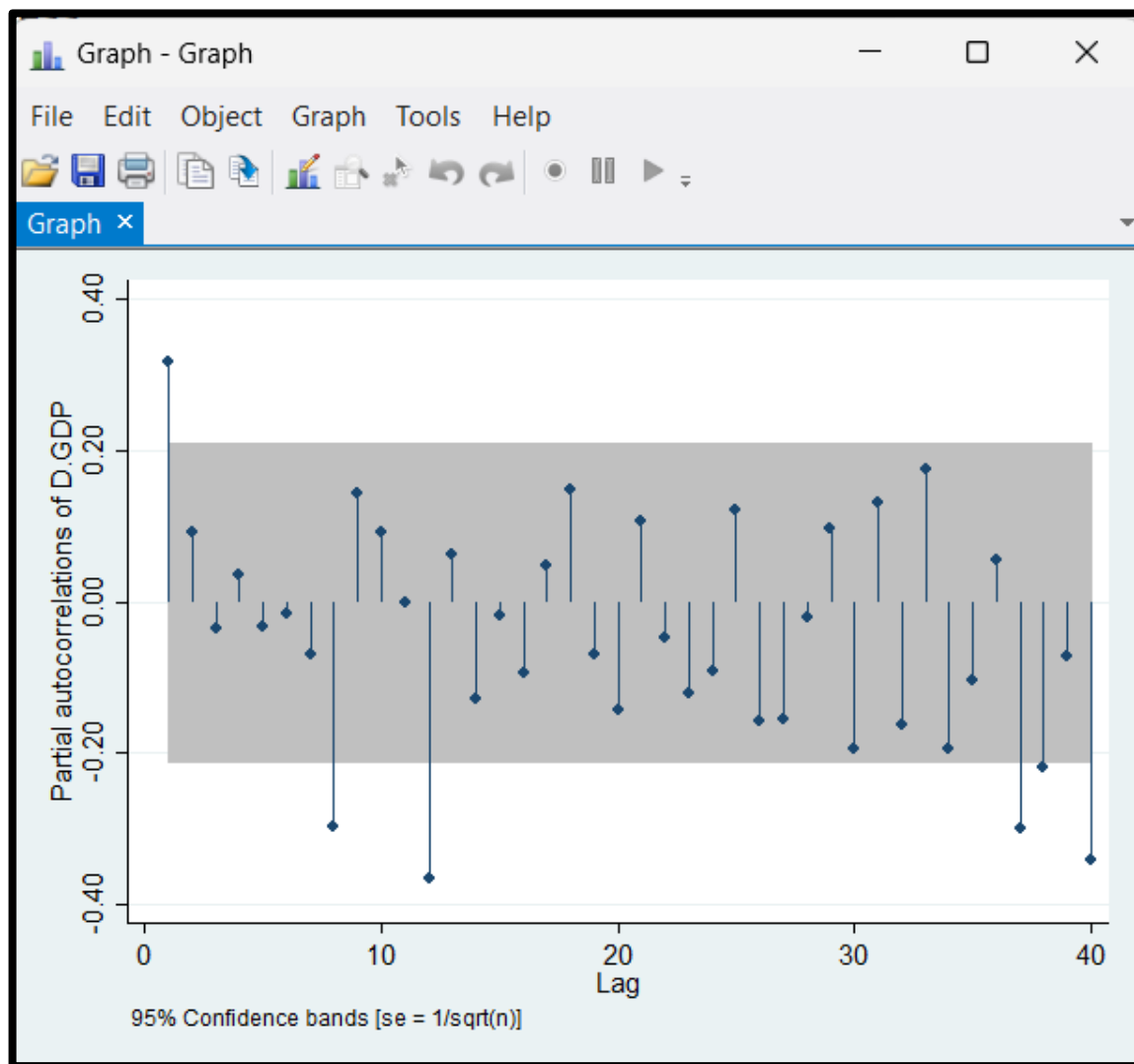
#### ACF plot



It suggests that we have only **1 significant lag** at 95% confidence. The MA model has degree 1.

## PACF PLOT





There is only 1 significant lag. The AR model has degree 1.

Our Identified Model is ARIMA(1,1,1).

The other model that we will check is ARIMA(2,1,1).

## **ESTIMATION**

**Arima GDP, arima(1,1,1)**

```
. arima GDP, arima(1,1,1)
```

```
(setting optimization to BHHH)
```

```
Iteration 0: log likelihood = -431.61324
Iteration 1: log likelihood = -429.85445
Iteration 2: log likelihood = -429.66798
Iteration 3: log likelihood = -429.65889
Iteration 4: log likelihood = -429.65638
(switching optimization to BFGS)
Iteration 5: log likelihood = -429.64546
Iteration 6: log likelihood = -429.64505
Iteration 7: log likelihood = -429.64501
```

```
ARIMA regression
```

```
Sample: 2 - 88                                Number of obs   =      87
                                                Wald chi2(2)    =     11.32
Log likelihood = -429.645                      Prob > chi2     =     0.0035
```

D.GDP	OPG		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
GDP						
_cons	22.57289	6.468824	3.49	0.000	9.894223	35.25155
ARMA						
ar						
L1.	.5211587	.2976916	1.75	0.080	-.0623061	1.104623
ma						
L1.	-.2264486	.3641402	-0.62	0.534	-.9401502	.487253
/sigma	33.74378	1.983092	17.02	0.000	29.85699	37.63057

```
Note: The test of the variance against zero is one sided, and the two-sided
confidence interval is truncated at zero.
```

```
. estat ic
```

```
Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	87	.	-429.645	4	867.29	877.1536

```
Note: N=Obs used in calculating BIC; see [R] BIC note.
```

ARIMA(2,1,1)

```
. arima GDP, arima(2,1,1)
```

```
(setting optimization to BHHH)
```

```
Iteration 0: log likelihood = -431.36024
```

```
Iteration 1: log likelihood = -429.82267
```

```
Iteration 2: log likelihood = -429.68462
```

```
Iteration 3: log likelihood = -429.5435
```

```
Iteration 4: log likelihood = -429.5144
```

```
(switching optimization to BFGS)
```

```
Iteration 5: log likelihood = -429.50089
```

```
Iteration 6: log likelihood = -429.48632
```

```
Iteration 7: log likelihood = -429.48047
```

```
Iteration 8: log likelihood = -429.47969
```

```
Iteration 9: log likelihood = -429.47964
```

```
Iteration 10: log likelihood = -429.47964
```

```
ARIMA regression
```

```
Sample: 2 - 88
```

```
Number of obs = 87
```

```
Wald chi2(3) = 4.89
```

```
Log likelihood = -429.4796
```

```
Prob > chi2 = 0.1798
```

D.GDP	OPG					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
GDP						
_cons	22.64445	6.381394	3.55	0.000	10.13715	35.15175
ARMA						
ar						
L1.	-.1360914	1.004	-0.14	0.892	-2.103895	1.831712
L2.	.2283343	.322455	0.71	0.479	-.4036659	.8603345
ma						
L1.	.4260338	1.054128	0.40	0.686	-1.640018	2.492086
/sigma	33.67806	2.001968	16.82	0.000	29.75428	37.60185

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

```
. estat ic
```

```
Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	87	.	-429.4796	5	868.9593	881.2888

Note: N=Obs used in calculating BIC; see [\[R\] BIC note](#).

# MODEL SELECTION CRITERIA

Criteria	Model A ARIMA(1,1,1)	Model B ARIMA(2,1,1)	Best Model
C,AR&MA	3/3	2/2	A=B
SigmaSQ	33.74378	33.67806	B
Log Likelihood	-429.645	-429.4796	B
AIC	867.29	868.9593	A
BIC	877.1536	881.2888	A
<b>Best Model</b>			<b>A</b>

We prefer to choose Model A because of the following reasons:-

- According to AIC and BIC values , Model A has lower values in both the cases , so A is better.
- To resolve the clash between the SigmaSQ and Log Likelihood values vs the AIC and BIC values , higher priority goes to the AIC and BIC values.
- Also observing the AR and MA graphs , we can visualise that they both are also significant at one lag .

Thus,our Model A works fine.

## Checking for white noise error term

**Stata command :** Predict error resid

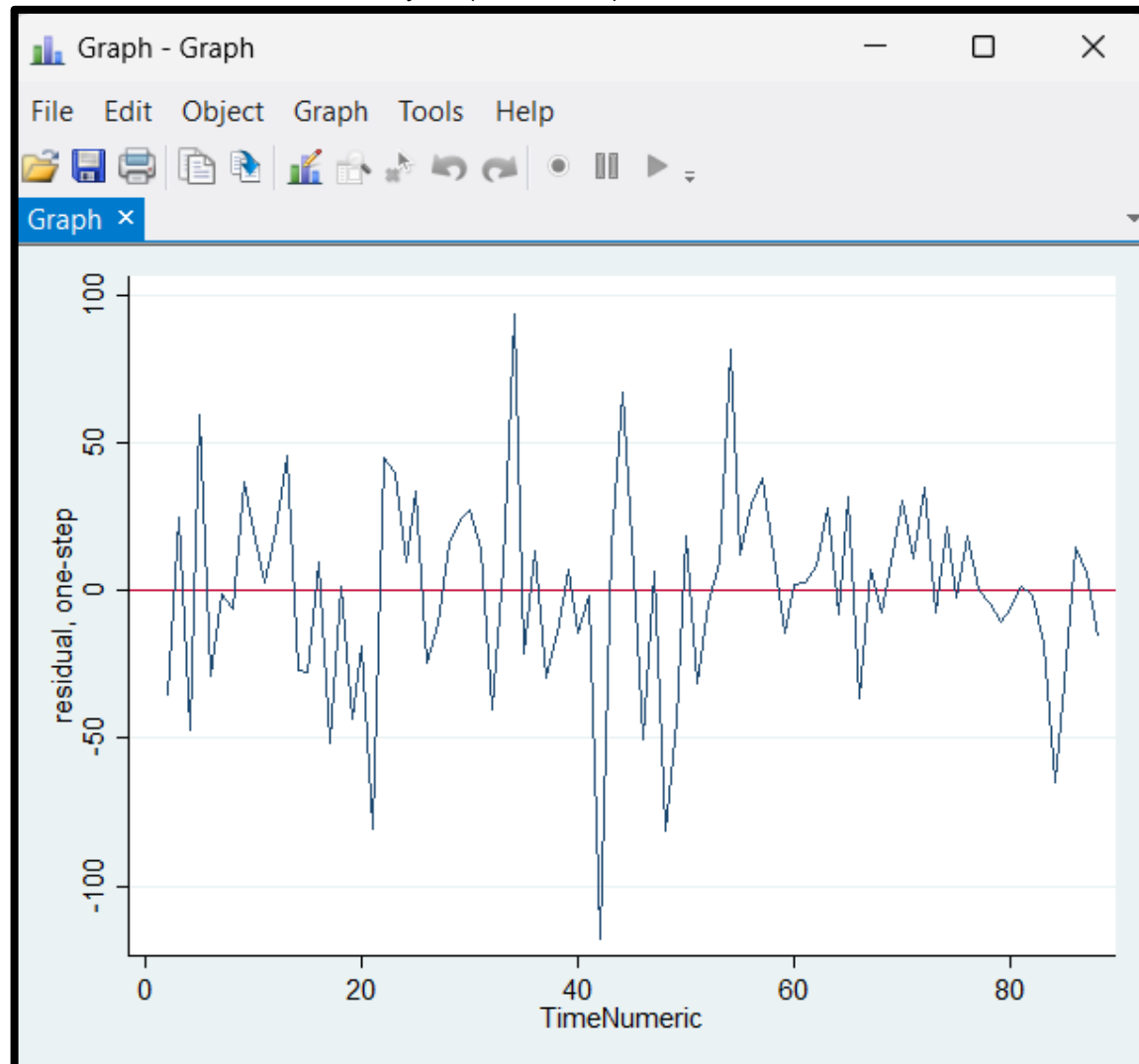
	YEAR	GDP	PDI	PCE	PROFITS	DIVIDENDS	year	quarter	TimeVariable	min_year	TimeNumeric	error
1	1970.1	2872.8	1990.6	1800.5	44.7	24.5	1970	1	1970q1	1970	1	.
2	1970.2	2860.3	2020.1	1807.5	44.4	23.9	1970	2	1970q2	1970	2	-35.07289
3	1970.3	2896.6	2045.3	1824.7	44.9	23.3	1970	3	1970q3	1970	3	24.90959
4	1970.4	2873.7	2045.2	1821.2	42.1	23.1	1970	4	1970q4	1970	4	-47.0168
5	1971.1	2942.9	2073.9	1849.9	48.8	23.8	1971	1	1971q1	1970	5	59.68178
6	1971.2	2947.4	2098	1863.5	50.7	23.7	1971	2	1971q2	1970	6	-28.85835
7	1971.3	2966	2106.6	1876.9	54.2	23.8	1971	3	1971q3	1970	7	-1.088973
8	1971.4	2980.8	2121.1	1904.6	55.7	23.7	1971	4	1971q4	1970	8	-5.948978
9	1972.1	3037.3	2129.7	1929.3	59.4	25	1972	1	1972q1	1970	9	36.63088
10	1972.2	3089.7	2149.1	1963.3	60.1	25.5	1972	2	1972q2	1970	10	20.44072
11	1972.3	3125.8	2193.9	1989.1	62.8	26.1	1972	3	1972q3	1970	11	2.611227
12	1972.4	3175.5	2272	2032.1	68.3	26.5	1972	4	1972q4	1970	12	20.66865
13	1973.1	3253.3	2300.7	2063.9	79.1	27	1973	1	1973q1	1970	13	45.76997
14	1973.2	3267.6	2315.2	2062	81.2	27.8	1973	2	1973q2	1970	14	-26.69043
15	1973.3	3264.3	2337.9	2073.7	81.3	28.3	1973	3	1973q3	1970	15	-27.60541
16	1973.4	3289.1	2382.7	2067.4	85	29.4	1973	4	1973q4	1970	16	9.459786
17	1974.1	3259.4	2334.7	2050.8	89	29.8	1974	1	1974q1	1970	17	-51.29141
18	1974.2	3267.6	2304.5	2059	91.2	30.4	1974	2	1974q2	1970	18	1.254713
19	1974.3	3239.1	2315	2065.5	97.1	30.9	1974	3	1974q3	1970	19	-43.2982
20	1974.4	3226.4	2313.7	2039.9	86.8	30.5	1974	4	1974q4	1970	20	-18.46063
21	1975.1	3154	2282.5	2051.8	75.8	30	1975	1	1975q1	1970	21	-80.7705
22	1975.2	3190.4	2390.3	2086.9	81	29.7	1975	2	1975q2	1970	22	45.03269
23	1975.3	3249.9	2354.4	2114.4	97.8	30.1	1975	3	1975q3	1970	23	39.91858
24	1975.4	3292.5	2389.4	2137	103.4	30.6	1975	4	1975q4	1970	24	9.821737
25	1976.1	3356.7	2424.5	2179.3	108.4	32.6	1976	1	1976q1	1970	25	33.41393
26	1976.2	3369.2	2434.9	2194.7	109.2	35	1976	2	1976q2	1970	26	-24.20068
27	1976.3	3381	2444.7	2213	110	36.6	1976	3	1976q3	1970	27	-11.00352
28	1976.4	3416.3	2459.5	2242	110.3	38.3	1976	4	1976q4	1970	28	15.84976
29	1977.1	3466.4	2463	2271.3	121.5	39.2	1977	1	1977q1	1970	29	24.48343
30	1977.2	3505	2490.3	2280.8	129.7	40	1977	2	1977q2	1970	30	27.22536
31	1977.3	3574.4	2541	2302.6	135.1	41.4	1977	3	1977q3	1970	31	14.21642
32	1977.4	3567.2	2556.2	2331.6	134.8	42.4	1977	4	1977q4	1970	32	-40.53478

```
. summarize error
```

Variable	Obs	Mean	Std. Dev.	Min	Max
error	87	.1541573	33.96331	-117.7946	93.46479

```
.
```

**Stata command :** `tsline error, yline(0.1541573)`



**Portmanteau Test for white noise error term**

```
. wntestq error
```

Portmanteau test for white noise

```
Portmanteau (Q) statistic =    41.7468
Prob > chi2(40)           =    0.3948
```

Clearly , p value is greater than 0.05 , so we accept the null hypothesis and hence , we conclude that there is existence of white noise error term.

Hence , the model that we estimated is fine.

## FORECASTING

**Stata Command : tsappend, add(10)**

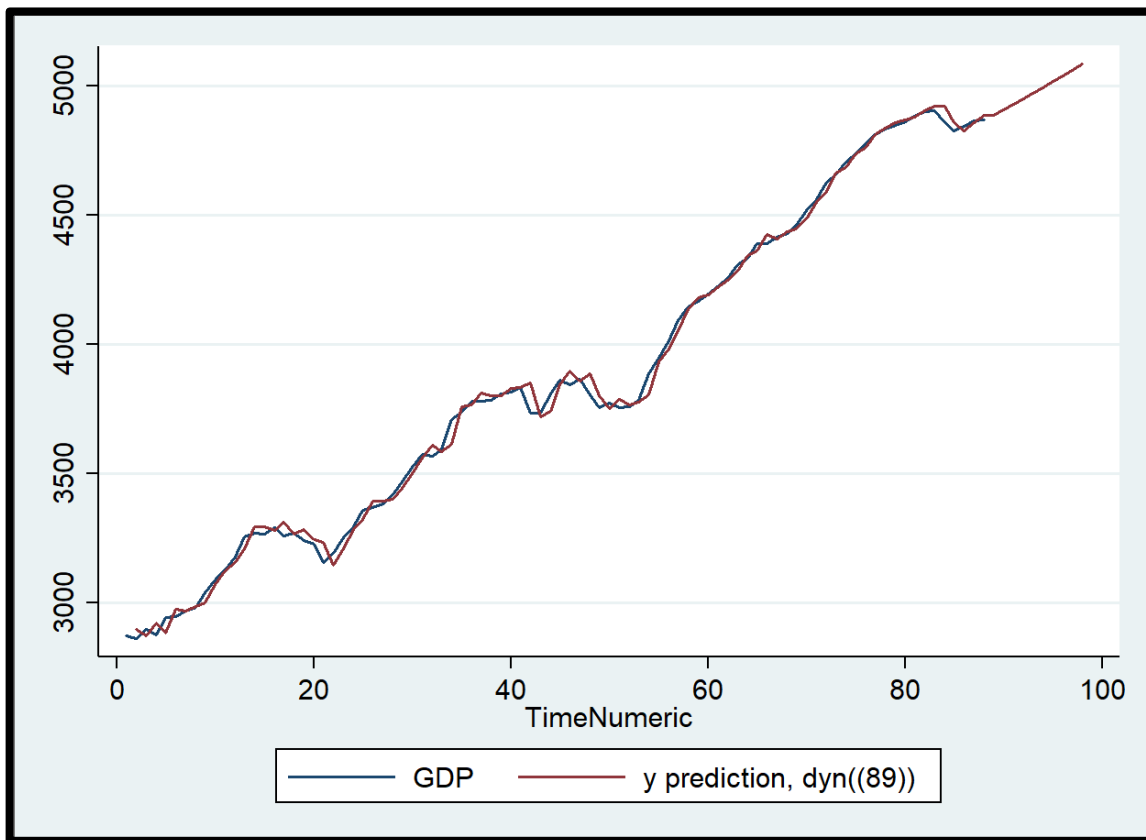
In Stata, the tsappend command is used to append or add new observations to an existing time-series dataset.

	YEAR	GDP	PDI	PCE	PROFITS	DIVIDENDS	year	quarter	TimeVariable	min_year	TimeNumeric	error
82	1990.2	4900.3	3545.3	3258.6	193.7	132.5	1990	2	1990q2	1970	82	-1.942172
83	1990.3	4903.3	3547	3281.2	196.3	133.8	1990	3	1990q3	1970	83	-18.41123
84	1990.4	4855.1	3529.5	3251.8	199	136.2	1990	4	1990q4	1970	84	-64.7415
85	1991.1	4824	3514.8	3241.1	189.7	137.8	1991	1	1991q1	1970	85	-31.44961
86	1991.2	4840.7	3537.4	3252.4	182.7	136.7	1991	2	1991q2	1970	86	14.97748
87	1991.3	4862.7	3539.9	3271.2	189.6	138.1	1991	3	1991q3	1970	87	5.879451
88	1991.4	4868	3547.5	3271.1	190.3	138.5	1991	4	1991q4	1970	88	-15.64293
89	.	.	.	.	.	.	.	.	.	.	89	.
90	.	.	.	.	.	.	.	.	.	.	90	.
91	.	.	.	.	.	.	.	.	.	.	91	.
92	.	.	.	.	.	.	.	.	.	.	92	.
93	.	.	.	.	.	.	.	.	.	.	93	.
94	.	.	.	.	.	.	.	.	.	.	94	.
95	.	.	.	.	.	.	.	.	.	.	95	.
96	.	.	.	.	.	.	.	.	.	.	96	.
97	.	.	.	.	.	.	.	.	.	.	97	.
98	.	.	.	.	.	.	.	.	.	.	98	.

**Stata Command : Predict FGDP, y dynamic(89)**

85	1991.1	4824	3514.8	3241.1	189.7	137.8	1991	1	1991q1	1970	85	-31.44961	4855.45
86	1991.2	4840.7	3537.4	3252.4	182.7	136.7	1991	2	1991q2	1970	86	14.97748	4825.723
87	1991.3	4862.7	3539.9	3271.2	189.6	138.1	1991	3	1991q3	1970	87	5.879451	4856.82
88	1991.4	4868	3547.5	3271.1	190.3	138.5	1991	4	1991q4	1970	88	-15.64293	4883.643
89	.	.	.	.	.	.	.	.	.	.	89	.	4885.113
90	.	.	.	.	.	.	.	.	.	.	90	.	4904.841
91	.	.	.	.	.	.	.	.	.	.	91	.	4925.931
92	.	.	.	.	.	.	.	.	.	.	92	.	4947.731
93	.	.	.	.	.	.	.	.	.	.	93	.	4969.901
94	.	.	.	.	.	.	.	.	.	.	94	.	4992.264
95	.	.	.	.	.	.	.	.	.	.	95	.	5014.728
96	.	.	.	.	.	.	.	.	.	.	96	.	5037.244
97	.	.	.	.	.	.	.	.	.	.	97	.	5059.787
98	.	.	.	.	.	.	.	.	.	.	98	.	5082.344

**Stata Command : tslne GPD, FGDP**



As can be seen , we have forecasted values for the next 10 quarters .  
So , this is our ARIMA Model built for GDP.

## QUESTION 2

We are trying to understand the dependence of GDP and PDI on its own past values and past values of the other variables.

Our understanding of their mutual dependence-

**How does GDP increase and decrease affect PDI?**

### 1. GDP(Gross Domestic Product):

- Imagine that the economy is like a big pie, and GDP represents the total size of that pie.
- When the economy produces more goods and services (like cars, phones, or haircuts), the pie gets bigger, and GDP increases.
- Conversely, if the economy slows down and produces fewer goods and services, the pie shrinks, and GDP decreases.

### 2. PDI(Personal Disposable Income):

- PDI is like the slice of the pie that each person gets to take home after taxes and other deductions.

- It's the money left in your pocket to spend or save after paying taxes and essential expenses (like rent, bills, and groceries).

### 3. How are they connected ?

- When GDP goes up (the economy grows), it usually has a positive effect on PDI.
  - **More Jobs:** A growing economy creates more jobs. When people work and earn money, their PDI increases.
  - **Higher Wages:** Companies may pay higher wages when they're doing well. So, your paycheck might get a boost.
  - **Business Profits:** When businesses make more profit (part of GDP), they might share it with employees through bonuses or raises.
- On the flip side, if GDP decreases (the economy shrinks):
  - **Job Losses:** Companies might cut jobs, leading to lower PDI for those who lose employment.
  - **Reduced Wages:** Businesses struggling to make money might freeze wages or even reduce them.
  - **Less Spending:** When people feel uncertain about the economy, they tend to spend less, affecting PDI.

### 4. Example :

- Imagine a small town where everyone works at the local bakery. If the bakery sells more cakes (increased GDP), they hire more people, pay higher wages, and everyone's PDI goes up.
- But if the bakery sells fewer cakes (decreased GDP), they might lay off workers, cut wages, and people have less money to spend.

### 5. Overall Impact :

- A healthy economy (higher GDP) generally leads to better PDI for most people.
- However, it's not always straightforward. Other factors like taxes, inflation, and government policies also play a role.

## How increase and decrease in PDI affect GDP?

### 1. PDI(Personal Disposable Income):



- Imagine you' re getting your allowance or paycheck. That' s your PDI.
- It' s the money you have left after paying taxes and other necessary stuff (like rent or bills).

## **2. GDP(Gross Domestic Product):**

- Think of GDP as the total money made by everyone in the whole country.
- It includes everything people produce or buy, like cars, pizzas, or haircuts.

## **3. How are they connected ?**

- When your PDI goes up (you have more money to spend):
  - You might buy more stuff (like that cool video game or a new dress).
  - Other people also spend more because they have more money.
  - Businesses notice this and produce more goods and services.
  - The economy grows, and GDP increases.
- But if your PDI goes down (you have less money):
  - You might cut back on spending (no more eating out or shopping sprees).
  - Others do the same.
  - Businesses sell fewer things, and the economy slows down.
  - GDP decreases.

## **4. Example :**

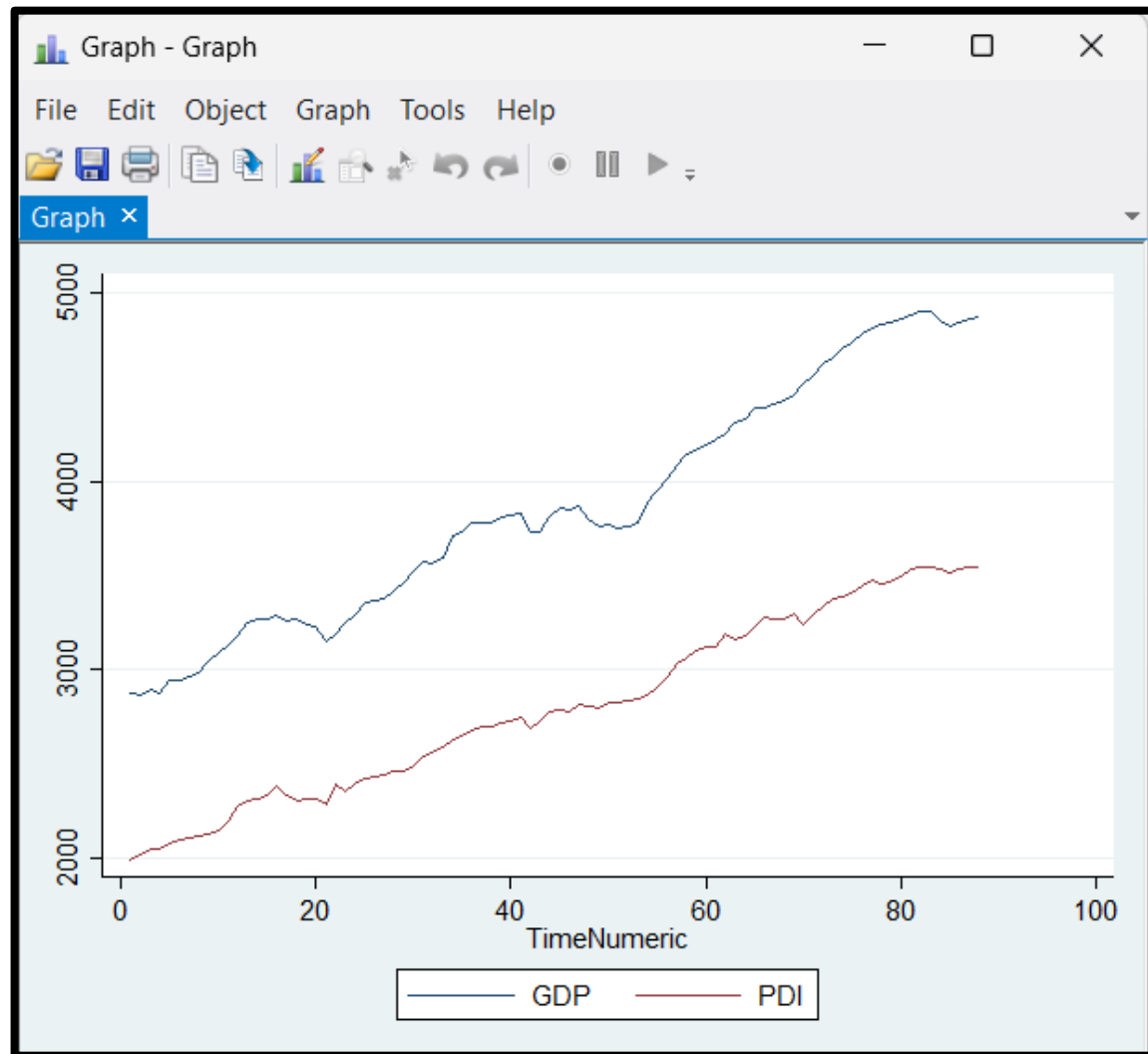
- Imagine a town where everyone gets a raise (higher PDI).
- People start buying more ice cream, going to movies, and fixing their houses.
- Businesses hire more workers, produce more, and GDP goes up.

## **5. Overall Impact:**

- When people have more money (higher PDI), they spend more.
- This spending boosts businesses, jobs, and the whole economy (higher GDP).
- So, PDI and GDP are like best friends—they help each other grow!

## **Checking for stationarity**

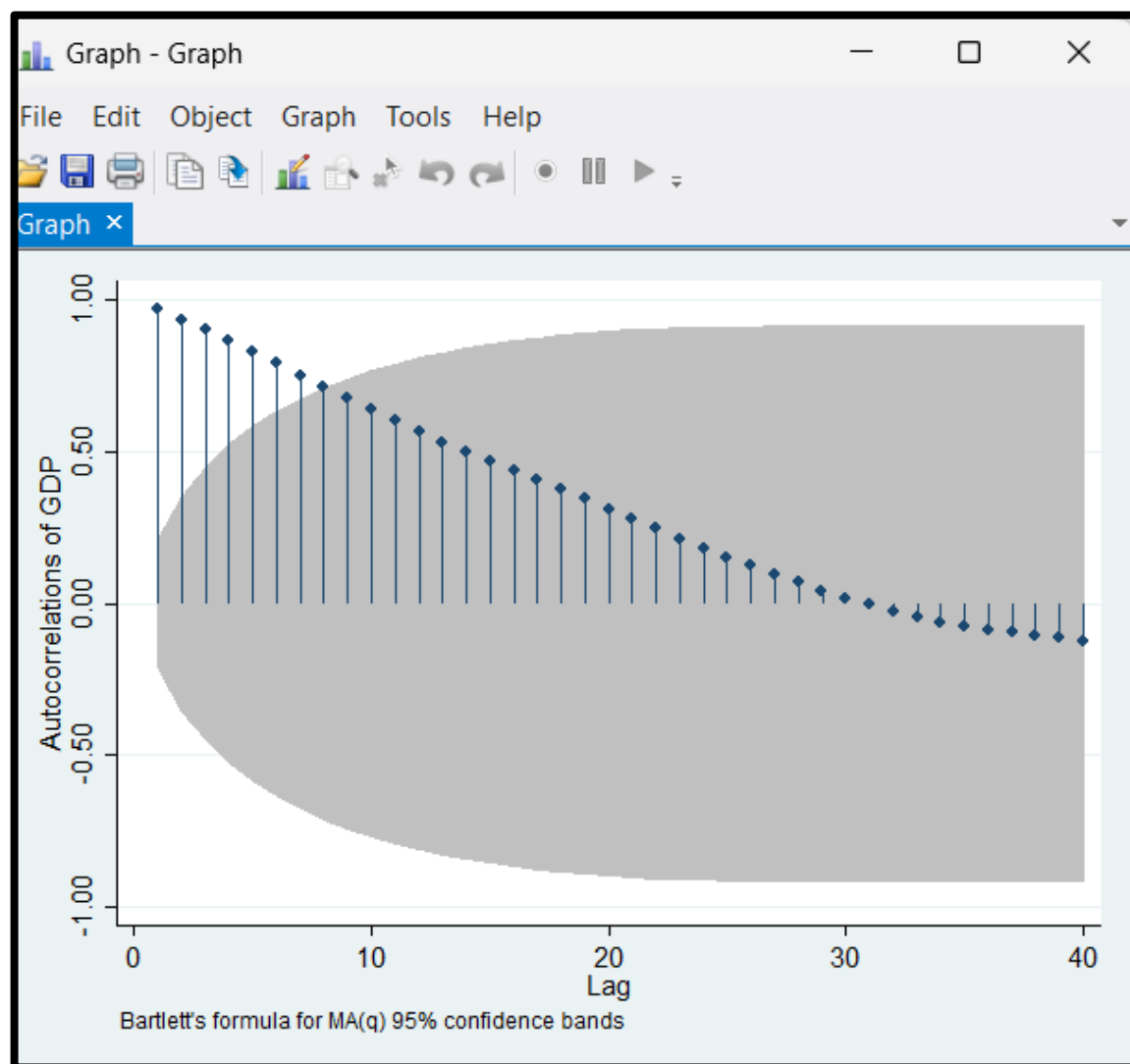
**Stata Command :** tsline GDP PDI



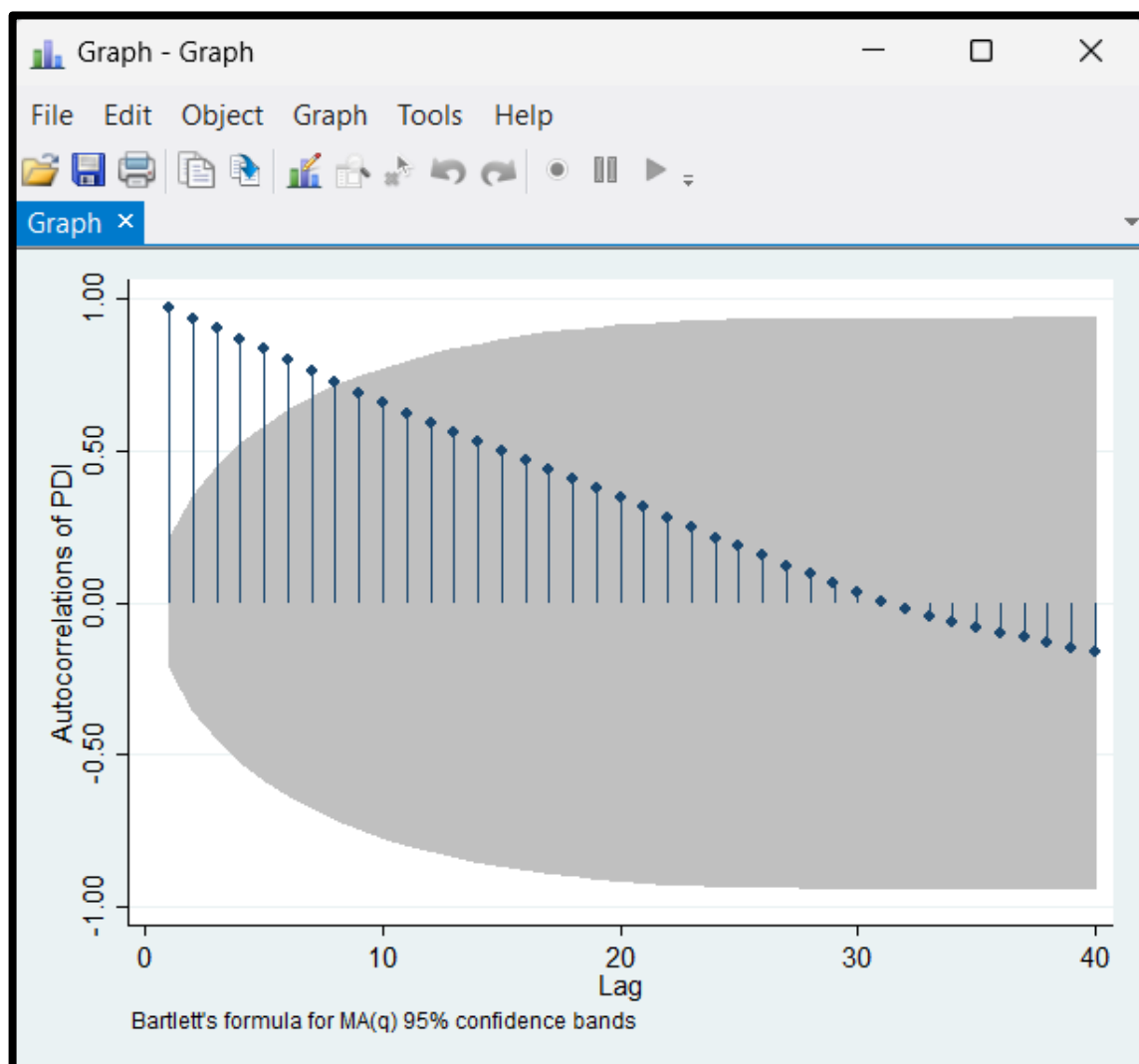
Clearly , both are non-stationary.

**Stata command:** ac GDP

In Stata, the "ac" command is used to perform autocorrelation tests on a time-series variable. Autocorrelation refers to the correlation between a variable and its lagged values over time.



**Stata command:** ac PDI



**Stata command:** `dfuller GDP, trend regress`

```
. dfuller GDP, trend regress
```

Dickey-Fuller test for unit root

Number of obs = 87

Test Statistic	Interpolated Dickey-Fuller			
	1% Critical Value	5% Critical Value	10% Critical Value	
Z(t)	-1.625	-4.069	-3.463	-3.158

MacKinnon approximate p-value for Z(t) = 0.7824

D.GDP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
GDP						
L1.	-.0603169	.0371113	-1.63	0.108	-.1341169	.013483
_trend	1.477641	.9172439	1.61	0.111	-.346399	3.301681
_cons	190.3837	103.5257	1.84	0.069	-15.48857	396.2559

**Stata command:** `dfuller PDI, trend regress`

```
. dfuller PDI, trend regress
```

Dickey-Fuller test for unit root Number of obs = 87

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.588	-4.069	-3.463

MacKinnon approximate p-value for Z(t) = 0.2853

D.PDI	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
PDI					
L1.	-.156942	.0606363	-2.59	0.011	-.2775239 - .0363602
_trend	2.875152	1.136078	2.53	0.013	.6159357 5.134368
_cons	329.508	119.6902	2.75	0.007	91.49091 567.5252

Both are non stationary

```
. dfuller D.GDP, trend regress
```

Dickey-Fuller test for unit root Number of obs = 86

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-6.588	-4.071	-3.464

MacKinnon approximate p-value for Z(t) = 0.0000

D2.GDP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
D.GDP					
L1.	-.6824587	.1035842	-6.59	0.000	-.8884835 - .476434
_trend	-.0282464	.1497305	-0.19	0.851	-.3260544 .2695615
_cons	17.22668	7.841891	2.20	0.031	1.629475 32.82389

After 1st differencing , it becomes stationary.

**Stata command:** var D.GDP D.PDI

```
. var d.GDP d.PDI
```

Vector autoregression

```
Sample: 4 - 88
Log likelihood = -804.4051
FPE = 719988.6
Det(Sigma_ml) = 568879.9

Number of obs = 85
AIC = 19.16247
HQIC = 19.27806
SBIC = 19.44984
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_GDP	5	34.0327	0.1547	15.55194	0.0037
D_PDI	5	27.131	0.1196	11.54804	0.0210

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
D_GDP	GDP						
	LD.	.2691171	.1246462	2.16	0.031	.0248151	.5134191
	L2D.	.1874404	.1178853	1.59	0.112	-.0436105	.4184912
	PDI						
	LD.	.1202326	.1525295	0.79	0.431	-.1787198	.419185
	L2D.	-.2518658	.1529432	-1.65	0.100	-.5516289	.0478973
	_cons	14.94721	5.005273	2.99	0.003	5.137052	24.75736
D_PDI	GDP						
	LD.	.1609622	.0993684	1.62	0.105	-.0337964	.3557207
	L2D.	.2459483	.0939786	2.62	0.009	.0617536	.430143
	PDI						
	LD.	-.2097618	.1215972	-1.73	0.085	-.4480878	.0285643
	L2D.	-.2702654	.1219269	-2.22	0.027	-.5092378	-.031293
	_cons	16.85565	3.990225	4.22	0.000	9.034952	24.67635

```
. dfuller D.PDI, trend regress
```

Dickey-Fuller test for unit root

Number of obs = 86

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-9.593	-4.071	-3.464

MacKinnon approximate p-value for Z(t) = 0.0000

D2.PDI	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
D.PDI						
L1.	-1.051376	.1095995	-9.59	0.000	-1.269365	-.8333875
_trend	-.0444036	.1232052	-0.36	0.719	-.2894538	.2006466
_cons	20.61757	6.540397	3.15	0.002	7.608987	33.62616

Clearly , stationarity can be seen after 1st differencing. So, after first differencing we have solved the problem of non stationarity.

## Estimating VAR model

```

. gen D_GDP = GDP - L.GDP
(11 missing values generated)

. gen D_PDI = PDI - L.PDI
(11 missing values generated)

. var D_GDP D_PDI

Vector autoregression

Sample: 4 - 88
Log likelihood = -804.4051
FPE = 719988.6
Det(Sigma_ml) = 568879.8

Number of obs = 85
AIC = 19.16247
HQIC = 19.27806
SBIC = 19.44984

Equation     Parms      RMSE      R-sq      chi2      P>chi2
-----
D_GDP          5      34.0327   0.1547   15.55194   0.0037
D_PDI          5      27.131    0.1196   11.54804   0.0210

```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
<b>D_GDP</b>						
D_GDP						
L1.	.2691171	.1246462	2.16	0.031	.0248151	.5134191
L2.	.1874404	.1178853	1.59	0.112	-.0436105	.4184912
D_PDI						
L1.	.1202326	.1525295	0.79	0.431	-.1787198	.4191849
L2.	-.2518658	.1529432	-1.65	0.100	-.5516289	.0478973
_cons	14.94721	5.005273	2.99	0.003	5.137052	24.75736
<b>D_PDI</b>						
D_GDP						
L1.	.1609621	.0993684	1.62	0.105	-.0337964	.3557207
L2.	.2459483	.0939786	2.62	0.009	.0617536	.430143
D_PDI						
L1.	-.2097618	.1215972	-1.73	0.085	-.4480878	.0285643
L2.	-.2702654	.1219269	-2.22	0.027	-.5092378	-.031293
_cons	16.85565	3.990225	4.22	0.000	9.034952	24.67635

D\_GDP is the value of GDP obtained after 1st differencing.

D\_PDI is the value of PDI obtained after 1st differencing.

At 5% significance level, the following two results can be observed :-

1. D\_GDP is affected by its own 1st lag and no lags of D\_PDI.
2. D\_PDI is affected by its own second lag and second lag of D\_GDP.

### Stata command : vargranger

In Stata, the “vargranger” command is used to conduct Granger causality tests for vector autoregressive (VAR) models. Granger causality tests help determine whether one time series variable "Granger causes" another, meaning that past values of one variable contain information that helps predict future values of another variable.

vargranger				
Granger causality Wald tests				
Equation	Excluded	chi2	df	Prob > chi2
D_GDP	D_PDI	4.1454	2	0.126
D_GDP	ALL	4.1454	2	0.126
D_PDI	D_GDP	11.063	2	0.004
D_PDI	ALL	11.063	2	0.004

From the probability values, when probability value is  $< 0.05$ , we can say that the result is significant and we can reject the null hypothesis.

Null hypothesis of Granger causality event states that one time series is not causing the other time series.

So, from the probability values we can say that,

D\_PDI is affected by D\_GDP, but the opposite is not true. Thus, D\_GDP granger causes D\_PDI.



## Conclusion

We selected two economic variables, GDP (Gross Domestic Product) and PDI (Personal Disposable Income), under the assumption that they are interrelated. Initially, to ensure our analysis was robust, we made both variables time stationary through differencing and we got D\_GDP and D\_PDI. Following this, we proceeded to estimate a VAR (Vector Autoregression) model.

To determine the direction of causality between the two variables, we conducted a Granger Causality test. This test helps identify whether one variable influences the behavior of the other over time. The results of the test indicated that changes in D\_GDP, cause changes in D\_PDI.

Therefore, our initial assumption that GDP and PDI are interrelated variables appears to be valid, as the Granger Causality test confirmed that changes in GDP have a causal effect on changes in PDI. This finding underscores the interconnectedness of economic variables and highlights the significance of understanding their dynamic relationships for economic analysis and policy-making.