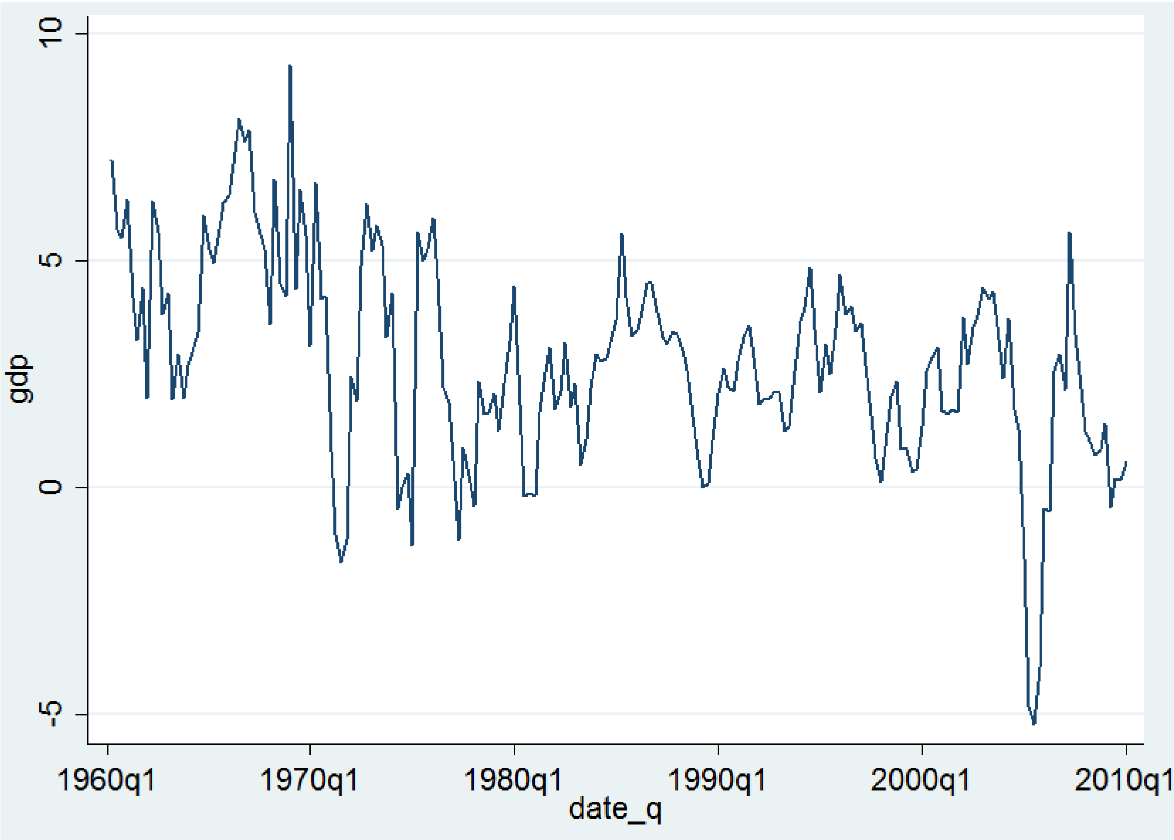
Coursework-2: Financial Modeling

a) Quarterly GDP Data for Austria

In the view of Jenkins (2006), the autoregressive integrated moving average (ARIMA) model is one of the important model classes that are used to describe s single time series. The assignment chooses this model to analyze the time series secondary data of a country. For this purpose, the assignment chooses Austria; an OECD nation and collect the quarterly GDP data for the last fifty years i.e. 1963 - 2013. The assignment uses STATA software as a base to perform time series test and graphical analysis in order to predict the quarterly GDP of Austria for the coming 50 years.

b) Time Series Plot

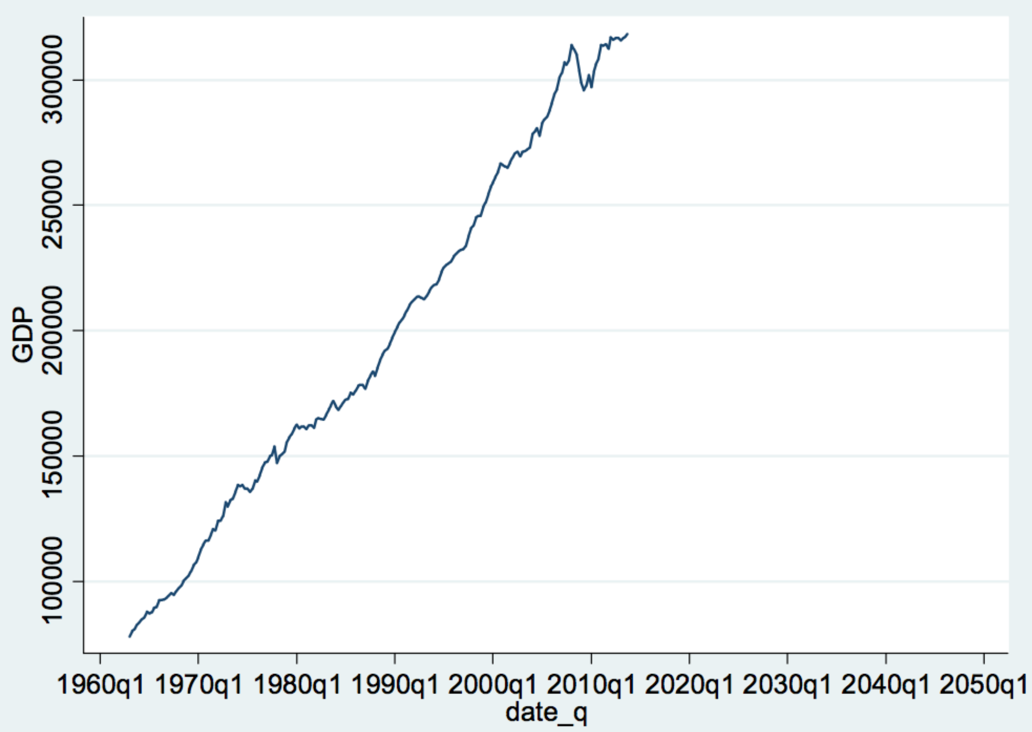
In Stata, simple time series command is used to plot the trend line of Austria's quarterly GDP over the last 50 years. The graph below provides the trend line of quarterly GDP rates as change over the same quarter and analysis shows downward GDP movement during the economic crisis of 2007-2009.



Graph 1: Quarterly GDP Growth Rates of Austria

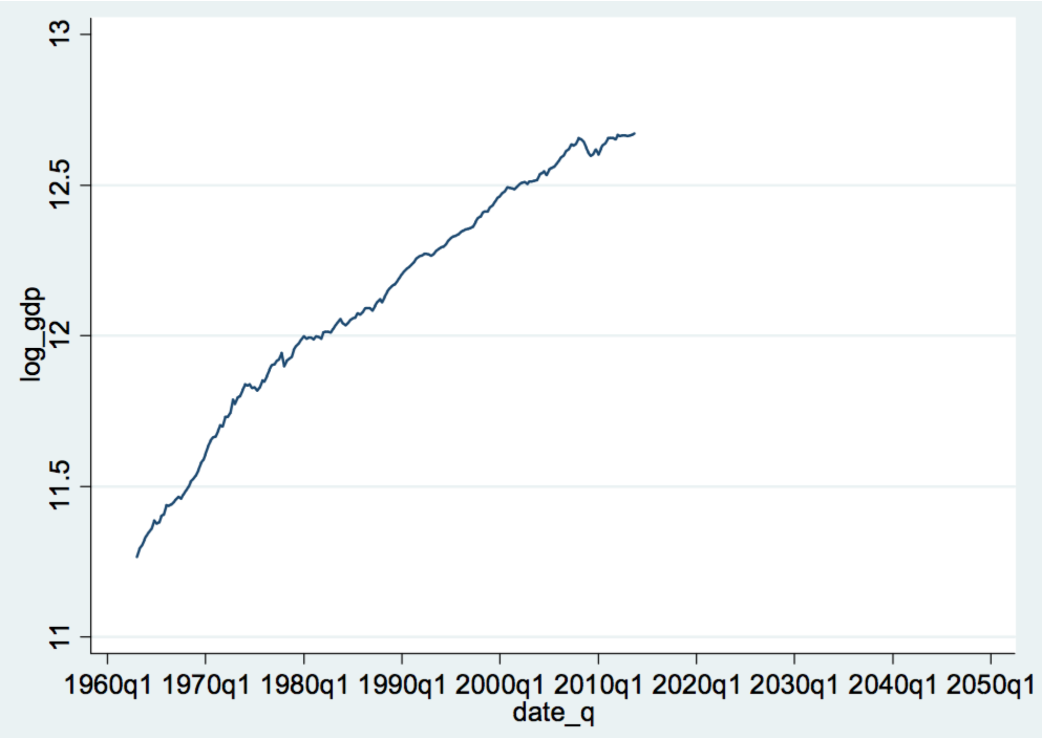
(Source: OECD, 2015)

A look at the graph below, however, depicts an upward movement with slight variations during the crisis period. The graph below depicts a rather sharp trend of GDP.



Graph 2: Quarterly GDP Trend

For better understanding, log function is used on the GDP data; the graph below shows that Austrian economy's connection with the European Union State members had significant affect on the GDP performance of the country. As a consequence of 2007-08 crises, Austrian GDP reported variations in the late 2009; however, the graph below depicts a visible recovery of Austrian economy due to subsidized government projects. Nonetheless, time series analysis shows that the GDP trend is non-stationary and non-static over the given time period.



Graph 3: Trend of Log_GDP

c) Autocorrelation Function (ACF) and the Order of AR and MA

In the Dickey-Fuller test, if test statistic is greater than all the values at three different critical levels then the null hypothesis can be rejected. Stata results in the figure below depict an opposite situation as the test statistics value is -0.175 and it is small than the three critical values i.e. -3.476 at 1%, -2.883 at 5% and -2.573 at 10%. In other words, Dickey-Fuller unit root test indicates that the null hypothesis of GDP series cannot be rejected.

```
. dfuller gdp

Dickey-Fuller test for unit root                   Number of obs   =       203

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -0.175            -3.476            -2.883            -2.573
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9414
```

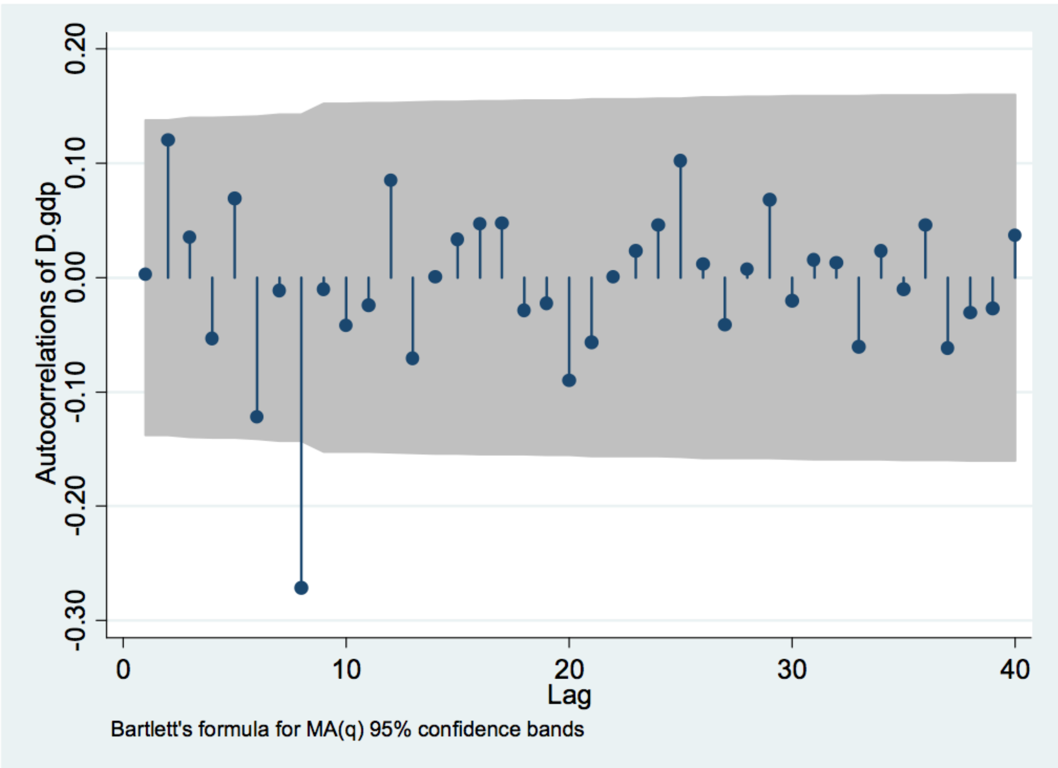
Figure 1: Dickey-Fuller Test

The above illustration provides an indication for the presence of unit root problem, which is solved through the first differential (See figure below). For this purpose, Dickey-Fuller test is re-performed with the first differential; this turns the non-stationary GDP series into a stationary series. The figure below shows that test statistics value is smaller than all the three critical values; hence, the series is stationary.

```
. dfuller d.gdp

Dickey-Fuller test for unit root                   Number of obs   =       202

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -14.116            -3.476            -2.883            -2.573
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Figure 2: Dickey-Fuller with First Differential

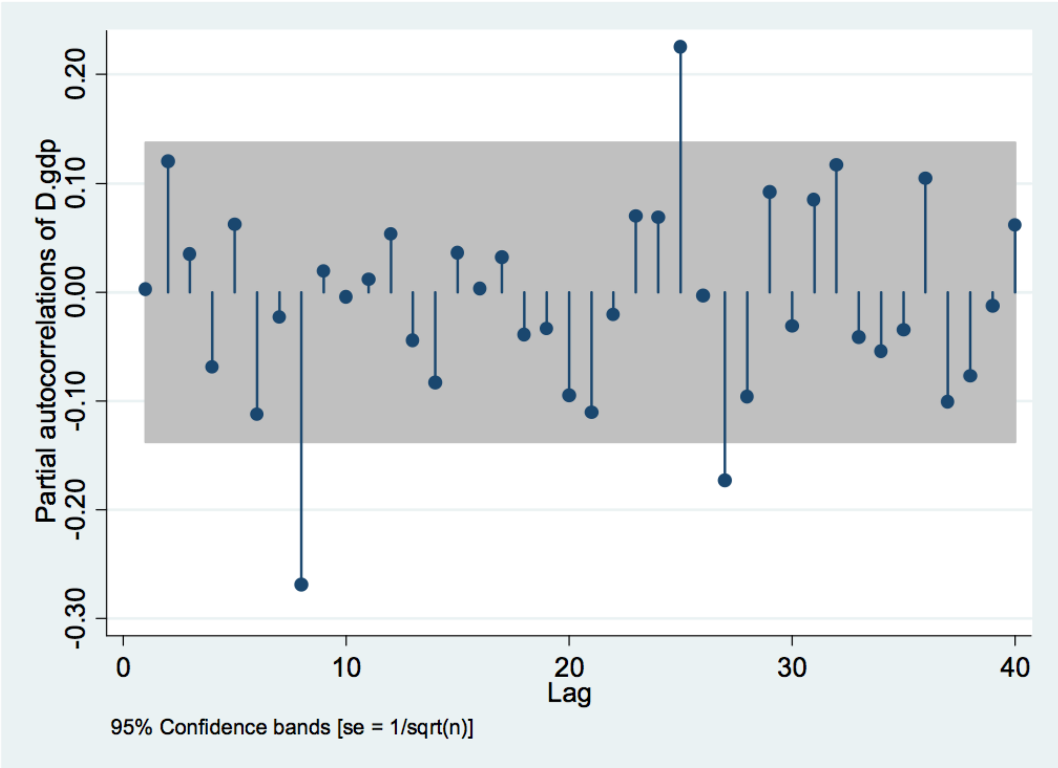
The auto-correlation graph (Ac) below provides evidence for the presence of higher lag in the data.



Graph 4: AC

i. Partial Autocorrelation Function (PACF) Plot

In line with Ac results, the Pac plot below also depicts higher lags, which means that the stationary series achieved through first differential above is providing insignificant values.



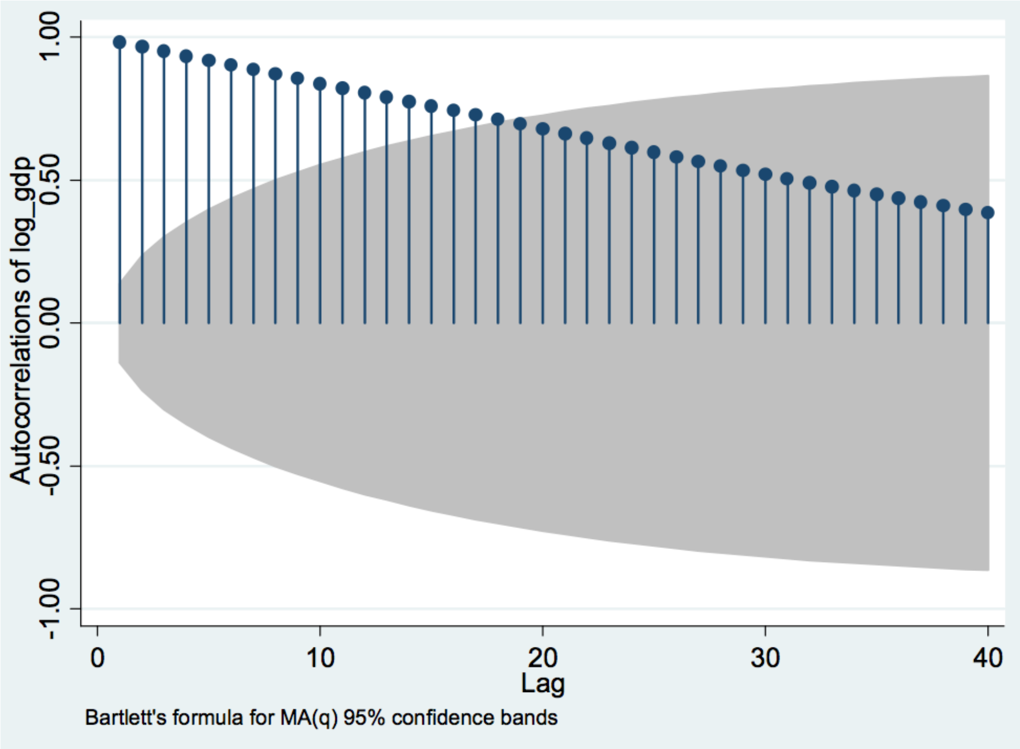
Graph 5: Pac

In order to choose the right type of ARIMA model, log_gdp command is performed in the Stata software. As can be seen in the figure below, z(t) value is lower than the standard value i.e. 0.05; this means that the series is stationary and the model selected for evaluation is Arima model with D=0.

```
. dfuller log_gdp

Dickey-Fuller test for unit root                   Number of obs   =       203

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.115            -3.476            -2.883            -2.573
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0009
```

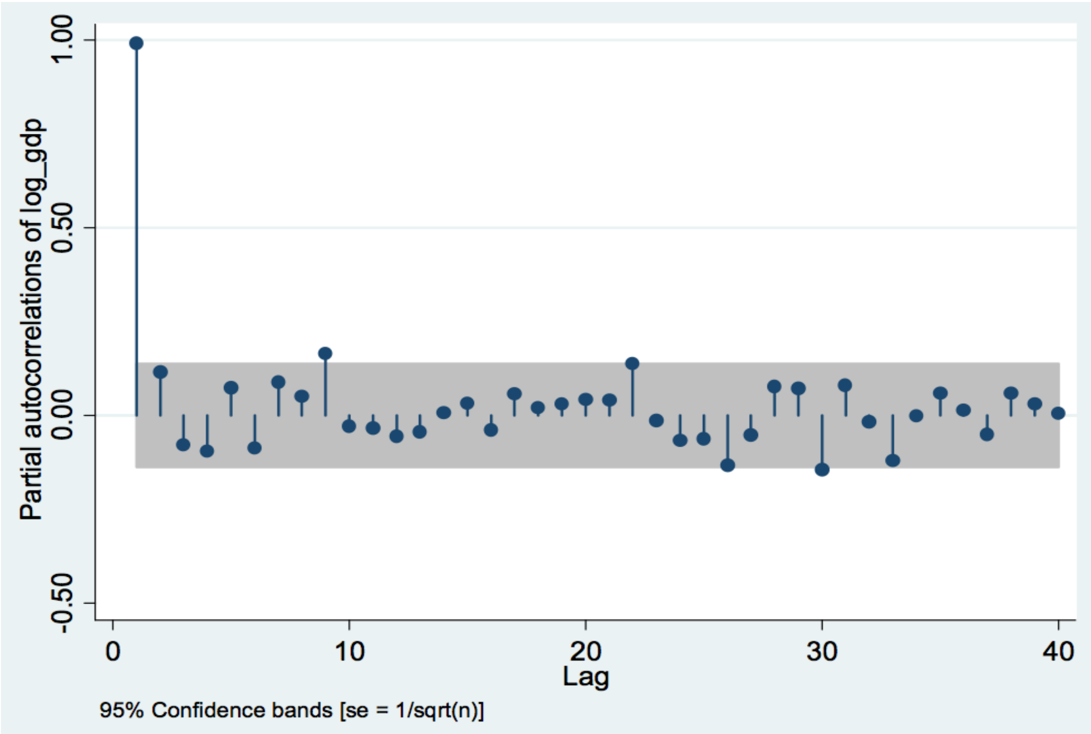
Figure 3: Dickey-Fuller log_GDP

The choice of model can be justified through Ac and Pac plots below, for example, the Ac graph below depicts gradual decline. Analysis shows significant values till the 16th lag and these are certainly different from zero.



Graph 6: Autocorrelation

The Pac graph below provides clear evidence of partial coefficient at points such as lag 1 and 9; thus, values at these lag points are significant and outside the 95% confidence interval. In contrast, other lags report insignificant values; hence, p-value for Arima model is suggested to be 1.



Graph 7: Partial Autocorrelation

d) Type of ARIMA Model and Rationale

Since the above testing provides one significant point in Pac plot and declining trend of Ac, the proposed ARIMA(p,d,q) is ARIMA(1,0,0). Normally, appropriate model is done through the AIC or BIC testing (Tsay, 2010); however, in the present context, the thumb rule of selecting the model with the lowest value may not be applicable. Keeping this into consideration, ARIMA(1,0,0) with Dickey-Fuller with log is selected as the appropriate model type because the above tests depict only one model i.e. ARIMA(1,0,0).

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
m1	204	.	601.5096	3	-1197.019	-1187.065

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

Figure 4: AIC

```
. wntestq uhat1, lag(5)

Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =     0.2428
 Prob > chi2(5)            =     0.9986
```

Figure 5: Portmanteau Test

e) Forecasting the GDP Growth

In the Stata, following commands are used to create a forecast the GDP of Austria over the next fifty years.

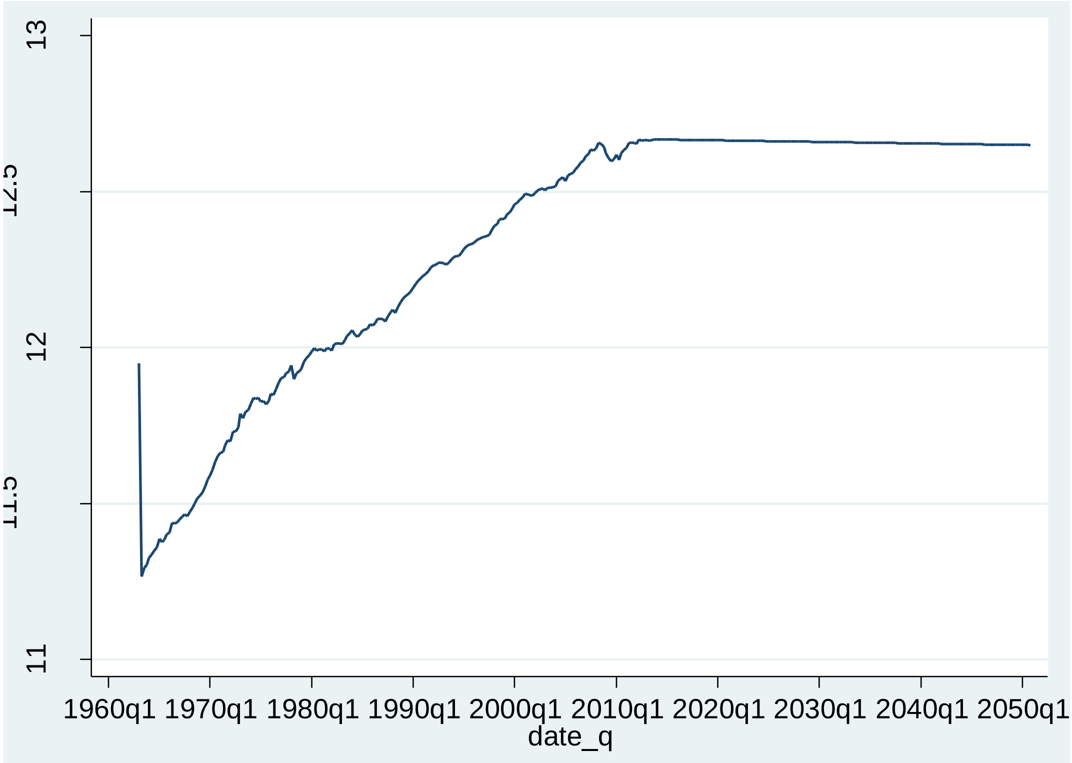
```
. arima log_gdp if date_q<tq(2007q4), arima(1,0,0)

(setting optimization to BHHH)
Iteration 0:   log likelihood =  189.57089
Iteration 1:   log likelihood =  442.07582
Iteration 2:   log likelihood =  501.10749
Iteration 3:   log likelihood =  513.34938
Iteration 4:   log likelihood =  516.24871
(switching optimization to BFGS)
Iteration 5:   log likelihood =  518.10305
Iteration 6:   log likelihood =  523.98001
Iteration 7:   log likelihood =  524.30337
Iteration 8:   log likelihood =  524.31996
Iteration 9:   log likelihood =  524.35032
Iteration 10:  log likelihood =  524.37211
Iteration 11:  log likelihood =  524.43026
Iteration 12:  log likelihood =  524.43211
Iteration 13:  log likelihood =  524.43215
Iteration 14:  log likelihood =  524.43217
(switching optimization to BHHH)
Iteration 15:  log likelihood =  524.43217

ARIMA regression

Sample:  1963q1 - 2007q3                        Number of obs      =        179
                                                Wald chi2(1)       = 120677.39
Log likelihood =  524.4322                      Prob > chi2        =     0.0000
```

log_gdp	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf. Interval]	
log_gdp						
_cons	11.94975	.679855	17.58	0.000	10.61726	13.28224
ARMA						
ar						
L1.	.9998252	.0028781	347.39	0.000	.9941841	1.005466
/sigma	.0126391	.0006273	20.15	0.000	.0114095	.0138687

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

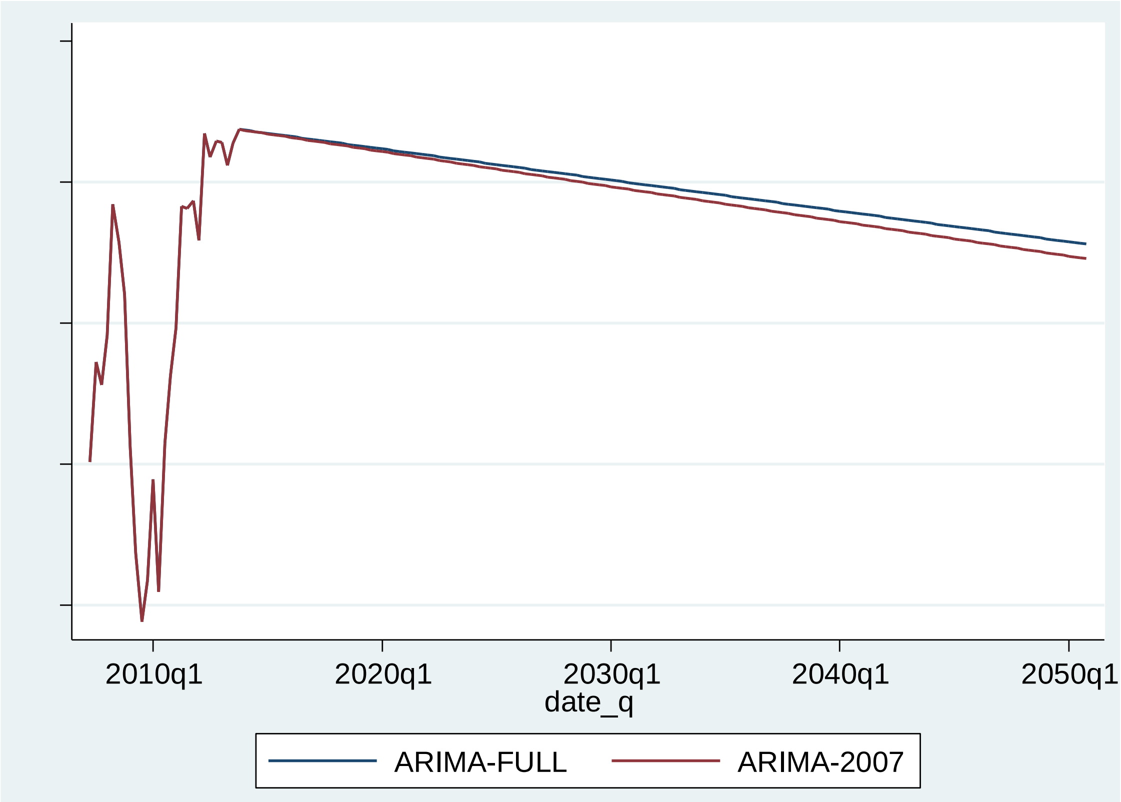
Figure 6: Forecasting Command

As illustrated in the graph below, Austrian GDP is expected to remain flat and stable in the coming fifty years; hence, the trend is plotted as a straight line. Since the model intends to study the effect of financial crisis on the forecast, ARIMA 2007 model is applied. The graph below forecasts the GDP trend with the influence of crisis.



Graph 8: ARIMA 2007

According to analysis, Austria's GDP remained under the sharp influence of economic crisis; evidence to the notion can be taken from the sharp GDP decline from 12.62% (2007) to 0.02% (2008).



Graph 9: ARIMA Full and ARIMA 2007

In the graph above, ARIMA FULL line moves above the ARIMA 2007 line; since ARIMA FULL values are higher than ARIMA 2007; the evaluation suggests that unlike ARIMA 2007, ARIMA FULL line indicates no impact of financial crisis on Austria's GDP.

f) The Monte-Carlo Experiment

Following are the commands to prove the statement that Dickey-Fuller model may not be suitable for stationary series if the model is based on time trend.

```
. arima log_gdp trend, arima(2,0,0)

(setting optimization to BHHH)
Iteration 0:   log likelihood =  626.01196
Iteration 1:   log likelihood =   636.8883
Iteration 2:   log likelihood =  638.19784
Iteration 3:   log likelihood =  640.93195
Iteration 4:   log likelihood =   641.2118
(switching optimization to BFGS)
Iteration 5:   log likelihood =  641.65035
Iteration 6:   log likelihood =  641.79818
Iteration 7:   log likelihood =  641.82383
Iteration 8:   log likelihood =   641.8381
Iteration 9:   log likelihood =  641.83978
Iteration 10:  log likelihood =  641.83994
Iteration 11:  log likelihood =  641.83995
Iteration 12:  log likelihood =  641.83995

ARIMA regression

Sample:  1963q1 - 2013q4                        Number of obs      =       204
                                                Wald chi2(3)       =  14011.80
Log likelihood =    641.84                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
     log_gdp |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
log_gdp      |
       trend |   .0069044   .0007867     8.78   0.000     .0053625    .0084463
       _cons |   11.31661   .1758973    64.34   0.000     10.97186    11.66136
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .9519725   .0592312    16.07   0.000     .8358814    1.068064
         L2. |   .0423179   .0619034     0.68   0.494    -.0790105    .1636463
-------------+----------------------------------------------------------------
      /sigma |   .0102952   .0003516    29.28   0.000      .009606    .0109843
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided confidence interval is
    truncated at zero.
```

Figure 7: Simulation

At x=0, the p-vale is 95.8%, which means the Dickey-Fuller test with no trend is more reliable than otherwise. The figure below indicates that the Dickey-Fuller value at x=1 is significant; however, p-value is only significant for 4.2% of the total 1000 frequency. Hence, in case of trend model, Dickey-Fuller is less suitable.

```
. simulate p=r(p), reps(1000): dftrend 204 .0069 .951 .042 .010

      command:  dftrend 204 .0069 .951 .042 .010
            p:  r(p)

Simulations (1000)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200
..................................................   250
..................................................   300
..................................................   350
..................................................   400
..................................................   450
..................................................   500
..................................................   550
..................................................   600
..................................................   650
..................................................   700
..................................................   750
..................................................   800
..................................................   850
..................................................   900
..................................................   950
..................................................  1000

. gen x=p<0.05

. tab x

          x |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        958       95.80       95.80
          1 |         42        4.20      100.00
------------+-----------------------------------
      Total |      1,000      100.00
```

Figure 8: Simulation Results

On a simple note, the evaluation suggests that the Dickey-Fuller test with trend model is less suitable for stationary test and it cannot be relied as the results are very weak.

References

Jenkins, M. G. (2006). Autoregressive–Integrated Moving Average (ARIMA) Models, in *Encyclopedia of Statistical Sciences*, 1-6.

OECD. (2015). Quarterly National Accounts. [online] Available from <https://stats.oecd.org/index.aspx?queryid=350#> [28th April 15]

Tsay, S. R. (2010). *Analysis of Financial Time Series*. New Jersey: John Wiley & Sons.