**Assignment - 3**

**ARIMA Estimation of Finland Real GDP**

**Course:** ECO489

**Section:** 01

**Submitted to:**

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**ARIMA estimation of Finland real GDP**

**. clear all**

**. set more off**

**. freduse CLVMNACSCAB1GQFI**

**. rename CLVMNACSCAB1GQFI rgdp**

**. gen lrgdp = log(rgdp)**

**\*\* set time variable**

**. generate time = q(1990q1) + \_n -1**

**. format time %tq**

**. tsset time**

**. tsline rgdp**



**. tsline d.rgdp**



**\*\* Step 1: Identification**

**. ac d.lrgdp if time < tq(2020q1)**



Here I took the data before COVID19 and it indicates MA (3) at 95% confidence bands.

**. pac d.lrgdp if time < tq(2020q1)**

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It indicates AR (3) at 95% confidence bands.

So, in this case, we identified that for this model ARMA (p, q) would be ARMA (3,3)

**\*\* Step 2: Estimation arima(p,d,q)**

**. arima d.lrgdp if time < tq(2020q1), arima(3,0,3)**

(setting optimization to BHHH)

Iteration 0: log likelihood = 366.33341

Iteration 1: log likelihood = 367.34548

Iteration 2: log likelihood = 368.08768

Iteration 3: log likelihood = 368.28257

Iteration 4: log likelihood = 368.31645

(switching optimization to BFGS)

Iteration 5: log likelihood = 368.34726

Iteration 6: log likelihood = 368.38661

Iteration 7: log likelihood = 368.39459

Iteration 8: log likelihood = 368.39751

Iteration 9: log likelihood = 368.39937

Iteration 10: log likelihood = 368.40051

Iteration 11: log likelihood = 368.4007

Iteration 12: log likelihood = 368.40072

ARIMA regression

Sample: 1990q2 thru 2019q4 Number of obs = 119

Wald chi2(6) = 47.01

Log likelihood = 368.4007 Prob > chi2 = 0.0000

------------------------------------------------------------------------------

| OPG

D.lrgdp | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lrgdp |

\_cons | .003359 .0028429 1.18 0.237 -.0022129 .008931

-------------+----------------------------------------------------------------

ARMA |

ar |

L1. | .133866 .2462486 0.54 0.587 -.3487723 .6165043

L2. | -.2723778 .2427492 -1.12 0.262 -.7481575 .2034019

L3. | .6089914 .2165835 2.81 0.005 .1844956 1.033487

|

ma |

L1. | .0877287 .2807461 0.31 0.755 -.4625236 .637981

L2. | .4860204 .261844 1.86 0.063 -.0271844 .9992253

L3. | -.2159059 .2275252 -0.95 0.343 -.6618472 .2300353

-------------+----------------------------------------------------------------

/sigma | .0109166 .0005158 21.17 0.000 .0099058 .0119275

**\*\* Step 3: Diagnostic checking**

**. predict resid, residual**

**. wntestq resid**

Portmanteau test for white noise

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Portmanteau (Q) statistic = 23.7617

Prob > chi2(40) = 0.9806

**. wntestb resid**

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**\*\* Step 4: Forecasting**

**// adding time 2022q4, 2023q1 for forecasting (Out of sample)**

**. tsappend, add(2)**

**. arima d.lrgdp, arima(3,0,3), if tin(,2019q3)**

(setting optimization to BHHH)

Iteration 0: log likelihood = 363.00216

Iteration 1: log likelihood = 364.00373

Iteration 2: log likelihood = 364.70544

Iteration 3: log likelihood = 364.89483

Iteration 4: log likelihood = 364.92498

(switching optimization to BFGS)

Iteration 5: log likelihood = 364.95171

Iteration 6: log likelihood = 364.99362

Iteration 7: log likelihood = 365.0002

Iteration 8: log likelihood = 365.00319

Iteration 9: log likelihood = 365.00438

Iteration 10: log likelihood = 365.00524

Iteration 11: log likelihood = 365.00541

Iteration 12: log likelihood = 365.00542

ARIMA regression

Sample: 1990q2 thru 2019q3 Number of obs = 118

Wald chi2(6) = 47.33

Log likelihood = 365.0054 Prob > chi2 = 0.0000

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| OPG

D.lrgdp | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lrgdp |

\_cons | .0035034 .0028667 1.22 0.222 -.0021153 .0091221

-------------+----------------------------------------------------------------

ARMA |

ar |

L1. | .1371192 .2510806 0.55 0.585 -.3549896 .6292281

L2. | -.2716296 .2457658 -1.11 0.269 -.7533217 .2100624

L3. | .6039898 .2191583 2.76 0.006 .1744473 1.033532

|

ma |

L1. | .0816527 .2859515 0.29 0.775 -.478802 .6421073

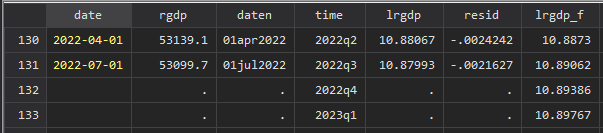
L2. | .4862875 .264004 1.84 0.065 -.0311508 1.003726

L3. | -.2101153 .230408 -0.91 0.362 -.6617067 .2414761

-------------+----------------------------------------------------------------

/sigma | .010944 .0005215 20.98 0.000 .0099218 .0119662

**. predict lrgdp\_f, y dynamic(q(2019q4))**



Here from the table, we can see, the forecasted log value of GDP for the next two quarters 2022q1 & 2023q1 is 10.89386 & 10.89767

Here I have used the GDP data up to quarter 4, 2019 (before COVID19) to predict or forecast GDP value up to 2023q1. So here we also got in sample forecast value (2020q1 – 2022q3). From the in-sample forecast value, we can find the forecast error. For example:

**= -0.00663**

From the in-sample forecast test, we can say that, predictive capabilities of the model developed using observed data is effective in reproducing data, where the forecast error is very small.