

# Econometrics III

## Assignment Part 1 & 2

### Tinbergen Insitute

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#### Question 1

##### Part (a)

```
# Part 1: Plot the Dutch GDP, ACF, and PACF
df <- readr::read_csv("./data/data_assign_p1.csv")

df <- ts(df$GDP_QGR,
         frequency = 4,
         start = c(1987, 2))
```

In the above figure, we observe the growth rates of Dutch GDP from 1987 to 2009.

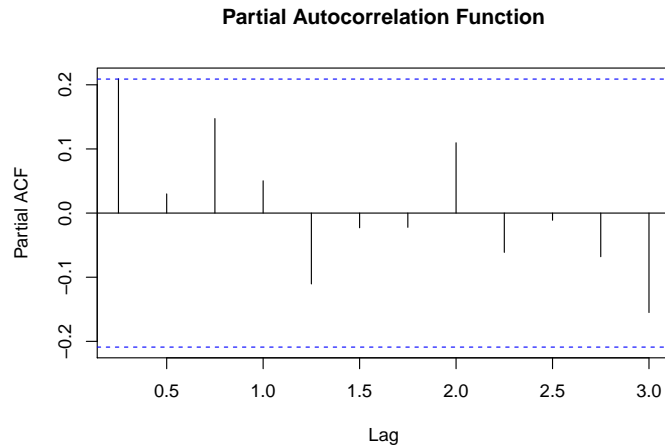
```
autoc <- acf(df,
             lag.max = 12, plot = F)

Box.test(df,
         lag = 12,
         type = "Ljung-Box")
```

```
##
## Box-Ljung test
##
## data:  df
## X-squared = 12.106, df = 12, p-value = 0.4372

pautoc <- pacf(df,
               lag.max = 12, plot = F)

plot(pautoc, main = "Partial Autocorrelation Function")
```



In the above figure, we plot the ACF and PACF, which is the ACF controlled for the other lagged correlations. The ACF tells us that the correlation of GDP growth with its lags is very low - hinting at very little time-dependence in this time-series. More precisely, the estimated correlation coefficients are not higher than 0.2 (for the lag of 1 period). If the GDP is indeed generated by an AR(p) process, the estimates show that the process has low  $\phi$ 's (in absolute value), indicating a low time dependence.

#### Part (b)

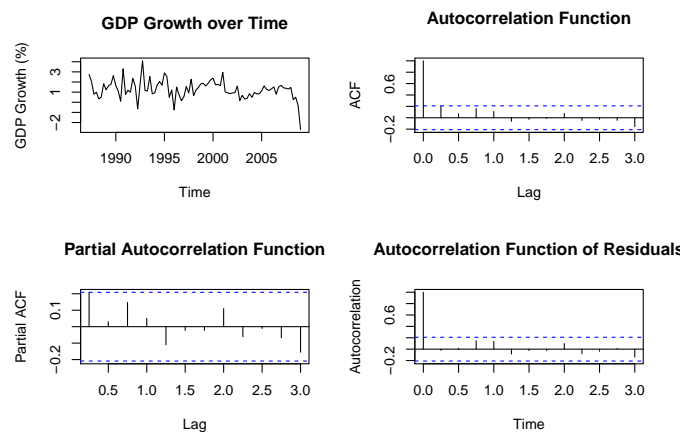
```
ar4 <- dynlm(df ~ L(df, 1) + L(df, 2) + L(df, 3) + L(df, 4))
ar3 <- dynlm(df ~ L(df, 1) + L(df, 3) + L(df, 4))
ar2 <- dynlm(df ~ L(df, 1) + L(df, 3))
ar1 <- dynlm(df ~ L(df, 1))

ar1_m <- forecast::Arima(df, c(1,0,0), method = "CSS")

stargazer(ar4, ar3, ar2, ar1, type = "latex", header = FALSE)
```

#### Part c

```
# Part 3: Plot ACF of residuals
autocred <- acf(ar1_m$resid, 12,
               plot = FALSE)
```



#### Part d

```
# Part 4: Forecast AR model for 2 years
df_pred <- predict(ar1_m, n.ahead = 8)$pred
```

#### Part e

Table 1:

	<i>Dependent variable:</i>			
	df			
	(1)	(2)	(3)	(4)
L(df, 1)	0.232* (0.124)	0.240* (0.122)	0.257** (0.119)	0.267** (0.117)
L(df, 2)	0.055 (0.126)			
L(df, 3)	0.203 (0.126)	0.210* (0.124)	0.210* (0.120)	
L(df, 4)	0.094 (0.125)	0.092 (0.124)		
Constant	0.479 (0.299)	0.533* (0.271)	0.631*** (0.238)	0.896*** (0.181)
Observations	84	84	85	87
R <sup>2</sup>	0.099	0.097	0.089	0.058
Adjusted R <sup>2</sup>	0.054	0.063	0.067	0.047
Residual Std. Error	0.902 (df = 79)	0.898 (df = 80)	0.891 (df = 82)	0.895 (df = 85)
F Statistic	2.181* (df = 4; 79)	2.873** (df = 3; 80)	4.019** (df = 2; 82)	5.229** (df = 1; 85)

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

```
# Part 5: Produce CI
df_ciu <- predict(ar1_m, n.ahead = 8)$pred + predict(ar1_m, n.ahead = 8)$se*1.96
df_cil <- predict(ar1_m, n.ahead = 8)$pred - predict(ar1_m, n.ahead = 8)$se*1.96
```

#### Part f

```
# Part 6: Check normality
jb.norm.test(ar1_m$resid)
```

```
##
##  Jarque-Bera test for normality
##
## data:  ar1_m$resid
## JB = 31.722, p-value = 0.001
# reject H0, innovations are not normally distributed
```