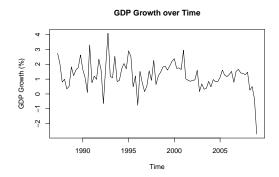
Econometrics III Assignment Part 1 & 2 Tinbergen Insitute

Stanislav Avdeev student no stnavdeev@gmail.com Bas Machielsen 590049bm 590049bm@eur.nl

March 11, 2021

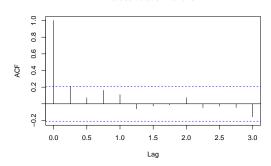
Question 1

Part (a)

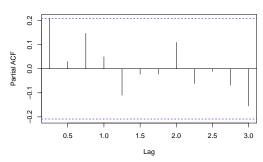


In the above figure, we observe the growth rates of Dutch GDP from 1987 to 2009.

Autocorrelation Function



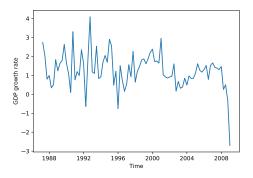
Partial Autocorrelation Function

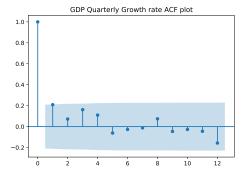


```
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.tsa.ar_model import AutoReg

# Data
df = pd.read_csv('./data/data_assign_p1.csv')
df['obs'] = pd.to_datetime(df['obs'])
df = df.set_index('obs')
```

```
## Question 1:
# General plot:
plt.plot(df['GDP_QGR'])
plt.xlabel('Time')
plt.ylabel('GDP growth rate')
plt.show()
# ACF plot:
```





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 ϕ '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))

stargazer(ar4, ar3, ar2, ar1, type = "latex", header = FALSE)</pre>
```

Table 1:

Table 1:				
	$\underline{\hspace{2cm}} Dependent \ variable: \\ df$			
	(1)	(2)	(3)	(4)
L(df, 1)	0.232^{*}	0.240^{*}	0.257**	0.267**
	(0.124)	(0.122)	(0.119)	(0.117)
L(df, 2)	0.055			
	(0.126)			
L(df, 3)	0.203	0.210^{*}	0.210^{*}	
	(0.126)	(0.124)	(0.120)	
L(df, 4)	0.094	0.092		
	(0.125)	(0.124)		
Constant	0.479	0.533^{*}	0.631***	0.896***
	(0.299)	(0.271)	(0.238)	(0.181)
Observations	84	84	85	87
\mathbb{R}^2	0.099	0.097	0.089	0.058
Adjusted R^2	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	$2.181^* \text{ (df} = 4; 79)$	$2.873^{**} (df = 3; 80)$	$4.019^{**} (df = 2; 82)$	$5.229^{**} (df = 1; 85)$

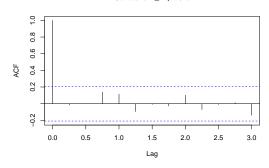
*p<0.1; **p<0.05; ***p<0.01

```
ar1_m <- arima(df, c(1, 0, 0))
```

Part c

```
# Part 3: Plot ACF of residuals
acf(ar1_m$resid, 12)
```

Series ar1_m\$resid



Part d

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

Part e

```
# 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</pre>
```

Part f

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

```
##
## Jarque-Bera test for normality
##
## data: ar1_m$resid
## JB = 26.298, p-value = 0.002
```

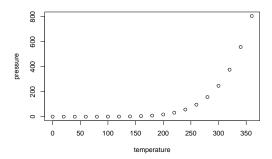
reject HO, innovations are not normally distributed

```
import pandas as pd
import numpy as np
r.mtcars.sum()
```

```
642.900
## mpg
            198.000
## cyl
           7383.100
## disp
           4694.000
## hp
## drat
            115.090
## wt
            102.952
## qsec
            571.160
             14.000
## vs
## am
             13.000
            118.000
## gear
## carb
             90.000
## dtype: float64
```

Including Plots

You can also embed plots, for example:



Note that the echo = FALSE parameter was added to the code chunk to prevent printing of the R code that generated the plot.

Including Matplotlib

```
hoi = np.arange(0,10)
hoi
```

```
## array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
#py$hoi
#gert::git_branch_checkout("attempt_bas")
#gert::git_add(c("*"))
#gert::git_commit(message = "Automatic commit")
#gert::git_push()
#gert::git_pull()
```