



Computer Lab in Economics Master in International Economics Time series analysis with Stata

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Time series analysis with Stata

What is a time serie?

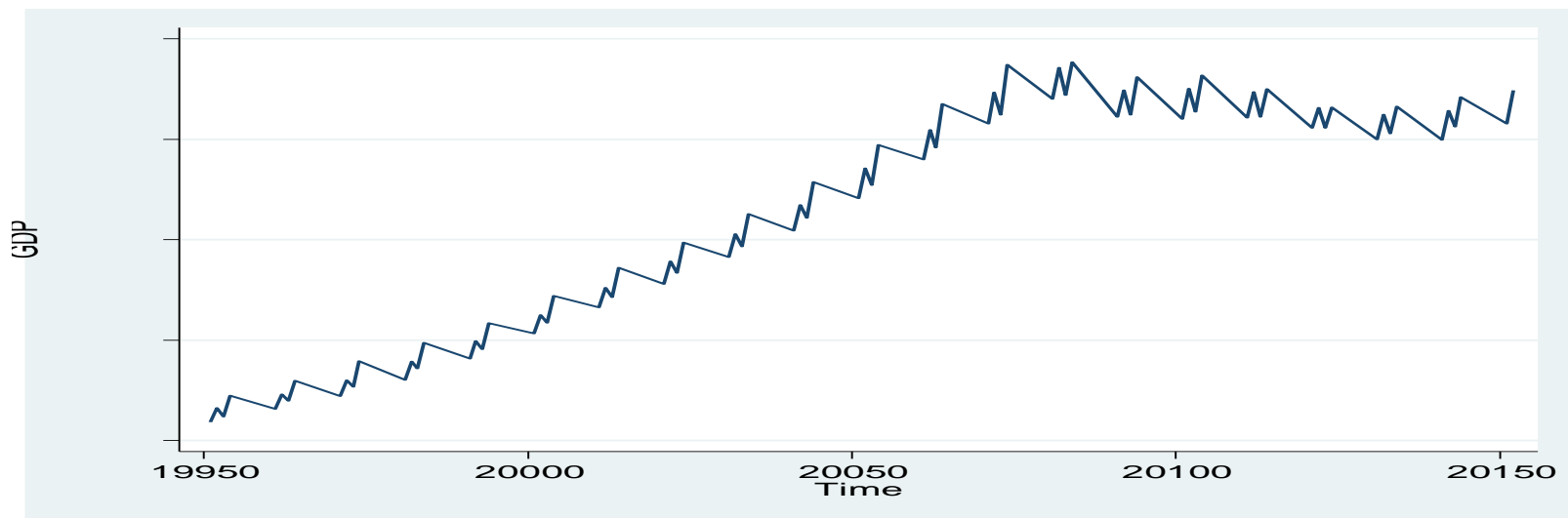
Some observations along time, discrete or continuous.

Example: national GDP in Spain:

. tsset time

time variable: time, 19951 to 20152, but with gaps delta: 1 unit

. twoway (tsline gdp)



Time series analysis with Stata

Classification:

- **Stationarity:** constant average and variance. To obtain stationary series we can apply two transformations:

First differences: to eliminate trends

Box-cox: to eliminate different variances

$$w_t = \begin{cases} (z_t^\lambda - 1)/\lambda & \lambda \neq 0 \\ \log z_t & \lambda = 0 \end{cases}$$

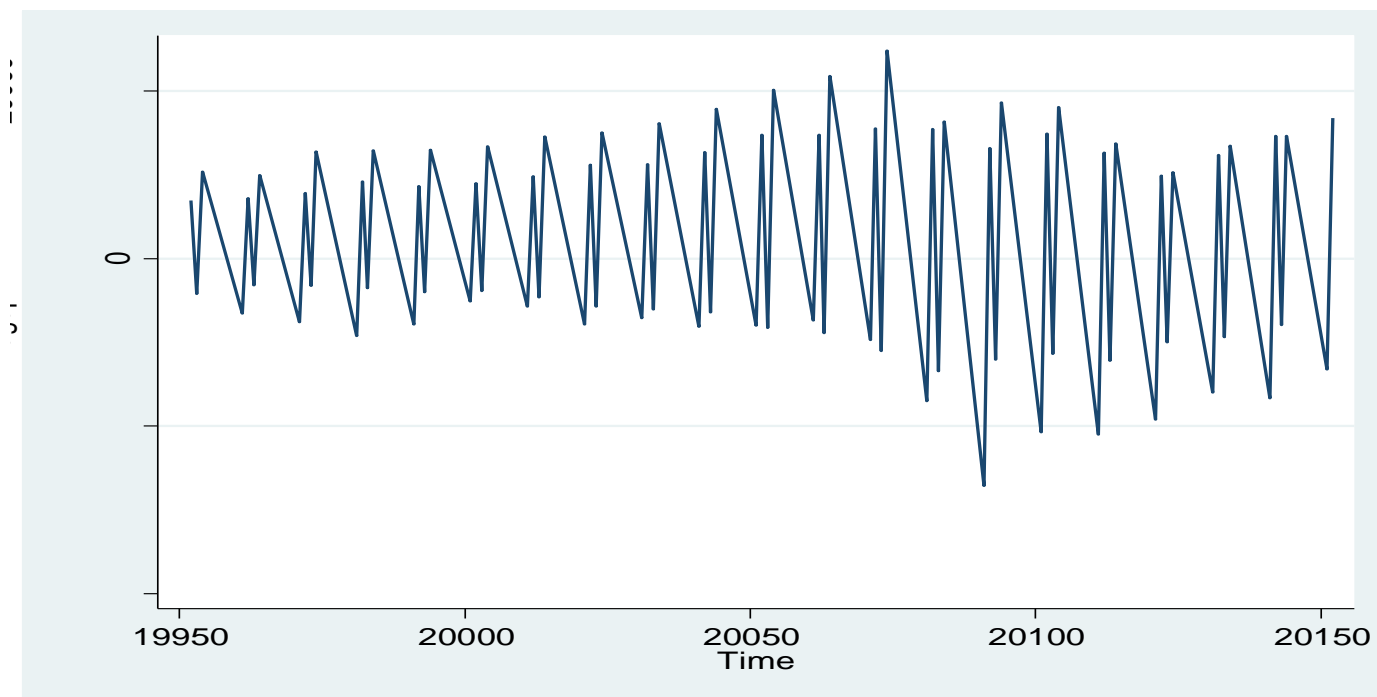
- **Seasonality:** seasonal trend

Time series analysis with Stata

Example: first differences in GDP

```
. generate gdp_1=gdp[_n-1]  
(1 missing value generated)
```

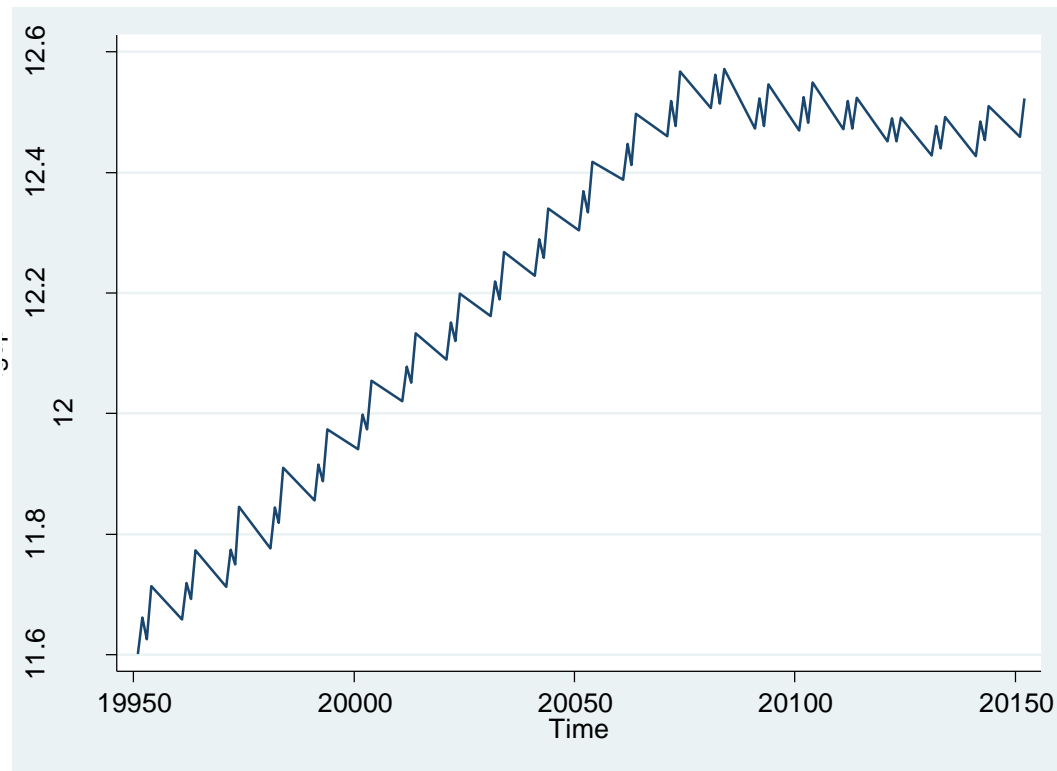
```
. generate dgdg=gdp-gdp_1  
(1 missing value generated)
```



Time series analysis with Stata

Example: logarithmic transformation of GDP

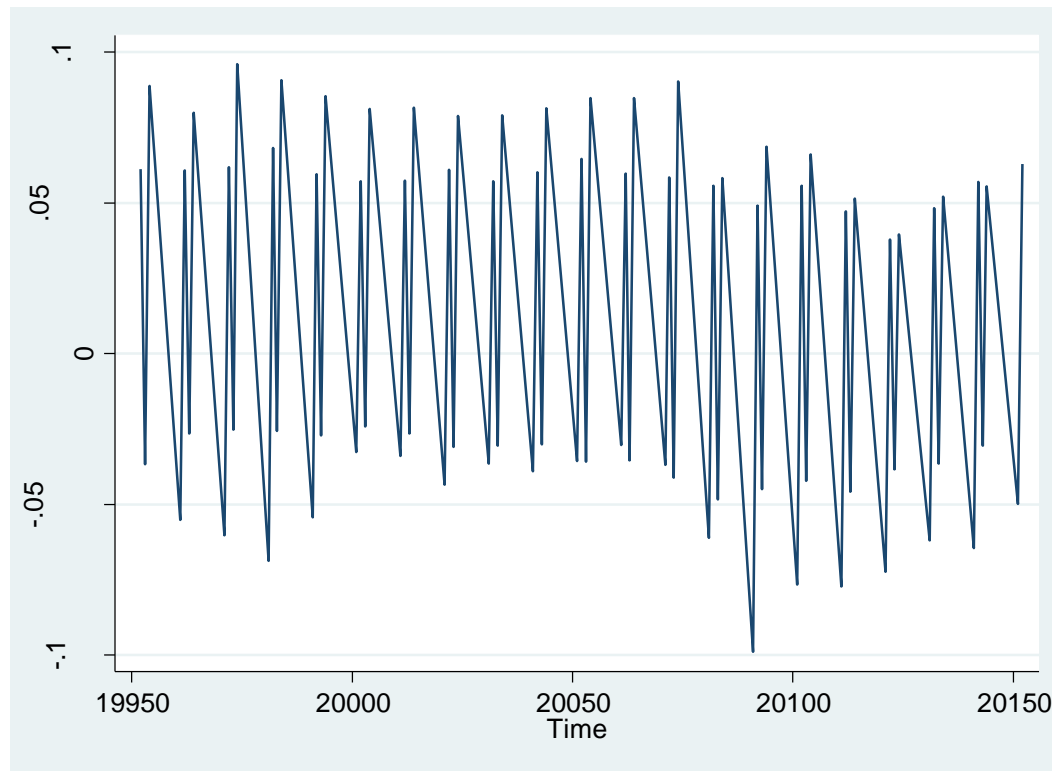
- . generate lgdp=ln(gdp)
- . twoway (tsline lgdp)



Time series analysis with Stata

Example: first differences in logarithmic transformation of GDP

```
. generate dlgdp=lgdp-lgdp[_n-1]  
(1 missing value generated)  
twoway (tsline dlgdp)
```



Time series analysis with Stata

Unit root tests: Dickey-Fuller

The Dickey–Fuller test involves fitting the model

$$y_t = \alpha + \rho y_{t-1} + \delta t + u_t$$

by ordinary least squares (OLS), perhaps setting $\alpha = 0$ or $\delta = 0$. However, such a regression is likely to be plagued by serial correlation. To control for that, the augmented Dickey–Fuller test instead fits a model of the form

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + \cdots + \zeta_k \Delta y_{t-k} + \epsilon_t \quad (1)$$

where k is the number of lags specified in the `lags()` option. The `noconstant` option removes the constant term α from this regression, and the `trend` option includes the time trend δt , which by default is not included. Testing $\beta = 0$ is equivalent to testing $\rho = 1$, or, equivalently, that y_t follows a unit root process.

Time series analysis with Stata

Unit root tests: Dickey-Fuller

Example: GDP

```
. dfuller gdp, lags(0)
```

Dickey-Fuller test for unit root

Number of obs = 61

----- Interpolated Dickey-Fuller -----				
Test	1% Critical	5% Critical	10% Critical	
Statistic	Value	Value	Value	

Z(t)	-0.109	-3.565	-2.921	-2.596

MacKinnon approximate p-value for Z(t) = 0.9485

we cannot reject the null hypothesis that GDP exhibits a unit root

Time series analysis with Stata

Unit root tests: Dickey-Fuller

Example: logarithmic transformation of GDP

```
. dfuller lgdp, lags(0)
```

Dickey-Fuller test for unit root

Number of obs = 61

----- Interpolated Dickey-Fuller -----				
	Test	1% Critical	5% Critical	10% Critical
	Statistic	Value	Value	Value

Z(t)	-1.433	-3.565	-2.921	-2.596

MacKinnon approximate p-value for Z(t) = 0.5665

we cannot reject the null hypothesis that log GDP exhibits a unit root

Time series analysis with Stata

Unit root tests: Dickey-Fuller

Example: first differences of logarithmic transformation of GDP

```
. dfuller dlgdp , lags(0)
```

Dickey-Fuller test for unit root Number of obs = 60

----- Interpolated Dickey-Fuller -----				
	Test	1% Critical	5% Critical	10% Critical
	Statistic	Value	Value	Value

Z(t)	-30.265	-3.566	-2.922	-2.596

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

Here we can overwhelmingly reject the null hypothesis of a unit root at all common Significance levels

Time series analysis with Stata

Decomposition of a time series

A time series can be decomposed into:

$$z_t = T_t + S_t + a_t$$

- Tendency (T)
- Seasonality (S)
- Irregular term (a)

We can use a filter to obtain these components.

Time series analysis with Stata

Decomposition of a time series

Example: decomposition of GDP.

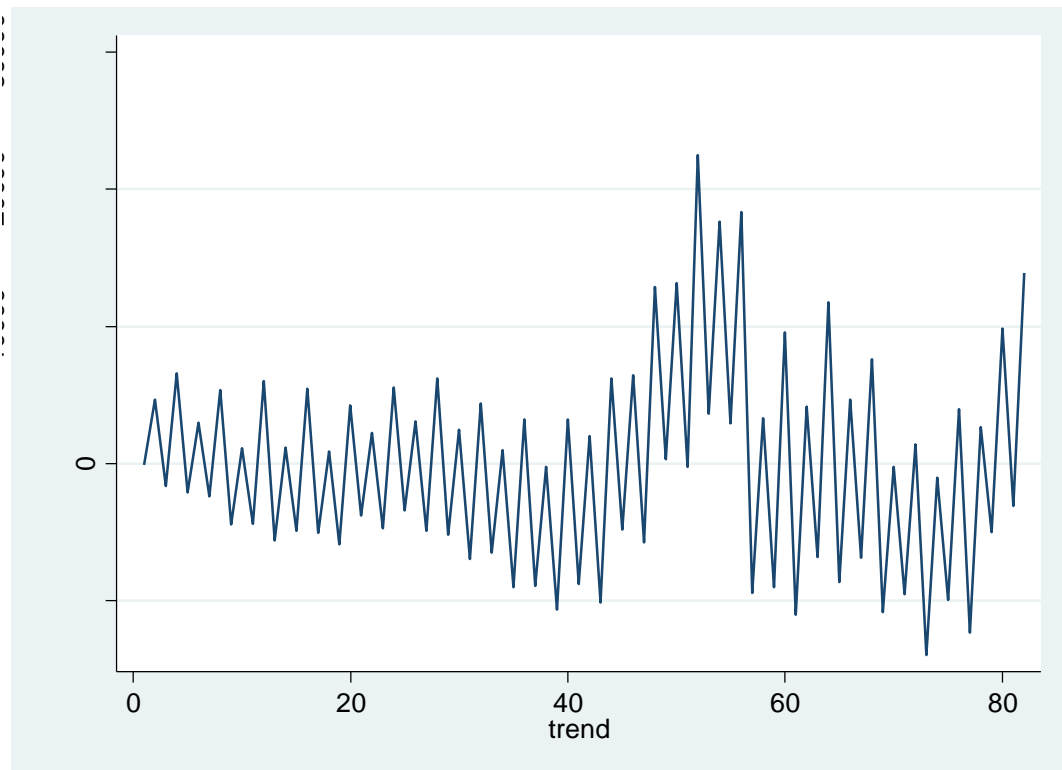
```
tsset trend
```

```
time variable: trend, 1 to 82
```

```
delta: 1 unit
```

```
hprescott gdp, stub(hp)
```

```
twoway (tsline hp_gdp_1)
```



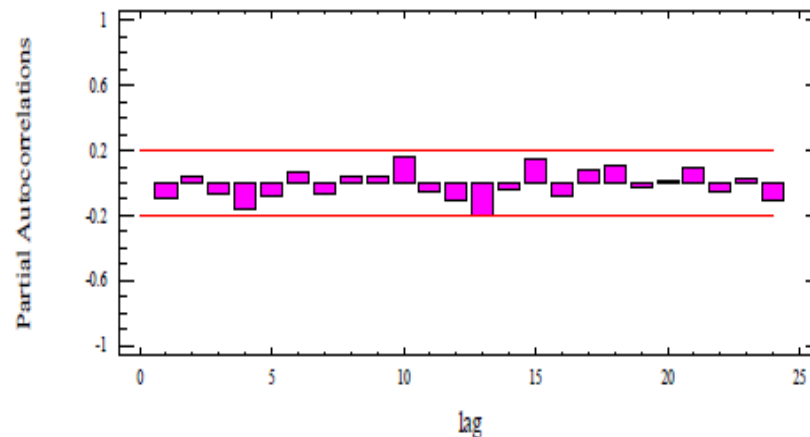
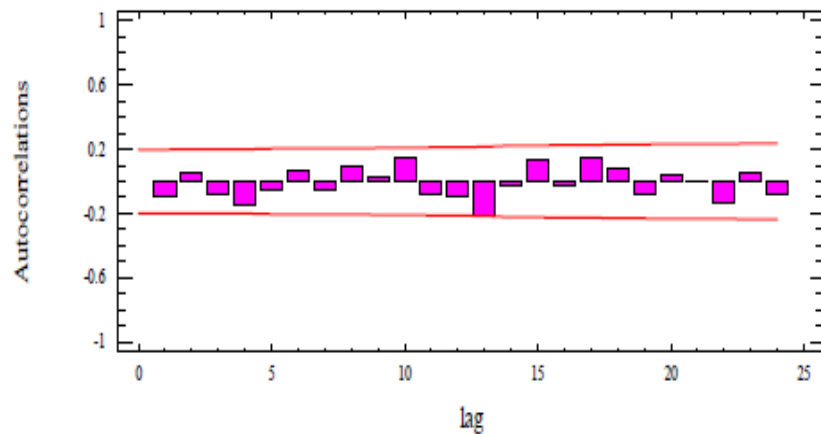
Time series analysis with Stata

Analysis of a time series

Simple Autocorrelation Function: autocorrelation between one observation and the followers.

Partial Autocorrelation Function: only direct correlation between one observation and those separated k lags.

White noise autocorrelation



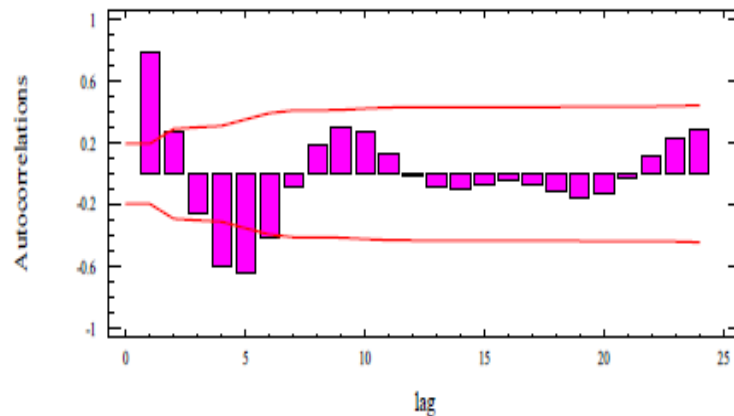
Time series analysis with Stata

Analysis of a time series Autoregressive process, AR(p)

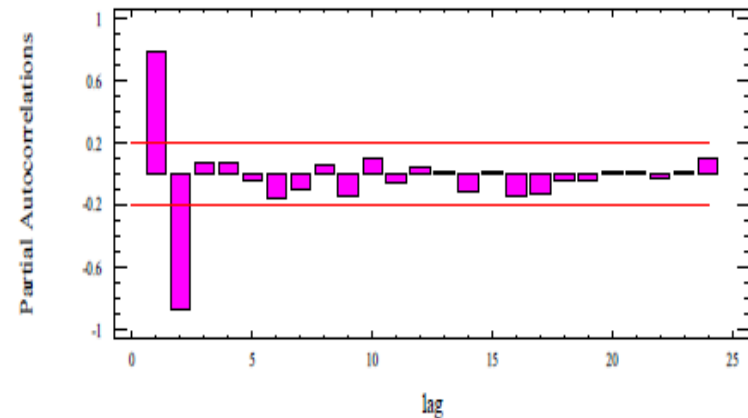
$$z_t = c + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} + a_t$$

AR(2)

Simple Autocorrelation Function
(more complex)



Partial Autocorrelation Function
(P significant elements)



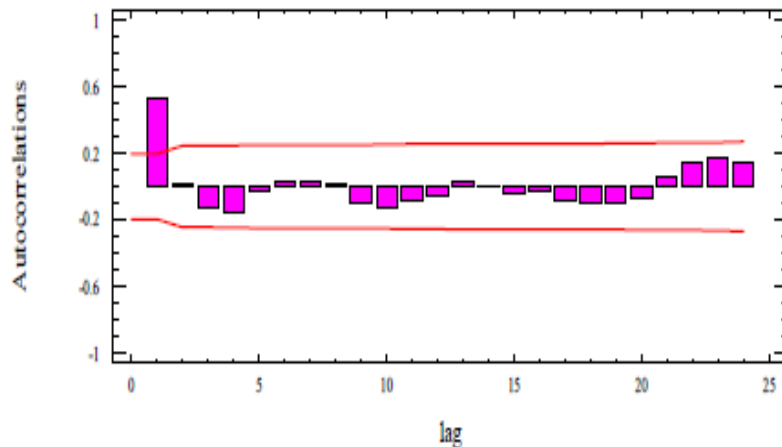
Time series analysis with Stata

Analysis of a time series Moving average process, MA(q)

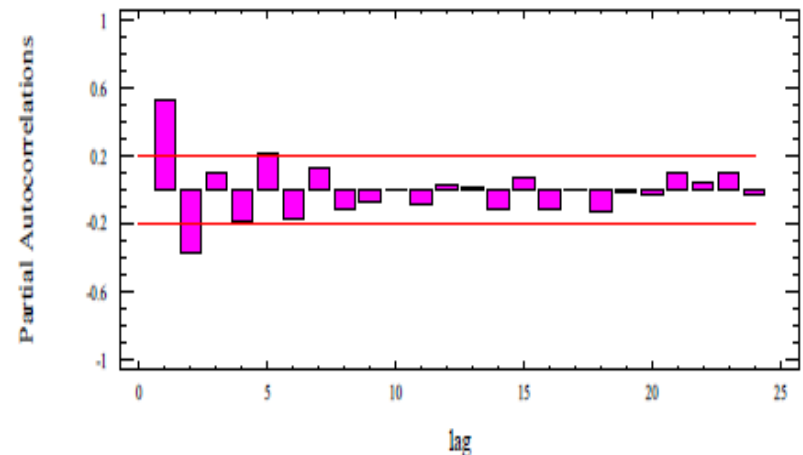
$$z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}$$

MA(1)

Simple Autocorrelation Function
(q significant elements)



Partial Autocorrelation Function
(decreasing)



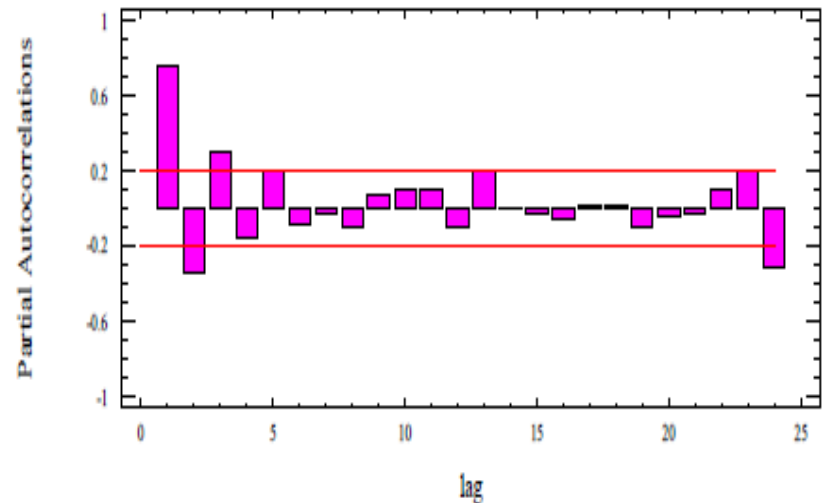
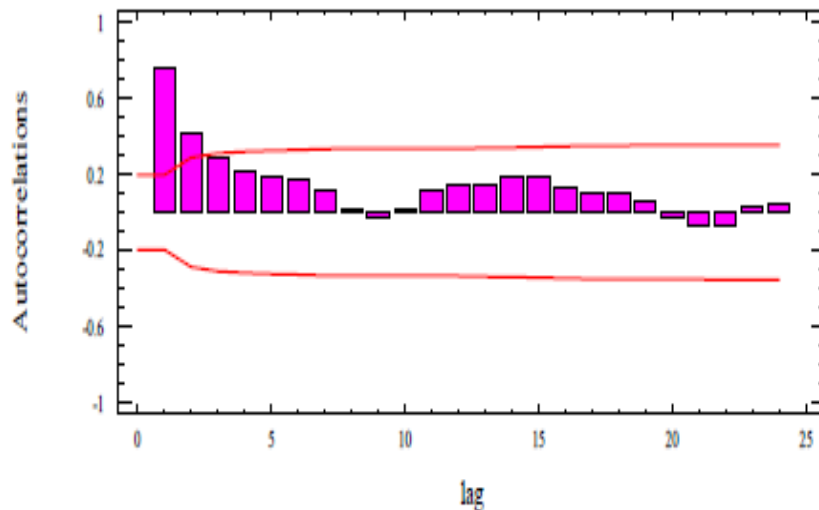
Time series analysis with Stata

Analysis of a time series ARMA(p,q)

ARMA(1,1)

Simple Autocorrelation Function
(q significant elements)

Partial Autocorrelation Function
(p significant elements)



Time series analysis with Stata

Analysis of a time series

ARIMA(p,d,q)

$$Y_t = -(\Delta^d Y_t - Y_t) + \phi_0 + \sum_{i=1}^p \phi_i \Delta^d Y_{t-i} - \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t$$

p: autorregresive order

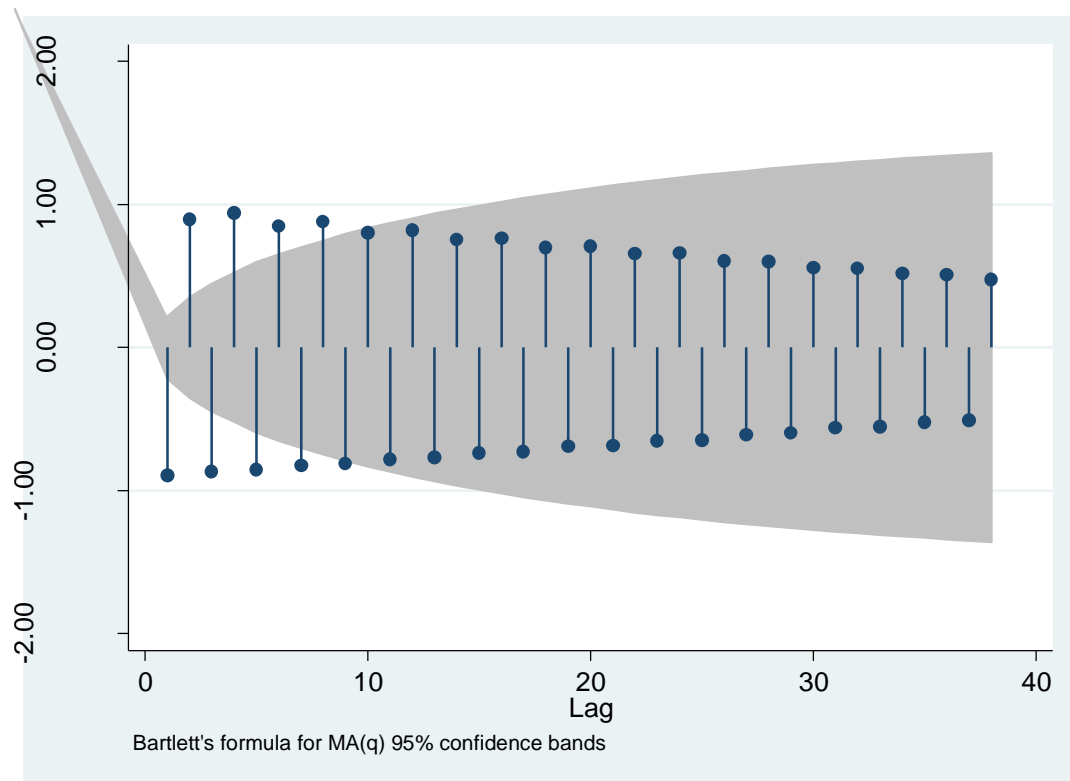
d: diferenciacion to became an stationary serie

q: moving average order

Time series analysis with Stata

Analysis of a time series

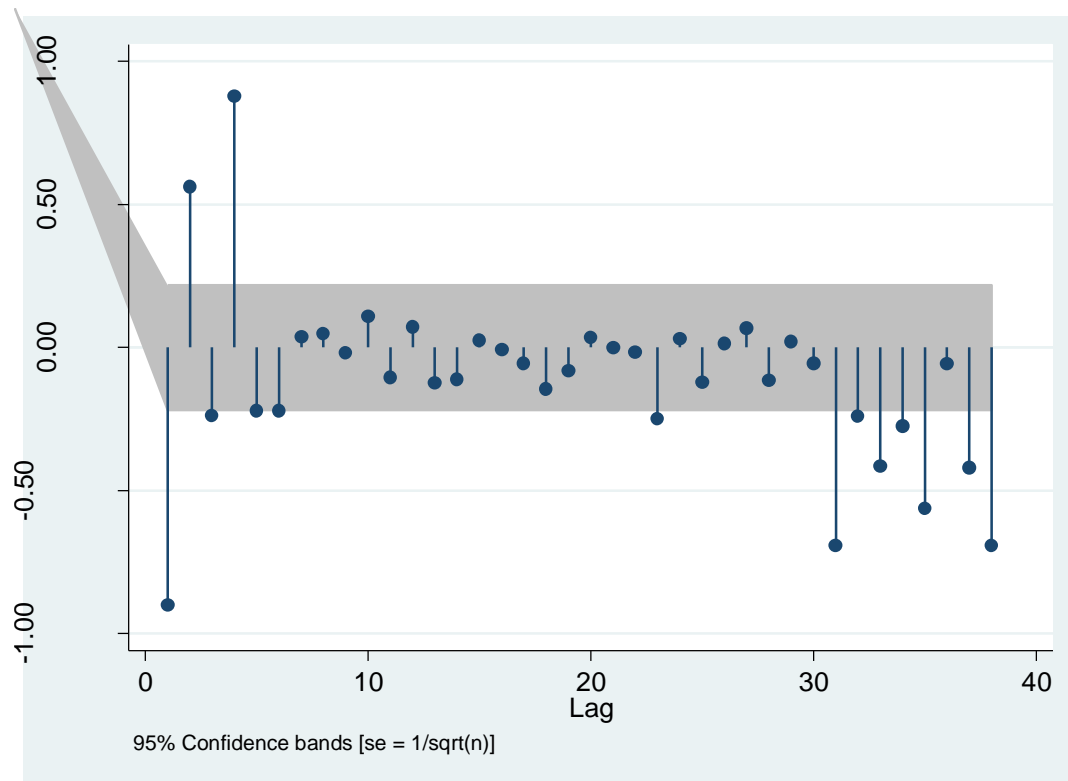
Example: analysis of GDP
ac dlgdp



Time series analysis with Stata

Analysis of a time series

`pac dlgdp`



Time series analysis with Stata

```
. arima lgdp, arima(2,1,0)
```

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

```
Iteration 0:    log likelihood =   198.37159
```

```
Iteration 1:    log likelihood =   198.41042
```

```
Iteration 2:    log likelihood =   198.41266
```

```
Iteration 3:    log likelihood =   198.41298
```

```
Iteration 4:    log likelihood =   198.41305
```

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

```
Iteration 5:    log likelihood =   198.41307
```

```
Iteration 6:    log likelihood =   198.41307
```

```
ARIMA regression
```

```
Sample:    2 - 82
```

```
Number of obs      =           81
```

```
Wald chi2(2)       =        395.63
```

```
Log likelihood =   198.4131
```

```
Prob > chi2        =           0.0000
```

D.lgdp	OPG		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
lgdp						
_cons	.010739	.0028034	3.83	0.000	.0052445	.0162336
ARMA						
ar						
L1.	-.4003017	.1097632	-3.65	0.000	-.6154337	-.1851698
L2.	.5544669	.1151749	4.81	0.000	.3287282	.7802056
/sigma	.0205855	.0022768	9.04	0.000	.016123	.0250481

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

Time series analysis with Stata

$$\begin{aligned} GDP_t \\ = -(\Delta GDP_t - GDP_t) + 0.01 - 0.40\Delta GDP_{t-1} \\ + 0.55\Delta GDP_{t-2} \end{aligned}$$