

*Unit root,  
differencing the time series, unit root test  
(ADF test)*

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Time series analysis

# Outline

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- What is a unit root and what is its consequence
- If we have unit root - how to transform the data, so that we can use the ARMA methodology
- How to find from the data that there is a unit root → unit root tests

# Examples

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- Consider the process  $y_t = y_{t-1} + u_t$ :
  - ◇ it is a nonstationary AR(1) process with a unit root
  - ◇ for its differences  $\Delta y_t = y_t - y_{t-1}$  we have
$$\Delta y_t = u_t$$
  - ◇ so  $\Delta y_t$  is a stationary process

- Consider a nonstationary process with a unit root

$$(1 - \frac{1}{2}L)(1 - L)x_t = 1 + (1 - \frac{1}{3}L)u_t$$

Then for the differences

$$\Delta y_t = y_t - y_{t-1} = (1 - L)y_t$$

we have

$$(1 - \frac{1}{2}L)\Delta y_t = 1 + (1 - \frac{1}{3}L)u_t,$$

so  $\Delta y_t$  is a stationary process

# Examples

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- Consider nonstationary process with a double unit root

$$(1 - \frac{1}{2}L)(1 - L)^2 x_t = 1 + (1 - \frac{1}{3}L)u_t$$

The for the second differences

$$\Delta^2 y_t = \Delta(\Delta y_t) = (1 - L)(1 - L)y_t = (1 - L)^2 y_t$$

we have

$$(1 - \frac{1}{2}L)\Delta^2 y_t = 1 + (1 - \frac{1}{3}L)u_t,$$

so  $\Delta^2 y_t$  is a stationary process

- In general:  
If the multiplicity of the unit root is  $k$  (and the others are outsider the unit circle), then its  $k$ -th differences are stationary.

# ARIMA models

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- We need need to differentiate the process  $k$  times, in order to get a stationary process, it is called **intergrated process of order  $k$** , denoted by  $I(k)$
- If these  $k$ -th differences follow ARMA(p,q), then we say that the original time series is **ARIMA(p,k,q)**.
- For example  $x_t$ , if

$$\left(1 - \frac{1}{2}L\right)(1 - L)^2 x_t = 1 + \left(1 - \frac{1}{3}L\right)u_t,$$

is ARIMA(1,2,1) process.

# Our aim

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- Consider firstly AR(1) model:  $x_t = \delta + \rho x_{t-1} + u_t$
- We want to:
  - ◇ test a hypothesis about a unit root (then, the process is nonstationary), so  $H_0 : \rho = 1$
  - ◇ find out it can be rejected in favour of the stationarity -  $H_1 : \rho < 1$

# Unit root and the t-statistics

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We try to use the hypothesis testing about coefficients of a regression model known from econometrics.

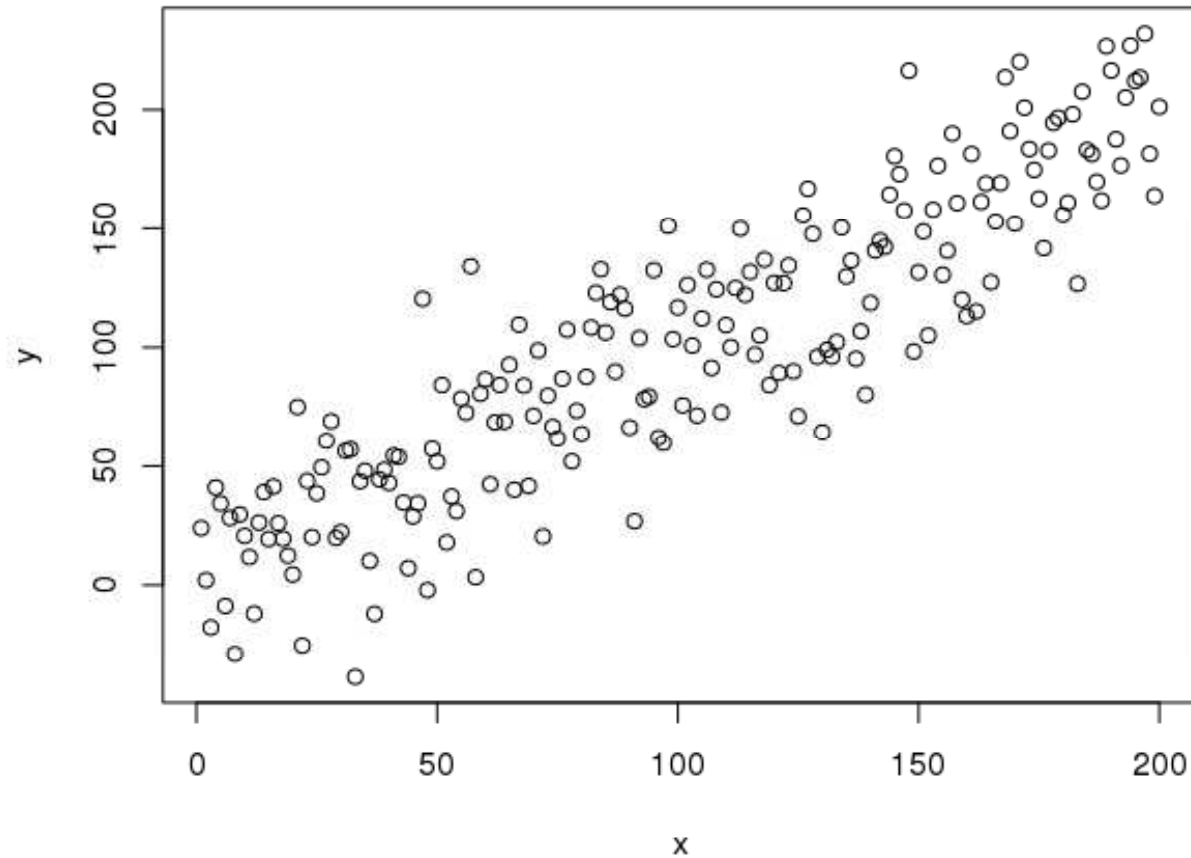
For example:

- Set  $x=1:200$
- Simulate  $y=x+rnorm(200)*sigma$
- Estimate the model  $y = c + \rho x + \varepsilon$
- We note:
  - ◇ estimate of the parameter  $\rho$
  - ◇ value of the t-statistics corresponding to hypothesis  $H_0 : \rho = 1$  (which holds)
- Repeat  $10^5$  times and plot the histogram

# Unit root and the $t$ -statistics

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- Example of the simulated data:





# Unit root and the t-statistics

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- Estimated regression:

```
Call:
lm(formula = y ~ x)

Residuals:
    Min       1Q   Median       3Q      Max
-75.067 -19.239   3.818  20.520  74.772

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.72079     4.00941   1.177   0.24
x            0.95689     0.03459  27.662 <2e-16 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

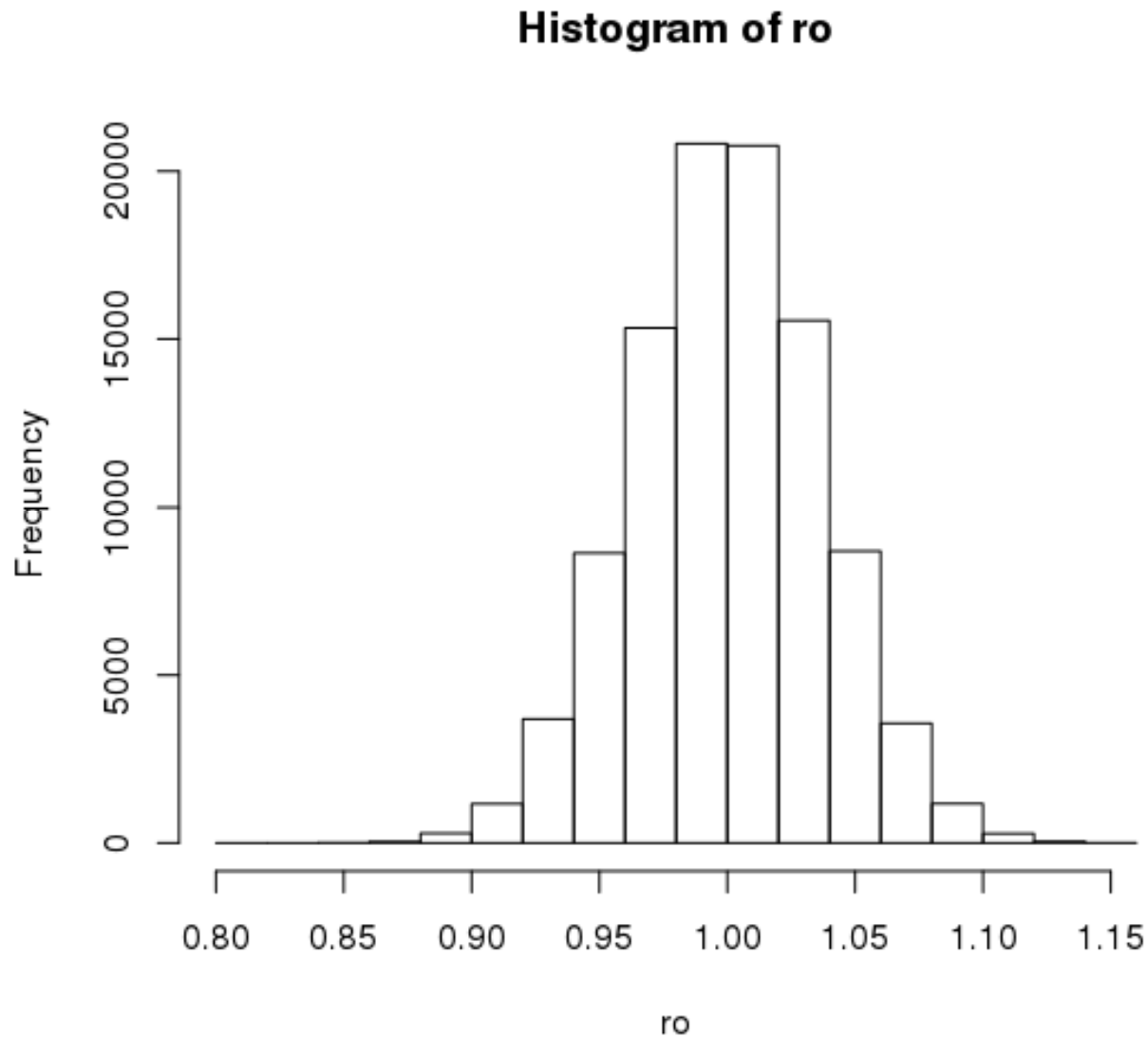
Residual standard error: 28.24 on 198 degrees of freedom
Multiple R-squared:  0.7944,    Adjusted R-squared:  0.7934
F-statistic: 765.2 on 1 and 198 DF,  p-value: < 2.2e-16
```

- Estimated coefficient  $\rho$  is 0.95689
- T-statistics to test  $\rho = 1$  is  $\frac{0.95689-1}{0.03459}$

# Unit root and the $t$ -statistics

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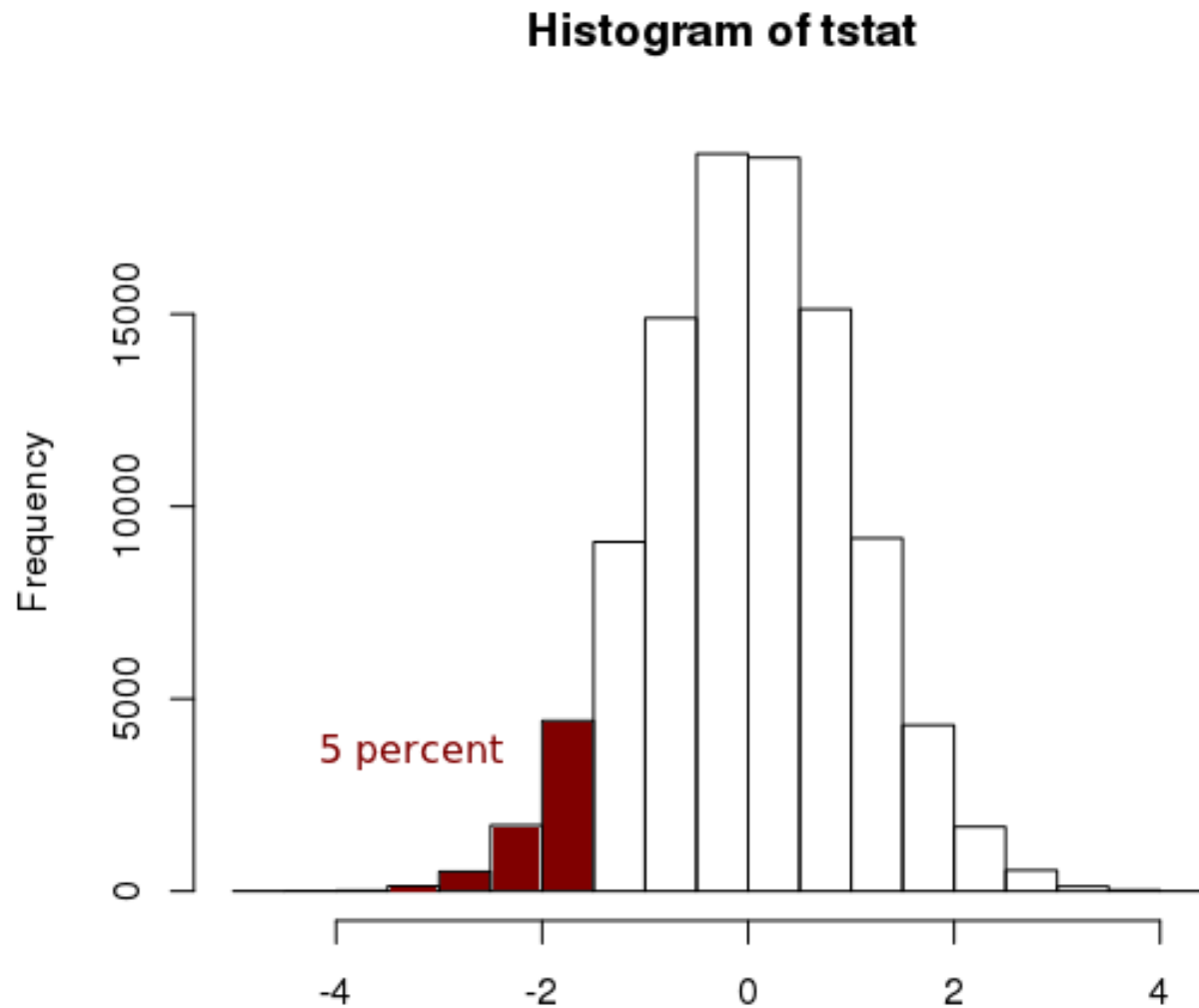
- Estimated of  $\rho$ : normal distribution



# Unit root and the $t$ -statistics

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- $t$ -statistics to test  $H_0 : \rho = 1$ : Student  $t$ -distribution



# Unit root and the t-statistics

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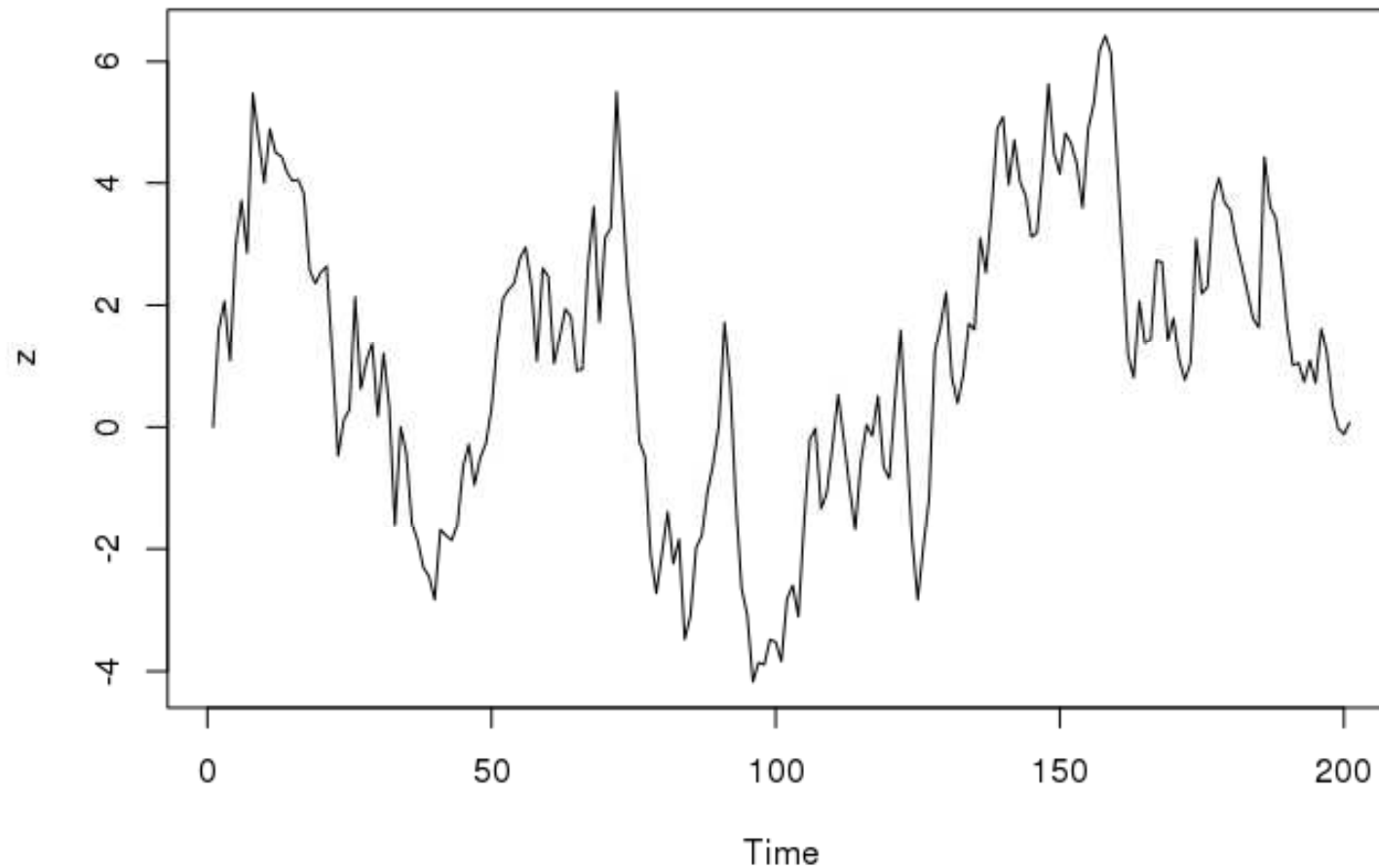
Another simulation:

- Consider vector  $\mathbf{z}$  generated as  $z_t = z_{t-1} + \varepsilon_t$
- Take  $\mathbf{x}=\mathbf{z}[1:200]$ ,  $\mathbf{y}=\mathbf{z}[2:201]$ , so  $y_t = z_t$ ,  $x_t = z_{t-1}$
- Estimate the model  $y = c + \rho x + \varepsilon$
- Note again:
  - ◇ estimate of parameter  $\rho$
  - ◇ value of t-statistics to test  $H_0 : \rho = 1$  (which holds)
- Repeat  $10^5$  times and plot the histogram

# Unit root and the $t$ -statistics

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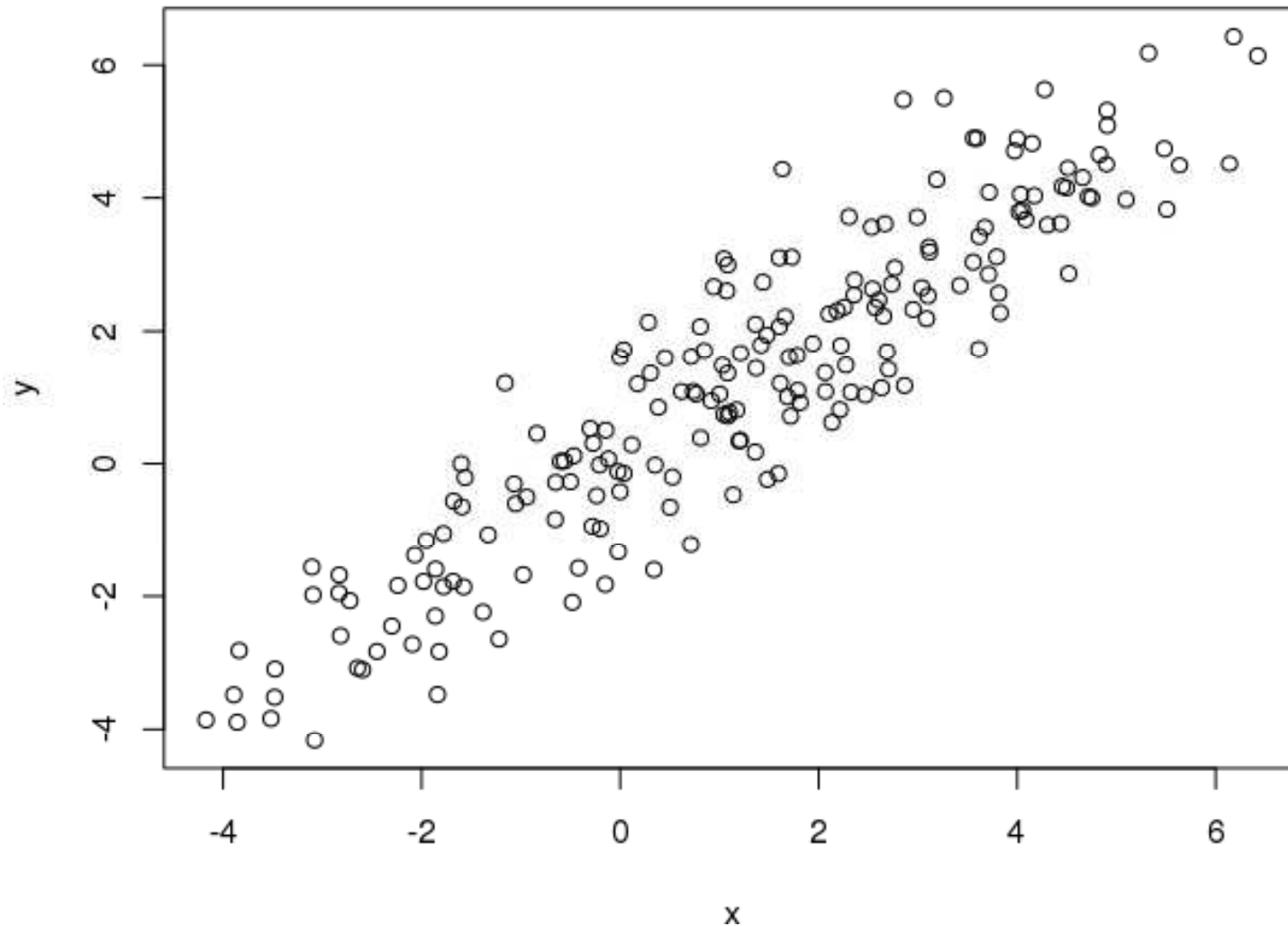
- Example of simulated data - time series  $z$ :



# *Unit root and the t-statistics*

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- Example of simulated data - data for regression



# Unit root and the t-statistics

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- Estimated regression:

```
Call:
lm(formula = y ~ x)

Residuals:
    Min       1Q   Median       3Q      Max
-2.01047 -0.64723  0.00159  0.53995  2.84017

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.09589   0.07489    1.28   0.202
x            0.91962   0.02790   32.96 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

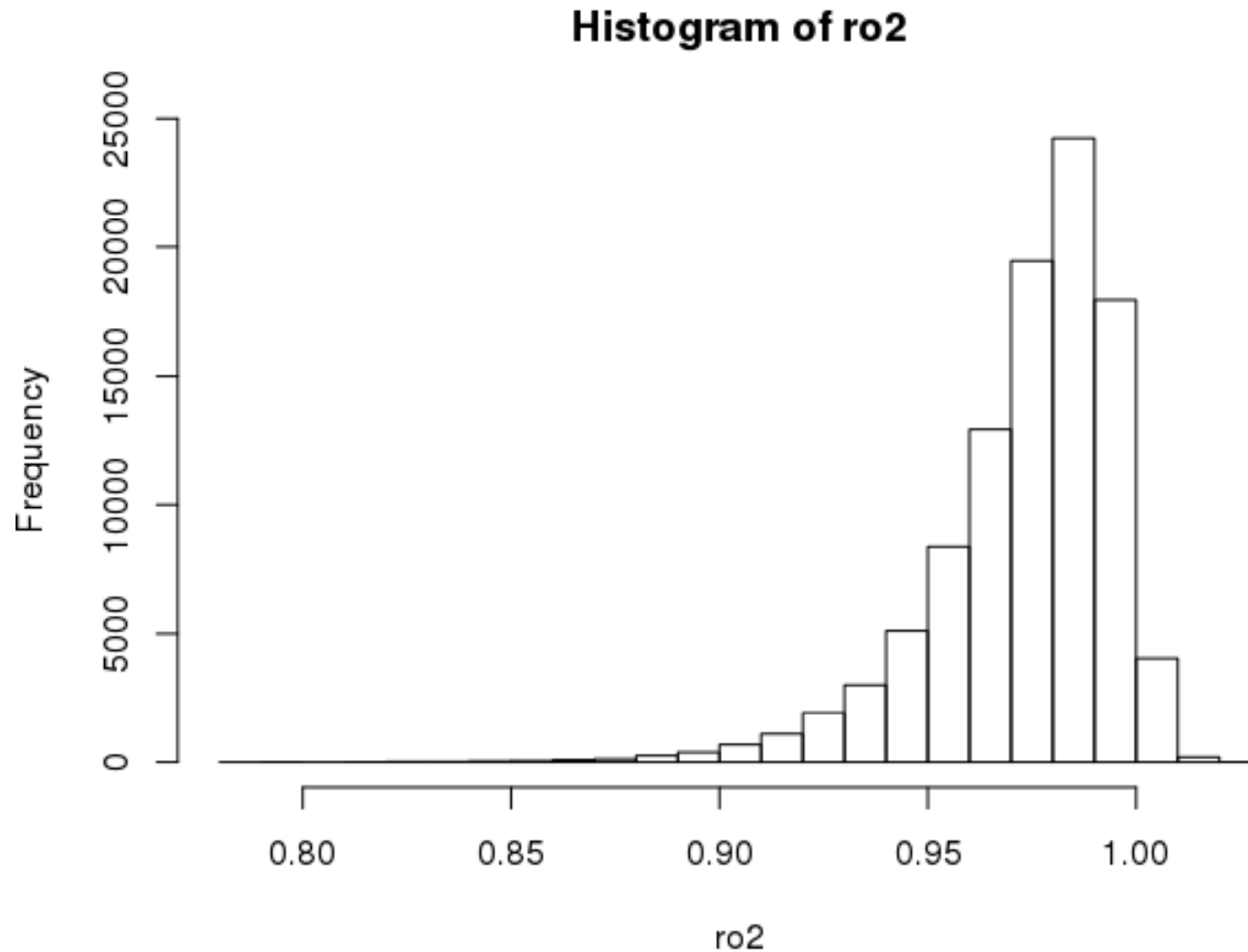
Residual standard error: 0.9496 on 198 degrees of freedom
Multiple R-squared:  0.8458,    Adjusted R-squared:  0.845
F-statistic: 1086 on 1 and 198 DF,  p-value: < 2.2e-16
```

- Estimated coefficient  $\rho$  is 0.91962
- t-statistics to test  $\rho = 1$  is  $\frac{0.91962-1}{0.02790} = -2.88$

# Unit root and the $t$ -statistics

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- Estimates of parameter  $\rho$ : not a normal distribution

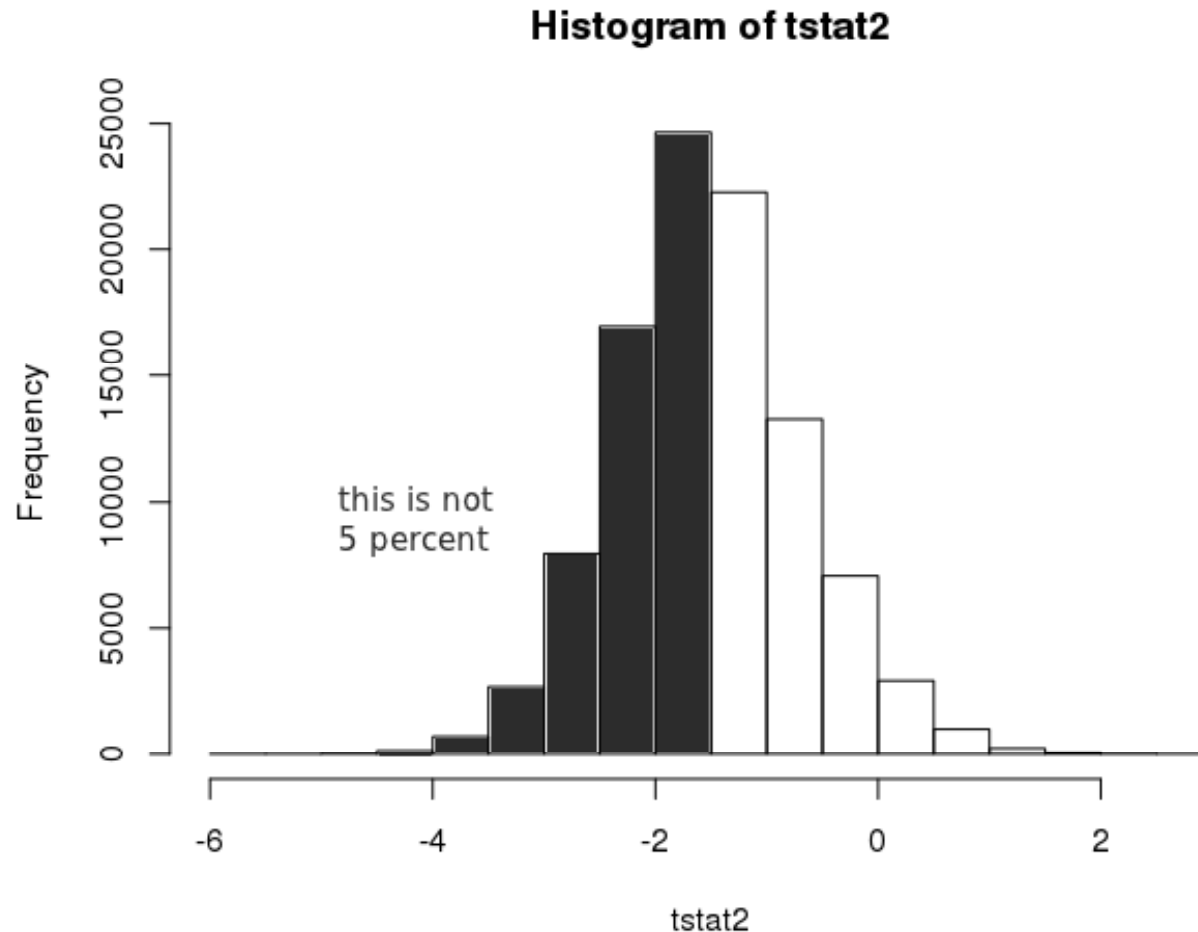




# Unit root and the $t$ -statistics

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- "t-statistics" to test  $H_0 : \rho = 1$ : does not have a  $t$ -distribution



- We cannot use critical values of the  $t$ -distribution

# Unit root and the $t$ -statistics

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- Solution - the main idea:
  - ◇ we keep the test statistics
  - ◇ but we use different critical values
- Quantiles from our simulations:

```
> quantile(tstat2,0.05)
      5%
-2.866481
> quantile(tstat2,0.01)
      1%
-3.462751
```

- critical values should be similar

- Question:
  - ◇ What if we have a process of a higher order instead of AR(1)?

# Unit root tests

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- AR(1) process:

$$(1) \quad y_t = \rho y_{t-1} + u_t$$

unit root means that  $\rho = 1$ .

- Equivalently:

$$\Delta y_t = (\rho - 1)y_{t-1} + u_t$$

and we are interested in t-statistics from the significance of coefficient at  $y_{t-1}$  - but with another critical value

- This critical value
  - ◇ depends on number of data
  - ◇ changes, if equation (1) has a constant term or a linear drift
- In general:  $\Delta y_t = \alpha + \beta t + (\rho - 1)y_{t-1} + u_t$

# Unit root tests

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- AR(p) process:  $y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \dots + \alpha_p y_{t-p} + u_t$   
unit root  $\rightarrow \alpha_1 + \dots + \alpha_p = 1$ .

- Write in the form:

$$y_t = \rho y_{t-1} + \theta_1 \Delta y_{t-1} + \theta_2 \Delta y_{t-2} + \dots + \theta_{p-1} \Delta y_{t-p+1} + u_t,$$

$$\text{where } \rho = \sum_{j=1}^p \alpha_j, \theta_i = -\sum_{j=i+1}^p \alpha_j \quad (i = 1, \dots, p-1)$$

- Equivalently:

$$\Delta y_t = (\rho - 1) y_{t-1} + \theta_1 \Delta y_{t-1} + \theta_2 \Delta y_{t-2} + \dots + \theta_{p-1} \Delta y_{t-p+1} + u_t$$

and we are interested in **t-statistics for coefficient at**

$$y_{t-1}$$

- In general:  $y$  can have a trend and/or intercept  $\Rightarrow$

$$\Delta y_t = \alpha + \beta t + (\rho - 1) y_{t-1} + \theta_1 \Delta y_{t-1} + \theta_2 \Delta y_{t-2} + \dots + \theta_{p-1} \Delta y_{t-p+1} + u_t$$

# Augmented Dickey-Fuller test (ADF)

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Wayne A. Fuller (1976)

David A. Dickey, Wayne A. Fuller (1979, 1981)

- We estimate

$$\Delta y_t = \alpha + \beta t + (\rho - 1)y_{t-1} + \theta_1 \Delta y_{t-1} + \dots + \theta_k \Delta y_{t-k} + u_t$$

where we have to

- ◇ decide whether to include a constant  $\alpha$  and/or linear trend  $\beta$  (depending on whether they are present in process  $y$ )
- ◇ choose  $k$
- Then, we are interested in t-statistics from significance test about coefficient in front of  $y_{t-1}$ , but with correct critical values

# ADF test - critical values

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- James G. MacKinnon (1991) - available as a part of an expanded version from 2010:

James G. MacKinnon: **Critical Values for Cointegration Tests**. Queen's Economics Department Working Paper No. 1227, 2010..

Dostupné online: <http://ideas.repec.org/p/qed/wpaper/1227.html>

- Values obtained by simulations:

Table 1. Response Surface Estimates of Critical Values

| $N$ | Variant     | Level | Obs. | $\beta_\infty$ | (s.e.)   | $\beta_1$ | $\beta_2$ |
|-----|-------------|-------|------|----------------|----------|-----------|-----------|
| 1   | no constant | 1%    | 600  | -2.5658        | (0.0023) | -1.960    | -10.04    |
|     |             | 5%    | 600  | -1.9393        | (0.0008) | -0.398    |           |
|     |             | 10%   | 560  | -1.6156        | (0.0007) | -0.181    |           |
| 1   | no trend    | 1%    | 600  | -3.4336        | (0.0024) | -5.999    | -29.25    |
|     |             | 5%    | 600  | -2.8621        | (0.0011) | -2.738    | -8.36     |
|     |             | 10%   | 600  | -2.5671        | (0.0009) | -1.438    | -4.48     |
| 1   | with trend  | 1%    | 600  | -3.9638        | (0.0019) | -8.353    | -47.44    |
|     |             | 5%    | 600  | -3.4126        | (0.0012) | -4.039    | -17.83    |
|     |             | 10%   | 600  | -3.1279        | (0.0009) | -2.418    | -7.58     |

# ADF test - critical values

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- If we use  $T$  data points in the regression, the critical value is  $\beta_{\infty} + \beta_1/T + \beta_2/T^2$
- In our example from the simulations: constant without trend,  $T = 200$ :

| $N$ | Variant  | Level | Obs. | $\beta_{\infty}$ | (s.e.)   | $\beta_1$ | $\beta_2$ |
|-----|----------|-------|------|------------------|----------|-----------|-----------|
| 1   | no trend | 1%    | 600  | -3.4336          | (0.0024) | -5.999    | -29.25    |
|     |          | 5%    | 600  | -2.8621          | (0.0011) | -2.738    | -8.36     |
|     |          | 10%   | 600  | -2.5671          | (0.0009) | -1.438    | -4.48     |

- ◇ for 1 percent:  
$$-3.4336 - 5.999/200 - 29.25/200^2 = -3.451$$
- ◇ for 5 percent:  
$$-2.8621 - 2.738/200 - 8.36/200^2 = -2.879$$
- Compare with t-distribution (different) and quantiles from simulations (ok)

# *ADF test in R*

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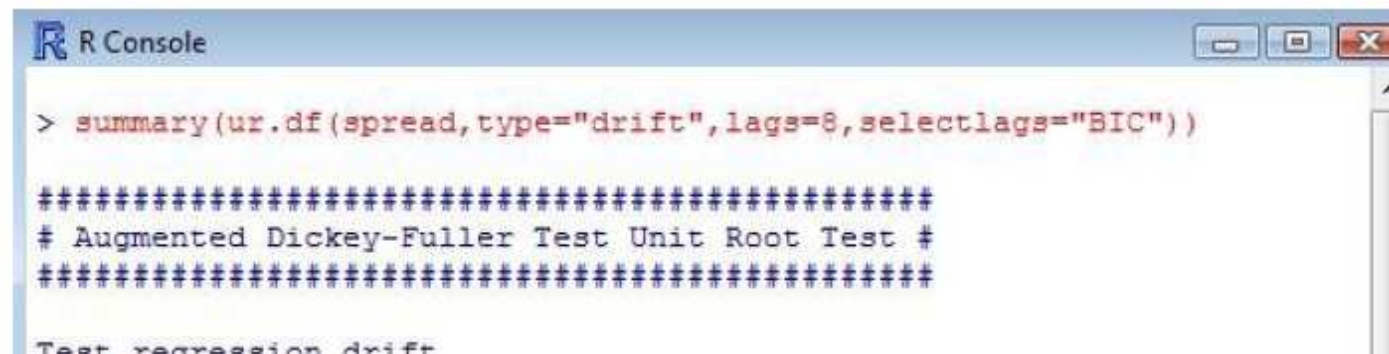
- Library `urca`
- Function `ur.df` (ur - unit root, df - Dickey-Fuller) with parameters:
  - ◇ `type`: possible values are `drift` (constant without linear trend), `trend` (constant and linear trend), `none` (nothing)
  - ◇ `lags`: maximal number of lags
  - ◇ `selectlags`: criterion for the choice of lags (information criteri: AIC, BIC)



# ADF test in R

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- Example: **spread** from the earlier lectures (difference between long-term and short-term rates)
- In R:  
`summary(ur.df(spread,type="drift",lags=8,selectlags="BIC"))`
- `summary` in order to obtain also critical values, not only the test statistics



```
R Console
> summary(ur.df(spread,type="drift",lags=8,selectlags="BIC"))

#####
# Augmented Dickey-Fuller Test Unit Root Test #
#####

Test regression drift
```

# ADF test in R

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- Výstup: estimated regression and the test statistics:

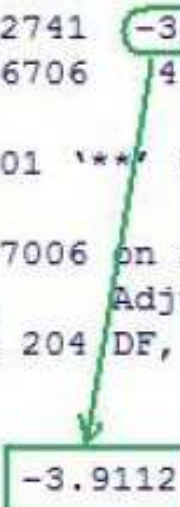
```
Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
    Min       1Q   Median       3Q      Max
-2.62148 -0.37475 -0.01138  0.35785  2.57280

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.10035    0.05592   1.794 0.074240 .
z.lag.1     -0.10720    0.02741  -3.911 0.000125 ***
z.diff.lag   0.29007    0.06706   4.326 2.38e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7006 on 204 degrees of freedom
Multiple R-squared: 0.1216,    Adjusted R-squared: 0.113
F-statistic: 14.12 on 2 and 204 DF,  p-value: 1.806e-06

Value of test-statistic is: -3.9112 7.6595
```



# ADF test in R

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- Output: test statistics and critical values:

```
Value of test-statistic is: -3.9112 7.6595
Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.46 -2.88 -2.57
```

- Criterion: Hypothesis about the unit root is rejected, if the statistics is less than the critical value