

Week 2: Unit roots tests

Handling strongly dependent time series,
Spurious regression, Cointegration and error
correction model (ECM)

Advanced Econometrics 4EK608

Vysoká škola ekonomická v Praze

Outline

- 1 Stochastic processes
- 2 Unit roots
- 3 Cointegration
- 4 Error correction models

Czech terminology

Testy jednotkových kořenů,
silně závislé časové řady,
zdánlivá regrese, kointegrace,
model korekce chyby,
MA proces, AR proces,
náhodná procházka s driftem,
integrovaná časová řada, řád integrace,
korelogram, ADF test,
stochastický trend, deterministický trend,
trendově stacionární časová řada,

Examples of stochastic processes

Weakly dependent time series

- Moving average process of order one MA(1)
 $x_t = e_t + \alpha_1 e_{t-1}$, where e_t is *i.i.d.* time series.
Observations with higher time distance than 1 are uncorrelated. This process is stationary.
- Autoregressive process of order 1: AR(1)
 $y_t = \rho_1 y_{t-1} + e_t \Rightarrow \text{cor}(y_t, y_{t+h}) = \rho_1^h$

If stability condition $|\rho| < 1$ holds, the process is weakly dependent because correlation converges to zero with growing h . Also, this process is stationary for $y_0 = 0$.

Examples of stochastic processes

Random walk:

$$y_t = y_{t-1} + e_t$$

$$y_t = y_{t-2} + e_{t-1} + e_t$$

$$y_t = y_{t-3} + e_{t-2} + e_{t-1} + e_t$$

...

$$y_t = y_0 + e_1 + \cdots + e_{t-1} + e_t$$

Shocks have permanent effects, the series is not covariance stationary and is strongly dependent.

$$E(y_t) = E(y_0)$$

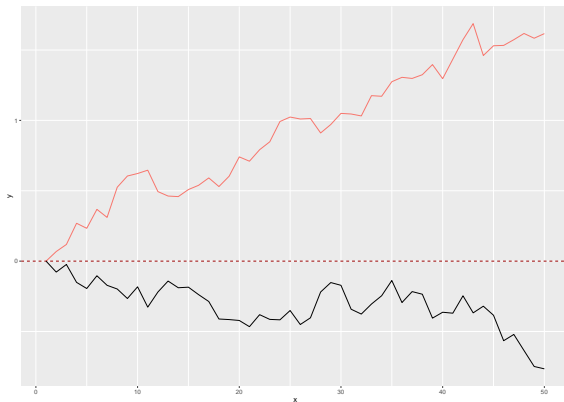
$$\text{var}(y_t) = \sigma_e^2 t$$

$$\text{cor}(y_t, y_{t+h}) = \sqrt{t/(t+h)}$$

Correlation decreases very slowly and speed depends on t .

Examples of stochastic processes

- Two realizations of a random walk



Examples of stochastic processes

- Random walk with a drift

$$y_t = \alpha_0 + y_{t-1} + e_t \Rightarrow y_t = \alpha_0 t + e_t + e_{t-1} + \cdots + e_1 + y_0$$

A linear trend with random walk around the trend.

It is neither covariance stationary nor weakly dependent.

$$E(y_t) = \alpha_0 t + E(y_0)$$

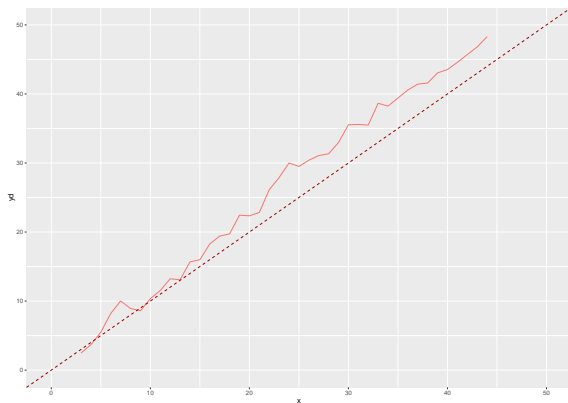
$$\text{var}(y_t) = \sigma_e^2 t$$

$$\text{cor}(y_t, y_{t+h}) = \sqrt{t/(t+h)}$$

Correlation decreases very slowly and decline speed depends on t .

Examples of stochastic processes

- Realization of random walk with a drift



- Different realizations of trending TS may produce similar time series.

Examples of stochastic processes

$$y_t = [1 \cdot y_{t-1}] + [u_t] = y_{t-1} + u_t$$

- Unit root process: $y_t = y_{t-1} + u_t$; u_t is a weakly dependent series.
- Random walk is a special case of the unit root process where: $u_t \sim \text{Distr}(0, \sigma_u^2), iid$

We need to distinguish strongly and weakly dependent TS:

- Economic reasons:
In strongly dependent series, shocks or policy changes have long or permanent effects; in weakly dependent series, their effect is only temporary.
- Statistical reasons:
Analysis with strongly dependent series must be handled in specific ways.

Integrated series

Terminology - Order of integration

- Weakly dependent TS are integrated of order zero: $I(0)$.
- If we have to difference a TS once to get a weakly dependent TS, then it is integrated of order 1: $I(1)$.
- Example of a $I(1)$ process:

$$y_t = y_{t-1} + e_t \quad \Rightarrow \quad \Delta y_t = y_t - y_{t-1} = e_t$$

$$\log y_t = \log y_{t-1} + e_t \Rightarrow \Delta \log y_t = e_t$$

- A time series is integrated of order d : $I(d)$, if it becomes a weakly dependent TS after being differenced d times.

Unit roots tests

Unit root tests help to decide if a time series is $I(0)$ or not

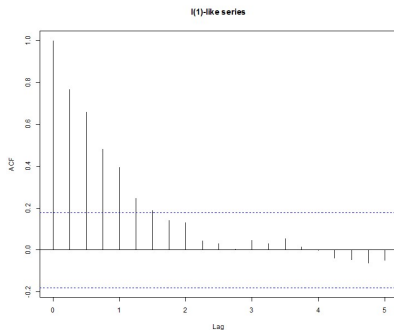
- Use either some informal procedure or a unit root test
- Informal procedures
 - Analyze autocorrelation of the first order

$$\hat{\rho}_1 = \text{corr}(y_t, y_{t-1})$$

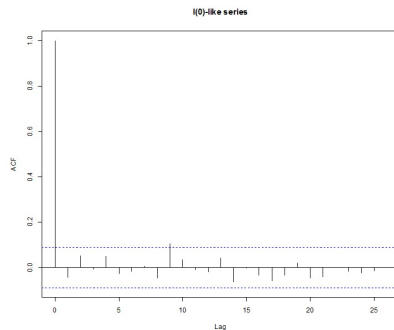
- If $\hat{\rho}_1$ approaches 1, it indicates that the series can have unit root. Alternatively, it could have a deterministic trend.
- We can analyze sample autocorrelations using a correlogram

Unit root tests

Correlogram: $\rho_h = \frac{\text{cov}(y_t, y_{t-h})}{\sigma_{y_t} \cdot \sigma_{y_{t-h}}}$



$I(1)$ -like series



$I(0)$ -like series

Unit root tests

Dickey-Fuller (DF) test – motivation

Unit root test in an $ar(1)$ process:

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

$$H_0 : \rho = 1, \quad H_1 : \rho < 1$$

- Under H_0 , y_t has a unit root.
 - For $\rho = 1 \wedge \alpha = 0 \rightarrow y_t$ is a random walk.
 - For $\rho = 1 \wedge \alpha \neq 0 \rightarrow y_t$ is a random walk with a drift and $E(y_t)$ is a linear function of t .
- Under H_1 , y_t is a weakly dependent $ar(1)$ process.

Unit root tests

Dickey-Fuller (DF) test – motivation

Unit root test in an $ar(1)$ process:

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

$$H_0 : \rho = 1, \quad H_1 : \rho < 1$$

For DF tests, $H_1 : \rho < 1$ is a common simplification to the full space of alternatives to $H_0 : \rho = 1$.

- For $|\rho| < 1$, y_t is weakly dependent (as $\text{plim } \rho^h = 0$)
However, if unit root is likely to be present, the probability of $\rho < 0$ is negligible.
- We usually ignore the possibility of $\rho > 1$, as it would lead to explosive behavior in y_t .
... $|\rho| > 1$ would allow for explosive oscillations in y_t .

Dickey Fuller (DF) test

- Basic equation for unit root test in an $ar(1)$ process:

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

- For DF test, we apply a suitable transformation to y_t :
we subtract y_{t-1} from both sides of the equation:

$$\Delta y_t = \alpha + (\rho - 1)y_{t-1} + e_t; \text{ apply substitution: } \theta = (\rho - 1)$$

i.e.

$$H_0 : \rho = 1 \Leftrightarrow H_0 : \theta = 0$$

$$\Delta y_t = \alpha + \theta y_{t-1} + e_t; \text{ now:}$$

$$H_1 : \rho < 1 \Leftrightarrow H_1 : \theta < 0$$

- We use a t -ratio for testing $H_0 : \theta = 0$. However:
Under H_0 , t -ratios don't have a t -distribution, but follow a DF -distribution. (-negative- critical values of the DF distribution are much farther from zero)
- Critical values for the DF distribution are available from statistical tables and implemented in most relevant SW packages.

DF test & ADF test

Unit root time series can manifest various levels of complexity. Hence, DF test is usually performed using the following three specifications:

$$\begin{aligned}
 \Delta y_t &= \theta y_{t-1} + e_t && \text{random walk} \\
 \Delta y_t &= \alpha + \theta y_{t-1} + e_t && \text{random walk with a drift} \\
 \Delta y_t &= \alpha + \theta y_{t-1} + \delta t + e_t && \text{random walk with a drift and trend}
 \end{aligned}$$

DF test is the same ($H_0 : \theta = 0$) for all specifications /critical values differ/

Augmented Dickey-Fuller (ADF) test is a common generalization of DF test
(example: Augmentation of the DF test for the 2^{nd} specification)

$$\Delta y_t = \alpha + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + e_t$$

- When estimating θ , we control for possible $ar(p)$ behavior in Δy_t .
- ADF test has the same null hypothesis as a DF test $\rightarrow H_0 : \theta = 0$.

Unit root tests in R: package {urca}

Description of the options for the `ur.df()` function:

❶ type "none"

$$\Delta y_t = \theta y_{t-1} + e_t$$

tau1: we test for $H_0 : \theta = 0$ (unit root)

❷ type "drift"

$$\Delta y_t = \alpha + \theta y_{t-1} + e_t$$

tau2: $H_0 : \theta = 0$ (unit root)

phi1: $H_0 : \theta = \alpha = 0$ (unit root and no drift)

❸ type "trend"

$$\Delta y_t = \alpha + \theta y_{t-1} + \delta t + e_t$$

tau3: $H_0 : \theta = 0$ (unit root)

phi2: $H_0 : \theta = \alpha = \delta = 0$ (unit root, no drift, no trend)

phi3: $H_0 : \theta = \delta = 0$ (unit root and no trend)

Unit root tests

- ADF test for TS with trend

$$\Delta y_t = \alpha + \theta y_{t-1} + \delta t + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + e_t$$

Under the alternative hypothesis of no unit root, the process is trend-stationary.

- The critical values in the ADF distribution with time trend are even more negative as compared to random walk and random walk with a drift.
- When using DF/ADF specification 1 or 2 (R-W, R-W with drift) to test for unit root in a clearly trending TS, the test would not have sufficient power (we would not reject H_0 for trending weakly dependent TS).

Unit roots and trend-stationary series

- $\Delta y_t = \alpha + \theta y_{t-1} + \delta t + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + e_t$
- Terminology:
 - Stochastic trend: $\theta = 0$
Also called **difference-stationary process**: y_t can be turned into $I(0)$ series by differencing. Terminology emphasizes stationarity after differencing y_t instead of weak dependence in differenced TS.
 - Deterministic trend: $\delta \neq 0, \quad \theta < 0$
Also called **trend-stationary process**: has a linear trend, not a unit root. y_t is weakly dependent - $I(0)$ - around its trend. We can use such series in LRMs, if trend is also used as regressor.
- DF/ADF tests are not precise tools. Distinguishing between stochastic and deterministic trend is not easy (sample size!).

Handling trend-stationary time series

- Trend-stationary TS fulfill TS.1' assumption (look at Week1 presentation).

We can use them in regressions if we have time trend among regressors.

Handling strongly dependent time series

- Strongly dependent time series do not fulfill TS.1' assumption (look at Week1 presentation). We cannot use them in regressions directly.
- Sometimes, taking logarithms helps.
- Sometimes, we can transform such series into weakly dependent time series.
- Differencing is popular, but it has drawbacks.

Handling strongly dependent time series

Example

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \qquad y_t, x_t \sim I(1) \qquad (1)$$

$$y_{t-1} = \beta_0 + \beta_1 x_{t-1} + \varepsilon_{t-1} \qquad \varepsilon_t \sim i.i.d. \qquad (2)$$

$$\Delta y_t = \beta_1 \Delta x_t + v_t \qquad v_t = \varepsilon_t - \varepsilon_{t-1} \qquad (3)$$

- ❶ Coefficient β_1 does not change between (1) and (3). However, equations (1) and (3) are different.
 $\Rightarrow \beta_1$ is the change in y_t for a unit change in x_t , but is it also the change in the growth of y for a unit change in the growth of x .
- ❷ Three problems
 - ❶ v_t is no longer i.i.d.
 - ❷ We loose information linked with the levels of variables, short term relation are stressed.
 - ❸ Estimates often generate bad long-term predictions:
 $\Delta \hat{y}_t = \hat{\beta}_1 \Delta x_t; \dots$ what if $\beta_0 \neq 0$?

Handling strongly dependent time series

Some properties of integrated processes

- ❶ The sum of stationary and non-stationary series must be non-stationary.
- ❷ Consider a process $y_t = \alpha + \beta x_t$:
 - If x_t is stationary then y_t will be stationary.
 - If x_t is non-stationary then y_t will be non-stationary.
- ❸ If two time series are integrated of different orders, then any linear combination of the series will be integrated at the higher of the two orders of integration.
- ❹ Sometimes it turns out a linear combination of two $I(d)$ series is integrated of order less than d .

Spurious regression or cointegration

- **Spurious regression** Regressing one $I(1)$ -series on another $I(1)$ -series may lead to extremely high t -statistics even if the series are completely independent. Similarly, the R^2 of such regressions tend to be very high. Regression analysis involving time series that have a unit root may generate completely misleading inferences.
- **Cointegration** Fortunately, regressions with $I(1)$ -variables are not always spurious: If there is a stable relationship between time series that, individually, display unit root behavior, these time series are called “cointegrated”.

Spurious regression or cointegration

General definition of cointegration

Two $I(1)$ -time series y_t , x_t are said to be cointegrated if there exists a stable relationship between them, where:

$$y_t = \alpha + \beta x_t + e_t, \quad e_t \sim I(0)$$

Cointegration (CI) test if CI parameters are known

For residuals of the known CI relationship:

$$e_t := y_t - \alpha - \beta x_t,$$

test whether the residuals have a unit root (DF/ADF and other unit root tests may be applied “directly”).

If the unit root H_0 is rejected, y_t , x_t are cointegrated.

Spurious regression or cointegration

- **Testing for CI if the parameters are unknown**

If the potential relationship is unknown, it can be estimated by OLS. After that, we test whether the regression residuals have a unit root. If the unit root is rejected, this means that y_t , x_t are cointegrated. Due to the pre-estimation of parameters, critical values are different than in the case of known parameters.

(Software handles this automatically.)

- **The CI relationship may include a time trend**

If the two series have differential time trends (drifts in this case), the deviation between them may still be $I(0)$ but with a linear time trend. In this case one should include a time trend in the CI-regression. Also, we have to use different critical values when testing residuals.

(Software handles this automatically.)

Cointegration tests based on regression residuals

Engle-Granger test estimates a p -lag ADF equation:

$$\Delta \hat{u}_t = \theta \hat{u}_{t-1} + \sum_{j=1}^p \Delta \hat{u}_{t-j} + e_t$$

- Essentially, this is an ADF test on \hat{u}_t [$\theta = (\rho - 1)$]
- Specific critical values apply (farther from 0 than t or DF).

Phillips-Ouliaris test estimates a DF equation:

$$\Delta \hat{u}_t = \theta \hat{u}_{t-1} + e_t$$

- The t -ratio is based on robust standard errors, different estimators exist for the robust standard errors.

In both cases (EG and PO), H_0 of unit root in \hat{u}
i.e. “no-cointegration” is tested.

Error correction model (ECM)

- It can be shown that when variables are cointegrated, i.e. when there exists a long-term relationship among them, their short-term dynamics are related as in a so-called error correction model (ECM).

Error Correction Models - motivation

Autoregressive distributed lag models

- Autoregressive distributed lag model with one regressor

$$\text{ADL}(p, q): y_t = \beta_0 + \sum_{i=1}^p \beta_i y_{t-i} + \sum_{j=0}^q \gamma_j x_{t-j} + u_t, \quad u_t \sim iid(0, \sigma^2)$$

- There are many useful modifications/simplifications to the $\text{ADL}(p, q)$ process. For example:

$$\text{ADL}(1, 1): y_t = \beta_0 + \beta_1 y_{t-1} + \gamma_0 x_t + \gamma_1 x_{t-1} + u_t. \quad (4)$$

Additional $\text{ADL}(1, 1)$ restriction: $\beta_1 = 1$ and $\gamma_1 = -\gamma_0$

gives a model in 1st diffs.: $\Delta y_t = \beta_0 + \gamma_0 \Delta x_t + u_t$.

Error Correction Models - motivation

For ADL(1,1) model (4), suppose there is an equilibrium value x° and in the absence of shocks, $x_t \rightarrow x^\circ$ as $t \rightarrow \infty$. Then, assuming absence of u_t errors, y_t converges to steady state: y° .

Hence, the ADL(1,1) model (4) can be re-written as:

$$y^\circ = \beta_0 + \beta_1 y^\circ + (\gamma_0 + \gamma_1) x^\circ$$

Solving this for y° as a function of x° , we get

$$y^\circ = \frac{\beta_0}{1 - \beta_1} + \frac{\gamma_0 + \gamma_1}{1 - \beta_1} x^\circ = \frac{\beta_0}{1 - \beta_1} + \lambda x^\circ$$

where $\lambda \equiv \frac{\gamma_0 + \gamma_1}{1 - \beta_1}$ and $|\beta_1| < 1$ is assumed.

Error Correction Models - motivation

$$y^{\circ} = \frac{\beta_0}{1 - \beta_1} + \lambda x^{\circ}$$

$$\lambda \equiv \frac{\gamma_0 + \gamma_1}{1 - \beta_1}$$

- λ is the long-run derivative of y° with respect to x° .
- λ is an elasticity if both y° and x° are in logs.
- $\hat{\lambda}$ can be computed directly from the estimated parameters of the ADL(1,1) model (4).

Error Correction Models - motivation

The ADL(1,1) equation (4) - repeated here for convenience:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \gamma_0 x_t + \gamma_1 x_{t-1} + u_t,$$

can be equivalently rewritten as follows:

$$\Delta y_t = \beta_0 + (\beta_1 - 1)(y_{t-1} - \lambda x_{t-1}) + \gamma_0 \Delta x_t + u_t. \quad (5)$$

Again, $\lambda \equiv \frac{\gamma_0 + \gamma_1}{1 - \beta_1}$ and $|\beta_1| < 1$ is assumed.

Equation (5) is an error-correction model (ECM).

Error Correction Models

$$\text{ECM: } \Delta y_t = \beta_0 + (\beta_1 - 1)(y_{t-1} - \lambda x_{t-1}) + \gamma_0 \Delta x_t + u_t.$$

- $(y_{t-1} - \lambda x_{t-1})$ measures the extent to which the long run equilibrium between y_t and x_t is not satisfied (at $t - 1$).
- Consequently, $(\beta_1 - 1)$ can be interpreted as the proportion of the disequilibrium $(y_{t-1} - \lambda x_{t-1})$ that is reflected in the movement of y_t , i.e. in Δy_t .
- $(\beta_1 - 1)(y_{t-1} - \lambda x_{t-1})$ is the **error-correction term**.
- Many ADL(p, q) specifications can be re-written as ECMs.
- **ECMs can be used with non stationary TS** (Week 3).
- ECMs $(\beta_1 - 1)$ is essentially the same as θ from Partial adjustment model (see Week 4).

Box 1: Partial Adjustment Models

(Will be put into context in the 4th week)

$$Y_t^* = \alpha + \beta X_t + u_t \quad Y_t^* : \text{optimal or target value} \quad (6)$$

or long-run equilibrium value

$$Y_t - Y_{t-1} = \theta(Y_t^* - Y_{t-1}) \quad 0 < \theta < 1 \quad (7)$$

$\theta \sim$ coefficient of adjustment
 $Y_t = \theta Y_t^* + (1 - \theta)Y_{t-1}$

As $\theta \rightarrow 1$, the speed of contemporaneous adjustment of Y_t towards Y_t^* grows.

Substituting Y_t^* from (6) to (7) yields

$$Y_t = \alpha\theta + \beta\theta X_t + (1 - \theta)Y_{t-1} + \theta u_t \quad (8)$$

We estimate (8) and then calculate parameters in (6) and (7).

Error Correction Models

Some more complicated ECMs:

- 1) We can use higher order lags, e.g. ADL(2,2):

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \gamma_0 x_t + \gamma_1 x_{t-1} + \gamma_2 x_{t-2} + u_t,$$

to establish ECMs. It is again possible to rearrange and re-parametrize ADL(2,2) to get an ECM. More than one re-parameterization is possible.

- 2) More than two variables can enter into an equilibrium relationship.