

Macroeconomics

w. Josep Lluís Carrion-i-Silvestre
Universitat de Barcelona

Complementary notes for the slides
by Thor Donsby Noe *

October 17, 2018

*Department of Economics, University of Copenhagen, Øster Farimagsgade 5, DK-1353 Copenhagen K, Denmark, (e-mail: jwz766@alumni.ku.dk)

CONTENTS

1	Theoretical issues	3
2	ARIMA modelling	3
2.1	AR(p) process	4
2.2	MA(q) model	4
3	...	4

1 THEORETICAL ISSUES

Convergence in distribution

$$\begin{aligned}\hat{\beta}_{OLS} &\xrightarrow{d} N(\beta, V(\beta)) \\ (\hat{\beta}_{OLS} - \beta) &\xrightarrow{d} N(0, V(\beta))\end{aligned}$$

$$\begin{aligned}\hat{\beta}_{OLS} &= (x'x)^{-1}x'y \\ &= \beta + (x'x)^{-1}x'u\end{aligned}$$

Asymptotic independence

If independent, the joint probability equals the product of probabilities, i.e.

$$P(A \cap B) = P(A) * P(B)$$

2 ARIMA MODELLING

Univariate TS strategy

Not based on Economic Theory
(reduced form modelling → the past is informative about the present)

$$y_t = f(y_{t-1}, y_{t-2}, y_{t-3} \dots)$$

The performance in terms of **forecasting** is key!

If you want to learn about main drivers, you need to use other models.

1. Stationary time series:

Sometimes 1st difference is required to ensure stationarity.

2. Identification:

Specify the model that explains the behaviour the best

AR: Autoregressive model

MA: Moving Average model

ARMA: AutoRegressive Moving Average model

To initially decide between them, plot the

- **ACF:** The Simple Autocorrelation Function.
Check if there is persistence/memory:

$$\frac{Cov(x_t, x_{t+k})}{\sqrt{V(x_t)}\sqrt{V(x_{t+k})}}, \text{ for } k = 0, \pm 1, \pm 2, \dots$$

Related to the asymptotic confidence interval

$$\left(\frac{-1.96}{\sqrt{(T)}}, \frac{1.96}{\sqrt{(T)}} \right)$$

or degrees of freedom corrected

$$\left(\frac{-1.96}{\sqrt{(T-k)}}, \frac{1.96}{\sqrt{(T-k)}} \right)$$

- **PACF:** The Partial Autocorrelation Function
e.g. The 3rd partial autocorrelation coefficient of the PACF, ϕ_{33} :

$$\tilde{x}_t = \phi_{31}\tilde{x}_{t-1} + \phi_{32}\tilde{x}_{t-2} + \phi_{33}\tilde{x}_{t-3} + \varepsilon_t$$

→ Using both functions helps us to make an initial specification.

- Helps us to decide on the number of lags.
- Too many lags can cause multicollinearity.

Better to choose an $f(t) \neq 0$ to test it.

3. Estimation

..

4. Validation

How well is the model specified?

-
- Residuals

Re-specify if not correctly validated (repeat step 2-4)

5. Forecasting

When model is valid, use it to forecast.

2.1 AR(p) process

Stationarity conditions for the AR model: Use the $\hat{\varepsilon}_t^0$ estimation algorithm.

1. The deterministic component f does not depend on t (rules out MA)
2. All roots of the autoregressive polynomial must, in module, be greater than one, e.g.

$$x_t = \phi_1 x_{t-1} + \varepsilon_t$$

$$\underbrace{(1 - \phi_1(L))}_{\text{AR polynomial}} x_{t-1} = \varepsilon_t, \quad L > 1 \text{ required!}$$

$$V(x_t) = V(\phi_1 x_{t-1}) + V(\varepsilon_t)$$

$$\sigma_x^2 = \phi_1^2 \sigma_x^2 +$$

$$\sigma_x^2 = \frac{1}{1 - \phi_1^2} \sigma_\varepsilon^2, \text{ requires } \sigma_1^2 < 1$$

2.2 MA(q) model

If MA is invertible

$$\Rightarrow MA(q) \equiv AR(\infty)$$

$$\simeq AR(p), \quad p \text{ is large}$$