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Financial Econometrics

Slides-05: Time Series Analysis using ARMA models

Part 2

<https://tutorcs.com>

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Time Series Models (Mainly Theoretical Aspects)

- MA process
- AR process
 - Wold Decomposition
 - AF and PACF patterns
 - Impulse response function

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Defining Moving Average Process $MA(q)$

■ Moving average models

- In Wold decomposition, $i \rightarrow 0$ as $i \rightarrow \infty$. A simple approximation to the G.P. is to restricting

$$b_i = 0 \text{ for all } i > q.$$

- The result is $MA(q)$ model:

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}, \epsilon_t \sim \text{i.i.d } WN(0, \sigma^2),$$

where y_t is the "average" of the current shock and its q recent lags. The shock ϵ_t and its lags are unobservable.

- Use lag operator $L: Lz_t = z_{t-1}$ to write $MA(q)$:

$$y_t = \mu + \Theta(L)\epsilon_t,$$

where

$$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_q L^q.$$

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■ MA(1) model

- MA(1) model (as a data generating process)

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$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1}, \epsilon_t \sim \text{i.i.d. } WN(0, \sigma^2),$$

- MA(1):

$$y_t = \mu + \Theta(L)\epsilon_t,$$

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where $\Theta(L) = 1 + \theta_1 L$.

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MA(1) model Characteristics

- It is always stationary.

$$E(y_t) = \mu, \text{Var}(y_t) = (1 + \theta_1^2)\sigma^2,$$

$$\gamma_j = \text{Cov}(y_t, y_{t-j}) = \begin{cases} \theta_1\sigma^2, & j = 1 \\ 0, & j > 1 \end{cases}$$

$$\rho_j = \frac{\gamma_j}{\gamma_0} = \begin{cases} \theta_1/(1 + \theta_1^2), & j = 1 \\ 0, & j > 1 \end{cases} \text{ (AC cutoff at } j = 1 \text{).}$$

- If the estimated $\hat{\rho}_j$ has a cutoff at $j = 1$, the time series may be fitted in an MA(1) model.

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■ MA(1) model: Conditional moments

- Conditional on $\Omega_t = \{\epsilon_t, \epsilon_{t-1}, \dots; y_t, y_{t-1}, \dots\}$

$$E(y_{t+h} | \Omega_t) = \begin{cases} \mu + b_1 \epsilon_t, & h = 1 \\ \mu, & h > 1 \end{cases}$$

$$Var(y_{t+h} | \Omega_t) = \begin{cases} \sigma^2, & h = 1 \\ 1 + \theta_1^2 \sigma^2, & h > 1 \end{cases}$$

- Conditional variance \leq unconditional variance (why?)

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■ MA(1) model: Impulse response function

- the effect on y_{t+h} of a one-std deviation increase in ϵ_t :

$$\sigma \frac{\delta y_{t+h}}{\delta \epsilon_t} = \begin{cases} \sigma \theta_1, & h = 1 \\ 0, & h > 1 \end{cases}.$$

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- Can we back out a **unique** θ_1 from.

$$\theta_j = \frac{\gamma_j}{\gamma_0} = \begin{cases} \theta_1/(1 + \theta_1^2), & j = 1 \\ 0, & j > 1 \end{cases}.$$

Can we get to know $\{\epsilon_t, \epsilon_{t-1}, \dots\}$ based on $\{y_t, y_{t-1}, \dots\}$?

- Yes** if MA is *invertible*
 - The $MA(q)$ process $y_t = \mu + \Theta(L)\epsilon_t$ is invertible if the roots of $\Theta(z) = 0$ are all outside the unit circle.
 - For $MA(1)$, the root of $1 + \theta_1 z = 0$ is $z = -1/\theta_1$. Hence, $MA(1)$ is invertible when $|-1/\theta_1| > 1$ or $|\theta_1| < 1$.
 - Invertible** in the sense that $\Theta(L)^{-1}$ exists properly.

MA(1) model: Invertibility

■ MA(1) model: Invertible

- When MA is invertible, the shock may be recovered from the observation: $\epsilon_t = \Theta(L)^{-1}(y_t - \mu)$. For MA(1), when invertible,

$$\Theta(L)^{-1} = (1 + \theta_1 L)^{-1} = 1 + (-\theta_1)L + (-\theta_1)^2 L^2 + \dots, \quad (1)$$

$$\epsilon_t = y_t - \mu - \sum_{i=1}^{\infty} (-\theta_1)^i (y_{t-i} - \mu) \quad (2)$$

$$= y_t + \sum_{i=1}^{\infty} (-\theta_1)^i y_{t-i} - \mu/(1 + \theta_1). \quad (3)$$

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Hint. Use expansion: $1/(1-x) = 1 + x + x^2 + \dots$

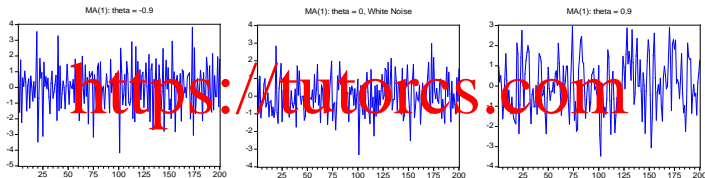
- Parameters can be estimated by minimizing $\sum_{t=1}^T \epsilon_t^2$
- The alternative expression: $y_t = \mu/(1 + \theta_1) - \sum_{i=1}^{\infty} (-\theta_1)^i y_{t-i} + \epsilon_t$ indicates that the PAC function of invertible MA(1) has no cutoffs and decays exponentially.

MA(1) model: Example

MA(1): simulated and fitted

eg. time series plots of simulated MA(1)

$$\hat{\theta}_1 = \hat{\theta}_1 / (1 + \hat{\theta}_1^2)$$



eg. M/SEcomp return

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.035311	0.02457	1.43729	0.1508
MA(1)	0.075177	0.02271	3.31031	0.0009

Variable	Coefficient	Std. Error	t-Statistic	Prob.
1	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000
5	0.000	0.000	0.000	0.000
6	0.000	0.000	0.000	0.000
7	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000
10	0.000	0.000	0.000	0.000
11	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000
13	0.000	0.000	0.000	0.000
14	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000
16	0.000	0.000	0.000	0.000
17	0.000	0.000	0.000	0.000
18	0.000	0.000	0.000	0.000
19	0.000	0.000	0.000	0.000
20	0.000	0.000	0.000	0.000

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MA(q) model: Dynamic Behaviour

■ Dynamic Behaviour of a Moving Average Process $MA(q)$

An MA process is simply a linear combination of white noise error terms ϵ_t .

These error terms can be seen as **impulses** or **innovations** or **shocks** while the MA model describes the **dynamic impact** of these shocks on the series y_t .

The **impulse response function**, i.e. the dynamic impact of an impulse ϵ_t on y_t, y_{t-1}, \dots is given by

$$\delta y_t / \delta \epsilon_t = 1$$

$$\delta y_t / \delta \epsilon_t = \theta_1$$

$$\delta y_{t+q} / \delta \epsilon_t = \theta_q$$

$$\delta y_{t+q+k} / \delta \epsilon_t = 0, \text{ for } k > 0$$

MA(q) model: Properties

■ General Properties of a Moving Average Process $MA(q)$

► $E(y_t) = \mu$

► $\gamma_0 = (1 + \theta_1^2 + \theta_2^2 + \dots + \theta_q^2)\sigma^2$

► The ACF:

$$\begin{aligned}\gamma_k &= (\theta_k + \theta_{k-1}\theta_1 + \theta_{k+2}\theta_2 + \dots + \theta_q\theta_{q-k})\sigma^2, \text{ for } k = 1, \dots, q. \\ \gamma_k &= 0, \text{ for } k > q.\end{aligned}$$

► The PACF? $p_k \neq 0 \forall k$ dies out slowly

■ Stationarity conditions for an MA process:

► γ_0 is finite

► γ_k is finite

⇒ a finite order MA process will always be stationary.

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- ▶ As the **ACF cuts off after q lags**, the order of an MA process can be determined from an inspection of the sample ACF.
- ▶ It can be shown (see below) that the **PACF dies out slowly**.
- ▶ A finite order MA process is **stationary by construction**, as it is a weighted sum of a fixed number of white noise processes, i.e. the mean, variance and autocovariances don't depend on time!

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Autoregressive Process: Definition

Defining an Autoregressive Process

Let ε_t be a white noise process. Then:

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \dots + \alpha_p y_{t-p} + \varepsilon_t \quad (12) \\ &= \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + \varepsilon_t \end{aligned}$$

is an **autoregressive process of order p** , denoted $AR(p)$.

→ y_t depends on its own lagged values and on the current value of a white noise disturbance term ε_t .

The model can conveniently be rewritten in so-called **lag operator notation** as

$$\begin{aligned} y_t &= \alpha_0 + \sum_{i=1}^p \alpha_i L^i y_t + \varepsilon_t \quad \text{with} \quad L^i y_t = y_{t-i} \\ \alpha(L) y_t &= \alpha_0 + \varepsilon_t \quad (13) \end{aligned}$$

where $\alpha(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \dots - \alpha_p L^p$ is a lag polynomial of order p

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In an AR process, the value for y_t is simply a linear combination of past values plus a white noise error term ε_t . Again, these error terms can be seen as **impulses** or **innovations** or **shocks** while the AR model describes the **dynamic impact** of these shocks on the series y_t .

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In order to trace out the dynamic impact of an impulse ε_t on y_t, y_{t+1}, \dots , it is very convenient to first 'solve' the AR model in terms of the ε sequence. For notational convenience, first consider an AR(1) process

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$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t$$

where ε_t is a white noise process.

AR Process: Impulse response function

The easiest way to express y_t as a function of the ε sequence is to

use backward substitution. This implies substituting

$$y_{t-1} = \alpha_0 + \alpha_1 y_{t-2} + \varepsilon_{t-1}$$

in the equation for y_t to obtain

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 (\alpha_0 + \alpha_1 y_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \\ &= (1 + \alpha_1) \alpha_0 + \alpha_1^2 y_{t-2} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t \end{aligned}$$

Next substitute

$$y_{t-2} = \alpha_0 + \alpha_1 y_{t-3} + \varepsilon_{t-2}$$

in the equation for y_t to obtain

$$y_t = (1 + \alpha_1 + \alpha_1^2) \alpha_0 + \alpha_1^3 y_{t-3} + \alpha_1^2 \varepsilon_{t-2} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t$$

AR Process: Impulse response function

After repeating this $t - 1$ times, we obtain

$$\begin{aligned} y_t &= (1 + \alpha_1 + \dots + \alpha_1^{t-1}) \alpha_0 + \alpha_1^t y_0 + \alpha_1^{t-1} \varepsilon_1 + \dots + \alpha_1 \varepsilon_{t-1} + \varepsilon_t \\ &= \alpha_0 \sum_{i=0}^{t-1} \alpha_1^i + \alpha_1^t y_0 + \sum_{i=0}^{t-1} \alpha_1^i \varepsilon_{t-i} \end{aligned} \quad (14)$$

where y_0 is the initial condition or the value for y in period 0.

The **impulse response function** can now easily be obtained

$$\begin{aligned} dy_t/d\varepsilon_t &= \alpha_1^0 = 1 \\ dy_{t+1}/d\varepsilon_t &= \alpha_1 \\ dy_{t+2}/d\varepsilon_t &= \alpha_1^2 \\ dy_{t+3}/d\varepsilon_t &= \alpha_1^3 \\ &\vdots \end{aligned}$$

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Note that whether an AR(1) series is mean-reverting after being hit by a shock depends on the particular value for α_1 . Two cases can be distinguished:

- ▶ The **convergence case** $|\alpha_1| < 1$
A shock affects all future observations but with a decreasing effect, i.e. the AR(1) process is mean-reverting.
- ▶ The **non-convergence case** $|\alpha_1| \geq 1$
A shock affects all future observations but with an equal impact ($\alpha_1 = 1$) or with an increasing impact ($\alpha_1 > 1$), i.e. the AR(1) series is not mean-reverting.

Properties of $AR(1)$ Process: Unconditional mean

Properties of an $AR(1)$ Process

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Let $t \rightarrow \infty$ in eq. (14):

$$y_t = \alpha_0 \sum_{i=0}^{\infty} \alpha_1^i + \alpha_1^{\infty} y_0 + \sum_{i=0}^{\infty} \alpha_1^i \varepsilon_{t-i} \quad (15)$$

- ▶ <https://tutorcs.com>
The expected value of y_t is given by

$$E(y_t) = E\left((1 + \alpha_1 + \alpha_1^2 + \dots) \alpha_0 + \alpha_1^{\infty} y_0 + \sum_{i=0}^{\infty} \alpha_1^i \varepsilon_{t-i}\right)$$

$$= E((1 + \alpha_1 + \alpha_1^2 + \dots) \alpha_0 + \alpha_1^{\infty} y_0)$$

$$\rightarrow \text{if } |\alpha_1| < 1 : E(y_t) \text{ converges to } \frac{\alpha_0}{(1 - \alpha_1)}$$

$$\rightarrow \text{if } |\alpha_1| \geq 1 : E(y_t) \text{ is time-dependent}$$

► The variance of y_t is given by

$$V(y_t) = E(y_t - E(y_t))^2$$

$$= E\left(\sum_{i=0}^{\infty} \alpha_1^i \varepsilon_{t-i}\right)^2$$

$$= E(\varepsilon_t^2 + \alpha_1^2 \varepsilon_{t-1}^2 + \alpha_1^4 \varepsilon_{t-2}^2 + \dots + \text{cross products})$$

$$= E(\varepsilon_t^2) + \alpha_1^2 E(\varepsilon_{t-1}^2) + \alpha_1^4 E(\varepsilon_{t-2}^2) + \dots$$

$$= (1 + \alpha_1^2 + \alpha_1^4 + \dots) \sigma^2$$

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→ if $|\alpha_1| < 1$: $V(y_t)$ converges to $\frac{\sigma^2}{(1 - \alpha_1^2)}$

→ if $|\alpha_1| \geq 1$: $V(y_t)$ is time-dependent

Properties of $AR(1)$ Process: ACF

► The autocovariances γ_k are given by

$$\begin{aligned}\gamma_1 &= \text{cov}(y_t, y_{t-1}) = E((y_t - E(y_t))(y_{t-1} - E(y_{t-1}))) \\&= E((\varepsilon_t + \alpha_1 \varepsilon_{t-1} + \alpha_1^2 \varepsilon_{t-2} + \dots)(\varepsilon_{t-1} + \alpha_1 \varepsilon_{t-2} + \alpha_1^2 \varepsilon_{t-3} + \dots)) \\&= E(\alpha_1 \varepsilon_{t-1}^2 + \alpha_1^3 \varepsilon_{t-2}^2 + \alpha_1^5 \varepsilon_{t-3}^2 + \dots + \text{cross-products}) \\&= \alpha_1 E(\varepsilon_{t-1}^2) + \alpha_1^3 E(\varepsilon_{t-2}^2) + \alpha_1^5 E(\varepsilon_{t-3}^2) + \dots \\&= (\alpha_1 + \alpha_1^3 + \alpha_1^5 + \dots) \sigma^2 \\&= \alpha_1 (1 + \alpha_1^2 + \alpha_1^4 + \dots) \sigma^2\end{aligned}$$

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→ if $|\alpha_1| < 1$: γ_1 converges to $\alpha_1 \frac{\sigma^2}{(1 - \alpha_1^2)}$

→ if $|\alpha_1| \geq 1$: γ_1 is time-dependent

Properties of $AR(1)$ Process: ACF

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$$\begin{aligned}\gamma_2 &= \text{cov}(y_t, y_{t-2}) = E((y_t - E(y_t))(y_{t-2} - E(y_{t-2}))) \\&= E((\varepsilon_t + \alpha_1 \varepsilon_{t-1} + \alpha_1^2 \varepsilon_{t-2} + \dots)(\varepsilon_{t-2} + \alpha_1 \varepsilon_{t-3} + \alpha_1^2 \varepsilon_{t-4} + \dots)) \\&= E(\alpha_1^2 \varepsilon_{t-2}^2 + \alpha_1^4 \varepsilon_{t-3}^2 + \alpha_1^6 \varepsilon_{t-4}^2 + \dots + \text{cross-products}) \\&= \alpha_1^2 E(\varepsilon_{t-2}^2) + \alpha_1^4 E(\varepsilon_{t-3}^2) + \alpha_1^6 E(\varepsilon_{t-4}^2) + \dots \\&= (\alpha_1^2 + \alpha_1^4 + \alpha_1^6 + \dots) \sigma^2 \\&= \alpha_1^2 (1 + \alpha_1^2 + \alpha_1^4 + \dots) \sigma^2\end{aligned}$$

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\rightarrow if $|\alpha_1| < 1$: γ_2 converges to $\alpha_1^2 \frac{\sigma^2}{(1 - \alpha_1^2)}$

\rightarrow if $|\alpha_1| \geq 1$: γ_2 is time-dependent

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$$\gamma_k = \text{cov}(y_t, y_{t-k}) = E((y_t - E(y_t))(y_{t-k} - E(y_{t-k})))$$

→ if $|\alpha_1| < 1$: γ_k converges to $\alpha_1^k \frac{\sigma^2}{(1 - \alpha_1^2)}$

→ if $|\alpha_1| > 1$: γ_k is time-dependent

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- ▶ The ACF (for stationary series!) is given by

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$$\begin{aligned}\rho_1 &= \gamma_1 / \gamma_0 = \alpha_1 \\ \rho_2 &= \gamma_2 / \gamma_0 = \alpha_1^2 \\ &\vdots \\ \rho_k &= \gamma_k / \gamma_0 = \alpha_1^k\end{aligned}$$

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Stationarity conditions for an AR(1) process

- ▶ $\alpha_1^\infty = 0$
- ▶ $(1 + \alpha_1 + \alpha_1^2 + \dots)$ is finite
- ▶ $(1 + \alpha_1^2 + \alpha_1^4 + \dots)$ is finite
- ▶ $\alpha_1 (1 + \alpha_1^2 + \alpha_1^4 + \dots)$ is finite
- ▶ ...

→ an AR(1) process is stationary is $|\alpha_1| < 1$

- ▶ The PACF cuts off after 1 lag.
- ▶ The ACF is infinite in extent (but dies out for covariance stationary processes).
- ▶ The properties of an AR(1) process crucially depend on the value for α_1
 - ▶ If $|\alpha_1| < 1$ the AR(1) process can be written as a stable infinite MA process (the so-called **MA representation**):

$$y_t = \frac{\alpha_0}{1 - \alpha_1} + \sum_{i=0}^{\infty} \alpha_1^i \varepsilon_{t-i}.$$

In this case the series is **stationary** as it has finite constant mean, variance and autocovariances.

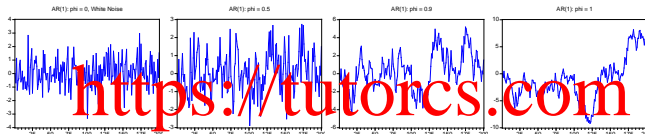
- ▶ If $|\alpha_1| \geq 1$ no stable MA representation exists. In this case the series is **non-stationary** as the mean, variance and autocovariances are time-varying.

AR(1) Example: Simulated and Fitted

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eg. time series plots of simulated AR(1)

$$y_j = \phi_1 y_{j-1} + \epsilon_j$$



eg. NYSE comp return: 'c' below is in fact $\mu = c/(1 - \phi_1)$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.035159	0.024547	1.43235	0.1522
AR(1)	0.068401	0.022727	3.00976	0.0026