

Lecture 3: ARIMA(p,d,q) models

Florian Pelgrin

University of Lausanne, École des HEC
Department of mathematics (IMEA-Nice)

Sept. 2011 - Jan. 2012

Motivation

- Characterize the main properties of ARIMA(p) models.
- Discuss asymptotic equivalence with ARMA(p,q) models

Road map

1 Introduction

2 ARIMA(p,d,q) model

- Definition
- Fundamental representations
- Equivalence with ARMA(p,q) models
- Autoregressive approximation
- Moving average approximation

3 Application

1. Definition

- To some extent, ARIMA(p,d,q) models are a generalization of ARMA(p,q) models : the d-differenced process $\Delta^d X_t$ is (asymptotically) an ARMA(p,q) process :
- On the other hand, the statistical properties of the two models are different, especially in terms of forecasting.

Definition

A stochastic process $(X_t)_{t \geq -p-d}$ is said to be an $ARIMA(p, d, q)$ —an integrated mixture autoregressive moving average model—if it satisfies the following equation :

$$\Phi(L)(1 - L)^d X_t = \mu + \Theta(L)\epsilon_t \quad \forall t \geq 0$$

where ϵ_t is a (weak) white noise process with variance σ_ϵ^2 , the lag polynomials are given by :

$$\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p \quad \text{with } \phi_p \neq 0$$

$$\Theta(L) = 1 + \theta_1 L + \dots + \theta_q L^q \quad \text{with } \theta_q \neq 0,$$

and the initial conditions :

$$Z_{-1} = \{X_{-1}, \dots, X_{-p-d}, \epsilon_{-1}, \dots, \epsilon_{-q}\}$$

are such that :

Remarks :

1. The stochastic process X_t also writes :

$$\Phi(L)\Delta^d X_t = \mu + \Theta(L)\epsilon_t \text{ or } \Phi(L)Y_t = \mu + \Theta(L)\epsilon_t$$

where $Y_t = \Delta^d X_t = (1 - L)^d X_t$.

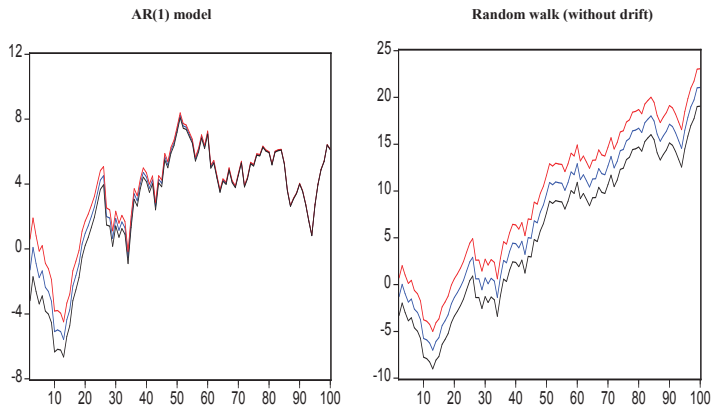
2. Initial conditions are fundamental.

Example : Consider the two stochastic processes :

$$X_t = \rho X_{t-1} + \epsilon_t$$

$$Y_t \equiv X_t - X_{t-1} = \eta_t$$

where $\rho = 0.9$, ϵ_t and η_t are (weak) white noises.



Note: The black, blue, and red solid lines correspond respectively to $X_0 = 0$, $X_0 = 2$, and $X_0 = -2$.

FIGURE: Initial conditions and stationarity

1.2. Fundamental representations

Definition (Fundamental representation)

Let $(X_t)_{t \geq -p-d}$ denote the following ARIMA(p,d,q) stochastic process :

$$\Phi(L)\Delta^d X_t = \mu + \Theta(L)\epsilon_t \quad \forall t \geq 0$$

where $\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p$ and $\Theta(L) = 1 + \theta_1 L + \dots + \theta_q L^q$, $\theta_q \neq 0, \phi_p \neq 0$, μ is a constant term, (ϵ_t) is a weak white noise, and the initial conditions are uncorrelated with ϵ_t ($t \geq 0$). This representation is said to be causal or fundamental if and only if :

- (i) All of the roots of the (inverse) characteristic equation associated to Φ are of modulus less (larger) than one.
- (ii) All of the roots of the (inverse) characteristic equation associated to Θ are of modulus less (larger) than one.

Definition (Fundamental minimal representation)

Let $(X_t)_{t \geq -p-d}$ denote the following ARIMA(p,d,q) stochastic process :

$$\Phi(L)\Delta^d X_t = \mu + \Theta(L)\epsilon_t \quad \forall t \geq 0$$

where $\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p$ and $\Theta(L) = 1 + \theta_1 L + \dots + \theta_q L^q$, $\theta_q \neq 0, \phi_p \neq 0$, μ is a constant term, (ϵ_t) is a weak white noise, and the initial conditions are uncorrelated with ϵ_t ($t \geq 0$). This representation is said to be causal or fundamental if and only if :

- (i) All of the roots of the (inverse) characteristic equation associated to Φ are of modulus less (larger) than one.
- (ii) All of the roots of the (inverse) characteristic equation associated to Θ are of modulus less (larger) than one.
- (iii) The (inverse) characteristic polynomials have no common roots.

1.3. Equivalence with ARMA(p,q) models

Proposition

Let $(X_t)_{t \geq -p-d}$ denote a minimal and causal ARIMA(p, d, q) stochastic process :

$$\Phi(L)(1-L)^d X_t = \mu + \Theta(L)\epsilon_t.$$

The stochastic process defined by :

$$Y_t = \Delta^d X_t = (1-L)^d X_t$$

is asymptotically equivalent to an ARMA(p, q) process.

1.4. Autoregressive approximation

Definition

The autoregressive approximation (and not the $AR(\infty)$ representation) of a causal and minimal $ARIMA(p,d,q)$ stochastic process is given by :

$$A_t(L)X_t = \mu_0 + \epsilon_t + h(t)'Z_{-1}.$$

where $A_t(L) = \sum_{j=0}^t a_j L^j$, $a_0 = 1$, and the a_j terms are the coefficients of the division (by increasing powers) of $\Phi(u)$ by $\Theta(u)$, μ_0 is a constant term, and $h(t) \in \mathbb{R}^{p+d+q}$ (with $\lim_{t \rightarrow +\infty} h(t) = 0$).

1.5. Moving average approximation

Definition

The moving average approximation (and not the $MA(\infty)$ representation) of a causal and minimal ARIMA(p,d,q) stochastic process is given by :

$$X_t = \mu_1 + B_t(L)\epsilon_t + \tilde{h}(t)'Z_{-1}.$$

where $B_t(L) = \sum_{j=0}^t b_j L^j$, $b_0 = 1$, and the b_j terms are the coefficients of the division (by increasing powers) of $\Theta(u)$ by $\Phi(u)$, μ_1 is a constant term, and $\tilde{h}(t) \in \mathbb{R}^{p+d+q}$ (with $\lim_{t \rightarrow +\infty} \tilde{h}(t) = 0$).

■ Example

- Starting from :

$$(1 - \phi L)(1 - L)X_t = \epsilon_t - \theta\epsilon_{t-1} \quad \forall t \geq 0$$

with the initial conditions ϵ_{-1} , X_{-1} and X_{-2} ;

- One gets :

$$\begin{aligned} \Delta X_t &= \frac{1 - \theta L}{1 - \phi L} \tilde{\epsilon}_t - \phi^t \theta \epsilon_{-1} + \phi^{t+1} (X_{-1} - X_{-2}) \\ &= \frac{1 - \theta L}{1 - \phi L} \tilde{\epsilon}_t + h'_t Z_{-1}. \end{aligned}$$

2. Application : modelling of the US stock market dividends

- Visual inspection of the autocorrelation function may indicate that the (log) US dividend is not stationary. The autocorrelogram of the first-differenced variable decreases quickly to zero—the first-difference variable may be stationary.
- Unit root tests tends to favor the assumption of non-stationarity (see later on).
- The chosen specification is then an ARIMA(p,1,q) model :

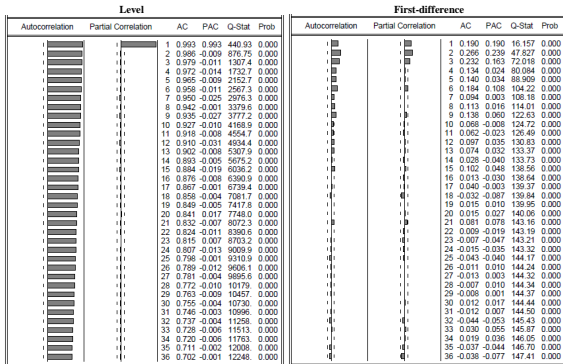
$$\Phi(L)(1 - L)d_t = \Theta(L)\epsilon_t$$

where ϵ_t is a white noise process, and :

$$\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p$$

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

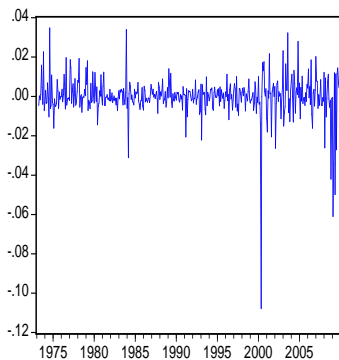
Figure 34: (Partial) autocorrelogram of (log) US stock market dividends



Estimation of an ARIMA(2,1,1) model

Parameter	Estimate	Std. Error	t-stat.	p-value
c	0.0007	0.0003	1.8777	0.0611
ϕ_1	0.7342	0.1096	6.6982	0.0000
ϕ_2	0.1206	0.0619	1.9477	0.0521
θ_1	-0.6442	0.1038	-6.2008	0.0000

Figure 35: Adjusted error terms



Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.001	0.001	0.0010	
		2 0.014	0.014	0.0984	0.769
		3 0.023	0.023	0.3279	0.849
		4 -0.075	-0.075	2.8206	0.420
		5 -0.033	-0.034	3.3126	0.507
		6 0.056	0.058	4.7386	0.449
		7 -0.039	-0.035	5.4104	0.492
		8 0.008	0.002	5.4404	0.606
		9 0.057	0.051	6.8873	0.549
		10 -0.021	-0.013	7.0953	0.627
		11 -0.013	-0.017	7.1738	0.709
		12 0.045	0.040	8.1109	0.703
		13 0.022	0.035	8.3220	0.759
		14 -0.019	-0.022	8.4876	0.810
		15 0.079	0.068	11.316	0.661
		16 -0.019	-0.009	11.486	0.717
		17 0.004	0.008	11.492	0.778
		18 -0.073	-0.087	13.963	0.670
		19 -0.017	-0.004	14.094	0.723
		20 0.007	0.017	14.114	0.777
		21 0.097	0.088	16.536	0.552
		22 0.007	-0.000	16.559	0.613
		23 -0.015	-0.024	18.660	0.666
		24 -0.026	-0.031	18.983	0.702
		25 -0.053	-0.044	20.304	0.679
		26 -0.011	-0.001	20.358	0.728
		27 -0.006	-0.011	20.377	0.773
		28 0.001	0.001	20.378	0.815
		29 0.004	-0.003	20.387	0.850
		30 0.029	0.019	20.783	0.867
		31 -0.006	0.005	20.801	0.864
		32 -0.041	-0.048	21.616	0.895
		33 0.063	0.072	23.533	0.961
		34 0.057	0.063	25.109	0.836
		35 -0.014	-0.011	25.209	0.863