

151163A - Financial Econometrics

IIb. Stationary Processes: Autoregressive (AR) Model

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An AR(1) model reads

$$X_t = a_0 + a_1 X_{t-1} + \varepsilon_t, \qquad \varepsilon_t \stackrel{\text{iid}}{\sim} (0, \sigma^2).$$
 (1)

Conditional on X_{t-1} ,

$$\mathbb{E}[X_t|X_{t-1}] = a_0 + a_1X_{t-1}, \quad \text{var}(X_t|X_{t-1}) = \sigma^2.$$

By repeated substitutions of Eq.(1),

$$X_{t} = a_{0} + a_{1}X_{t-1} + \varepsilon_{t}$$

$$= a_{0} + a_{1}[a_{0} + a_{1}X_{t-2} + \varepsilon_{t-1}] + \varepsilon_{t}$$

$$= (1 + a_{1})a_{0} + a_{1}^{2}X_{t-2} + a_{1}\varepsilon_{t-1} + \varepsilon_{t}$$

$$= \dots$$

$$= \lim_{J \to \infty} a_{1}^{J}X_{t-J} + a_{0} \sum_{j=0}^{\infty} a_{1}^{j} + \sum_{j=0}^{\infty} a_{1}^{j}\varepsilon_{t-j}.$$

Therefore, an AR(1) process is also a linear process if the summation converges and if its variance is finite.

If $|a_1| < 1$,

▶ the mean is

$$\mathbb{E}[X_t] = a_0 \sum_{j=0}^{\infty} a_1^j = \frac{a_0}{1 - a_1}$$

▶ the variance is

$$\gamma_X(0) = \sigma^2 \sum_{j=0}^{\infty} a_1^{2j} = \frac{\sigma^2}{1 - a_1^2}$$

If $|a_1| < 1$,

▶ the autocovariance is

$$\gamma_X(h) = \sigma^2 \sum_{j=0}^{\infty} a_1^j \cdot a_1^{j+h} = \frac{a_1^h \sigma^2}{1 - a_1^2}$$

▶ the autocorrelation is

$$\rho_X(h) = \frac{\gamma_X(h)}{\gamma_X(0)} = a_1^h.$$

The above results imply that

- 1. μ_X exists if $a_1 \neq 1$.
- 2. $\mu_X = 0$ if and only if $a_0 = 0$.
- 3. $\gamma_X(h)$ exists if $|a_1| < 1$.
- 4. If μ_X and $\gamma_X(h)$ exist, then X_t is weakly stationary.

Therefore, an AR(1) process is weakly stationary if and only if $-1 < a_1 < 1$, or $|a_1| < 1$. We can write an AR(1) process as

$$X_t = \mu_X + \sum_{j=0}^{\infty} a_1^j \varepsilon_{t-j}.$$



Using the property of the weak stationarity of X_t , we can find its moments more easily. Taking expectation on both sides of Eq.(1),

$$\mu_X = \mathbb{E}[X_t] = a_0 + a_1 \mathbb{E}[X_{t-1}]$$
$$= a_0 + a_1 \mu_X$$

Therefore,

$$\mu_X = \frac{a_0}{1 - a_1}.$$

Substitute
$$a_0 = \mu_X(1 - a_1)$$
 into Eq.(1),

$$X_t - \mu_X = a_1(X_{t-1} - \mu_X) + \varepsilon_t.$$
 (2)

Taking the square and then the expectation of Eq.(2),

$$\mathbb{E}\left[(X_t - \mu_X)^2\right] = \gamma_X(0) = a_1^2 \gamma_X(0) + \sigma^2$$
$$\Longrightarrow \gamma_X(0) = \frac{\sigma^2}{1 - a_1^2}.$$

Multiplying $(X_{t-h} - \mu_X)$ to Eq.(2) and taking expectation,

$$\gamma_X(h) = \begin{cases} a_1 \gamma_X(1) + \sigma^2 & \text{if } h = 0\\ a_1 \gamma_X(h-1) & \text{if } h > 0 \end{cases}$$

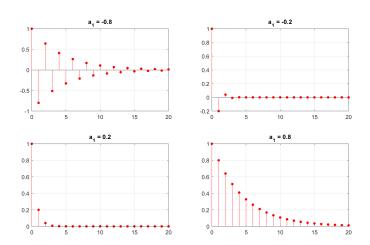
Using the fact that $\gamma_X(h) = \gamma_X(-h)$, we have

$$\gamma_X(0) = \frac{\sigma^2}{1 - a_1^2}, \qquad \gamma_X(h) = a_1 \gamma_X(h - 1) = a_1^h \gamma_X(0).$$

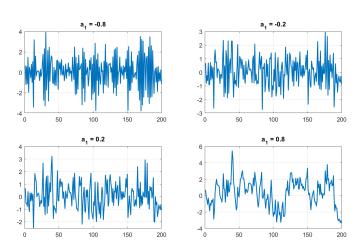
Therefore, the autocorrelation function (ACF) of X_t is

$$\rho_X(h) = a_1 \rho_X(h-1) = a_1^h.$$

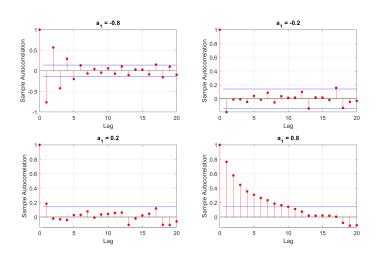














In general, an AR(p) process is given by

$$X_t = a_0 + a_1 X_{t-1} + \dots + a_p X_{t-p} + \varepsilon_t, \qquad \varepsilon_t \stackrel{\text{iid}}{\sim} (0, \sigma^2).$$

Similarly, if X_t is stationary, its mean can be obtained simply as

$$\mu_X = \mathbb{E}\left[X_t\right] = \frac{a_0}{1 - a_1 - \dots - a_p}.$$

Substituting $a_0 = (1 - a_1 - \cdots - a_p)\mu_X$, we have

$$X_t - \mu_X = a_1(X_{t-1} - \mu_X) + \dots + a_p(X_{t-p} - \mu_X) + \varepsilon_t.$$

Multiplying $X_{t-h} - \mu_X$ and taking expectation yield

$$\gamma_X(h) - a_1 \gamma_X(h-1) - \dots - a_p \gamma_X(h-p) = \begin{cases} 0 & \text{if } h > 0 \\ \sigma^2 & \text{if } h = 0 \end{cases}$$

Dividing $\gamma_X(0)$ from both equations, and noting that $\gamma_X(-h) = \gamma_X(h)$,

$$\sigma^{2} = \gamma_{X}(0)(1 - a_{1}\rho_{X}(1) - \dots - a_{p}\rho_{X}(p))$$

$$\rho_{X}(h) = a_{1}\rho_{X}(h-1) + \dots + a_{p}\rho_{X}(h-p), \qquad h > 0$$

We can then estimate σ^2 and a_1, \ldots, a_p from the autocorrelations.

Consider a weakly stationary AR(2) process

$$X_t = a_1 X_{t-1} + a_2 X_{t-1} + \varepsilon_t, \qquad \varepsilon_t \stackrel{\text{iid}}{\sim} (0, \sigma^2).$$

Express a_1 and a_2 as a function of the autocorrelations.

Let L be the lag operator, i.e., $LX_t = X_{t-1}$, $L^2X_t = X_{t-2}$, we can write the AR(p) process as

$$(1 - a_1L - \dots - a_pL^p)(X_t - \mu_X) = \varepsilon_t.$$

Theorem

An AR(p) process X_t is weakly stationary if the solutions of the characteristic equation

$$1 - a_1 L - \dots - a_p L^p = 0$$

are larger than one in absolute value.



Evaluate the stationarity property of the AR(2) process

$$X_t = 0.4X_{t-1} - 0.04X_{t-2} + \varepsilon_t, \qquad \varepsilon_t \stackrel{\text{iid}}{\sim} (0, \sigma^2).$$