Introduction to Computational Finance and Financial Econometrics

Time Series Concepts

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Spring 2015

Outline

1. Stochastic Processes
   - Stationary Processes
   - Nonstationary Processes
2. Time series models

Stochastic (Random) Process

$$\{\ldots, Y_1, Y_2, \ldots, Y_t, Y_{t+1}, \ldots\} = \{Y_t\}_{t=-\infty}^{\infty}$$

sequence of random variables indexed by time

Observed time series of length T:

$$\{Y_1 = y_1, Y_2 = y_2, \ldots, Y_T = y_T\} = \{y_t\}_{t=1}^{T}$$

$$p(x, y) = \Pr(X = x, Y = y) = \text{values in table}$$

$$e.g.,\ p(0, 0) = \Pr(X = 0, Y = 0) = \ 1/8$$

Outline

Stationary Processes

- Intuition: $\{Y_t\}$ is stationary if all aspects of its behavior are unchanged by shifts in time
- A stochastic process $\{Y_t\}_{t=1}^{\infty}$ is *strictly stationary* if, for any given finite integer r and for any set of subscripts $t_1, t_2, \ldots, t_r$ the joint distribution of

$$(Y_{t_1}, Y_{t_2}, \ldots, Y_{t_r})$$

depends only on $t_1 - t, t_2 - t, \ldots, t_r - t$ but not on t.

Remarks

1. For example, the distribution of (Y_1, Y_5) is the same as the distribution of (Y_{12}, Y_{16}).
2. For a strictly stationary process, Y_t has the same mean, variance (moments) for all t.
3. Any function/transformation $g(\cdot)$ of a strictly stationary process, $\{g(Y_t)\}$ is also strictly stationary. e.g., if $\{Y_t\}$ is strictly then $\{Y_t^2\}$ is strictly stationary.

Covariance (weakly) Stationary Processes $\{Y_t\}$

- $E[Y_t] = \mu$ for all t
- $\text{var}(Y_t) = \sigma^2$ for all t
- $\text{cov}(Y_t, Y_{t-j}) = \gamma_j$ depends on j and not on t

Note 1: $\text{cov}(Y_t, Y_{t-j}) = \gamma_j$ is called the j-lag *autocovariance* and measures the direction of linear time dependence

Note 2: A stationary process is covariance stationary if $\text{var}(Y_t) < \infty$ and $\text{cov}(Y_t, Y_{t-j}) < \infty$

Autocorrelations

$$\mathrm{corr}(Y_t, Y_{t-j}) = \rho_j = \frac{\mathrm{cov}(Y_t, Y_{t-j})}{\sqrt{\mathrm{var}(Y_t)\mathrm{var}(Y_{t-j})}} = \frac{\gamma_j}{\sigma^2}$$

Note 1: $\mathrm{corr}(Y_t, Y_{t-j}) = \rho_j$ is called the j-lag *autocorrelation* and measures the direction and strength of linear time dependence

Note 2: By stationarity $\mathrm{var}(Y_t) = \mathrm{var}(Y_{t-j}) = \sigma^2$.

Autocorrelation Function (ACF): Plot of ρ_j against j

Example

Example: Gaussian White Noise Process

$$Y_t \sim \text{iid } N(0, \sigma^2) \text{ or } Y_t \sim GWN(0, \sigma^2)$$

$$E[Y_t] = 0, \ \text{var}(Y_t) = \sigma^2$$

$$Y_t \text{ independent of } Y_s \text{ for } t \neq s$$

$$\Rightarrow \text{cov}(Y_t, Y_{t-s}) = 0 \text{ for } t \neq s$$

Note: "iid" = "**i**ndependent and **i**dentically **d**istributed".

Here, $\{Y_t\}$ represents random draws from the same $N(0, \sigma^2)$ distribution.

Example: Independent White Noise Process

$$Y_t \sim \text{iid } (0, \sigma^2) \text{ or } Y_t \sim IWN(0, \sigma^2)$$

$$E[Y_t] = 0, \text{ var}(Y_t) = \sigma^2$$

$$Y_t \text{ independent of } Y_s \text{ for } t \neq s$$

Here, $\{Y_t\}$ represents random draws from the same distribution. However, we don't specify exactly what the distribution is - only that it has mean zero and variance σ^2. For example, Y_t could be *iid* Student's t with variance equal to σ^2. This is like GWN but with fatter tails (i.e., more extreme observations).

Example

Example: Weak White Noise Process

$$Y_t \sim WN(0, \sigma^2)$$

$$E[Y_t] = 0, \ \text{var}(Y_t) = \sigma^2$$

$$\text{cov}(Y_t, Y_s) = 0 \text{ for } t \neq s$$

Here, $\{Y_t\}$ represents an uncorrelated stochastic process with mean zero and variance σ^2. Recall, the uncorrelated assumption does not imply independence. Hence, Y_t and Y_s can exhibit non-linear dependence (e.g. Y_t^2 can be correlated with Y_s^2).

Outline

Nonstationary Processes

Definition: A nonstationary stochastic process is a stochastic process that is not covariance stationary.

Note: A non-stationary process violates one or more of the properties of covariance stationarity.

Example: Deterministically trending process

$$Y_t = \beta_0 + \beta_1 t + \varepsilon_t,\ \varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$$

$$E[Y_t] = \beta_0 + \beta_1 t \text{ depends on } t$$

Note: A simple detrending transformation yield a stationary process:

$$X_t = Y_t - \beta_0 - \beta_1 t = \varepsilon_t$$

Exmaple

Example: Random Walk

$$Y_t = Y_{t-1} + \varepsilon_t,\ \varepsilon_t \sim WN(0, \sigma_\varepsilon^2),\ Y_0 \text{ is fixed}$$

$$= Y_0 + \sum_{j=1}^{t} \varepsilon_j \Rightarrow \text{var}(Y_t) = \sigma_\varepsilon^2 \times t \text{ depends on } t$$

Note: A simple detrending transformation yield a stationary process:

$$\Delta Y_t = Y_t - Y_{t-1} = \varepsilon_t$$

Outline

1. Stochastic Processes
2. Time series models
   - Moving Average (MA) Processes
   - Autoregressive (AR) Processes

Time series models

Definition: A time series model is a probability model to describe the behavior of a stochastic process $\{Y_t\}$.

Note: Typically, a time series model is a simple probability model that describes the time dependence in the stochastic process $\{Y_t\}$.

Outline

Moving Average (MA) Processes

Idea: Create a stochastic process that only exhibits one period linear time dependence.

MA(1) Model:

$$Y_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}, \quad -\infty < \theta < \infty$$

$\varepsilon_t \sim iid\ N(0, \sigma_\varepsilon^2)$ (i.e., $\varepsilon_t \sim GWN(0, \sigma_\varepsilon^2)$)

θ determines the magnitude of time dependence

Properties:

$$E[Y_t] = \mu + E[\varepsilon_t] + \theta E[\varepsilon_{t-1}]$$

$$= \mu + 0 + 0 = \mu$$

Moving Average (MA) Processes cont.

$$
\begin{aligned}
\text{var}(Y_t) &= \sigma^2 = E[(Y_t - \mu)^2] \\
&= E[(\varepsilon_t + \theta\varepsilon_{t-1})^2] \\
&= E[\varepsilon_t^2] + 2\theta E[\varepsilon_t \varepsilon_{t-1}] + \theta^2 E[\varepsilon_{t-1}^2] \\
&= \sigma_\varepsilon^2 + 0 + \theta^2\sigma_\varepsilon^2 = \sigma_\varepsilon^2(1+\theta^2) \\
\text{cov}(Y_t, Y_{t-1}) &= \gamma_1 = E[(\varepsilon_t + \theta\varepsilon_{t-1})(\varepsilon_{t-1} + \theta\varepsilon_{t-2})] \\
&= E[\varepsilon_t\varepsilon_{t-1}] + \theta E[\varepsilon_t\varepsilon_{t-2}] \\
&+ \theta E[\varepsilon_{t-1}^2] + \theta^2 E[\varepsilon_{t-1}\varepsilon_{t-2}] \\
&= 0 + 0 + \theta\sigma_\varepsilon^2 + 0 = \theta\sigma_\varepsilon^2
\end{aligned}
$$

Moving Average (MA) Processes cont.

Furthermore,

$$\begin{aligned}\text{cov}(Y_t, Y_{t-2}) &= \gamma_2 = E[(\varepsilon_t + \theta\varepsilon_{t-1})(\varepsilon_{t-2} + \theta\varepsilon_{t-3})] \\ &= E[\varepsilon_t\varepsilon_{t-2}] + \theta E[\varepsilon_t\varepsilon_{t-3}] \\ &+ \theta E[\varepsilon_{t-1}\varepsilon_{t-2}] + \theta^2 E[\varepsilon_{t-1}\varepsilon_{t-3}] \\ &= 0 + 0 + 0 + 0 = 0\end{aligned}$$

Similar calculation show that:

$$\text{cov}(Y_t, Y_{t-j}) = \gamma_j = 0 \text{ for } j > 1$$

Moving Average (MA) Processes cont.

Autocorrelations:

$$\rho_1 = \frac{\gamma_1}{\sigma^2} = \frac{\theta\sigma_\varepsilon^2}{\sigma_\varepsilon^2(1+\theta^2)} = \frac{\theta}{(1+\theta^2)}$$

$$\rho_j = \frac{\gamma_j}{\sigma^2} = 0 \text{ for } j > 1$$

Note:

$$\rho_1 = 0 \text{ if } \theta = 0$$

$$\rho_1 > 0 \text{ if } \theta > 0$$

$$\rho_1 < 0 \text{ if } \theta < 0$$

Result: MA(1) is covariance stationary for any value of θ.

Example

Example: MA(1) model for overlapping returns

Let r_t denote the 1−month cc return and assume that:

$$r_t \sim \text{iid } N(\mu_r, \sigma_r^2)$$

Consider creating a monthly time series of 2−month cc returns using:

$$r_t(2) = r_t + r_{t-1}$$

These 2−month returns observed monthly overlap by 1 month:

$$\begin{aligned} r_t(2) &= r_t + r_{t-1} \\ r_{t-1}(2) &= r_{t-1} + r_{t-2} \\ r_{t-2}(2) &= r_{t-2} + r_{t-3} \\ &\vdots \end{aligned}$$

Claim: The stochastic process $\{r_t(2)\}$ follows a MA(1) process.

Outline

Autoregressive (AR) Processes

Idea: Create a stochastic process that exhibits multi-period geometrically decaying linear time dependence.

AR(1) Model (mean-adjusted form):

$$Y_t - \mu = \phi(Y_{t-1} - \mu) + \varepsilon_t, \ \ -1 < \phi < 1$$

$$\varepsilon_t \sim \text{iid } N(0, \sigma_\varepsilon^2)$$

Result: AR(1) model is covariance stationary provided $-1 < \phi < 1$.

Autoregressive (AR) Processes cont.

Properties:

$$E[Y_t] = \mu$$

$$\text{var}(Y_t) = \sigma^2 = \sigma_\varepsilon^2/(1-\phi^2)$$

$$\text{cov}(Y_t, Y_{t-1}) = \gamma_1 = \sigma^2\phi$$

$$\text{corr}(Y_t, Y_{t-1}) = \rho_1 = \gamma_1/\sigma^2 = \phi$$

$$\text{cov}(Y_t, Y_{t-j}) = \gamma_j = \sigma^2\phi^j$$

$$\text{corr}(Y_t, Y_{t-j}) = \rho_j = \gamma_j/\sigma^2 = \phi^j$$

Note: Since $|\phi| < 1$,

$$\lim_{j\to\infty} \rho_j = \phi^j = 0$$

AR(1) Model (regression model form)

$$
\begin{aligned}
Y_t - \mu = \phi(Y_{t-1} - \mu) + \varepsilon_t \Rightarrow \\
Y_t &= \mu - \phi\mu + \phi Y_{t-1} + \varepsilon_t \\
&= c + \phi Y_{t-1} + \varepsilon_t
\end{aligned}
$$

where,

$$
c = (1 - \phi)\mu \Rightarrow \mu = \frac{c}{1 - \phi}
$$

Remarks:

- Regression model form is convenient for estimation by linear regression

The AR(1) model and Economic and Financial Time Series

The AR(1) model is a good description for the following time series:

- Interest rates on U.S. Treasury securities, dividend yields, unemployment
- Growth rate of macroeconomic variables
  - Real GDP, industrial production, productivity
  - Money, velocity, consumer prices
  - Real and nominal wages

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