

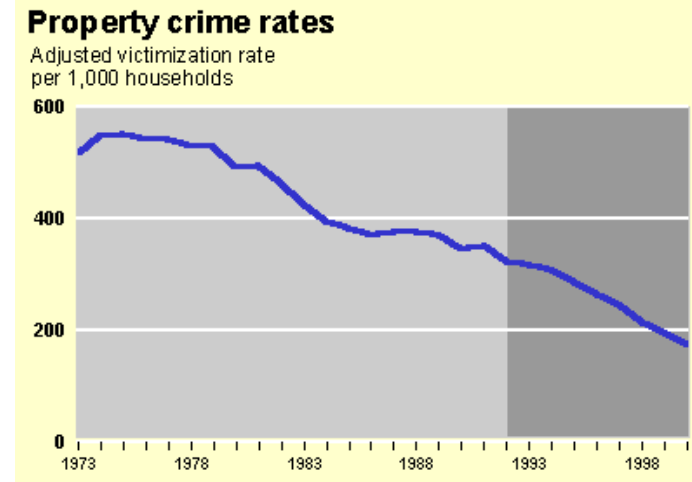
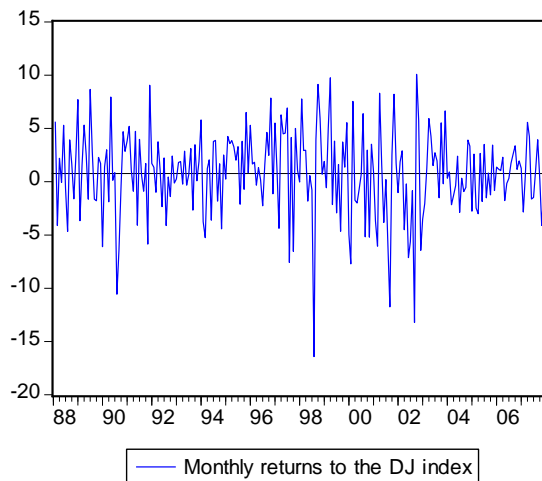
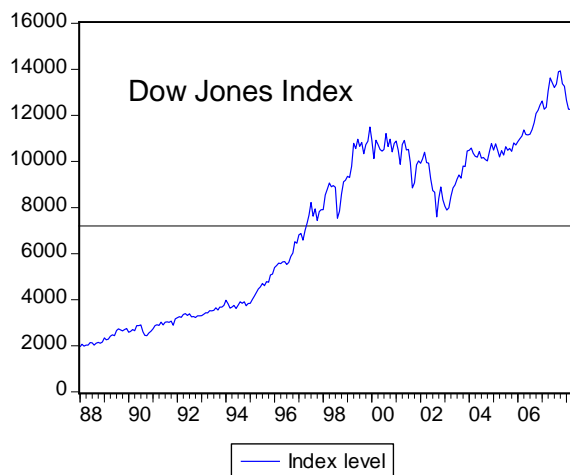
# CHAPTER 3

## STATISTICS AND TIME SERIES

A time series is a collection of records indexed by time.

$$\{y_t, t = 1, 2, \dots, T\} = \{y_1, y_2, \dots, y_T\}, \text{ where } T \text{ is the number of periods}$$

**Figure 3.1** Examples of Time Series



These slides are based on:

González-Rivera: Forecasting for Economics and Business, Copyright © 2013 Pearson Education, Inc.

Slides adapted for this course. We thank Gloria González-Rivera and assume full responsibility for all errors due to our changes which are mainly in red

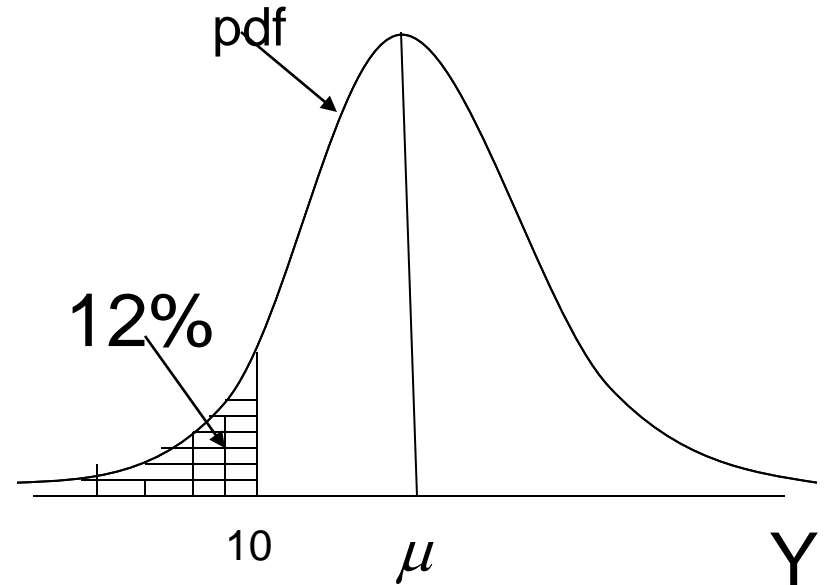
### 3.1 Stochastic Process and Time Series

Random variables can be characterized in two ways:

- probability density/mass function (full characterization)
- moments (partial characterization)

$$\bar{y} = \sum_{t=1}^T \frac{y_t}{T}$$

$$\overline{\sigma^2} = \sum_{t=1}^T \frac{(y_t - \bar{y})^2}{T}$$

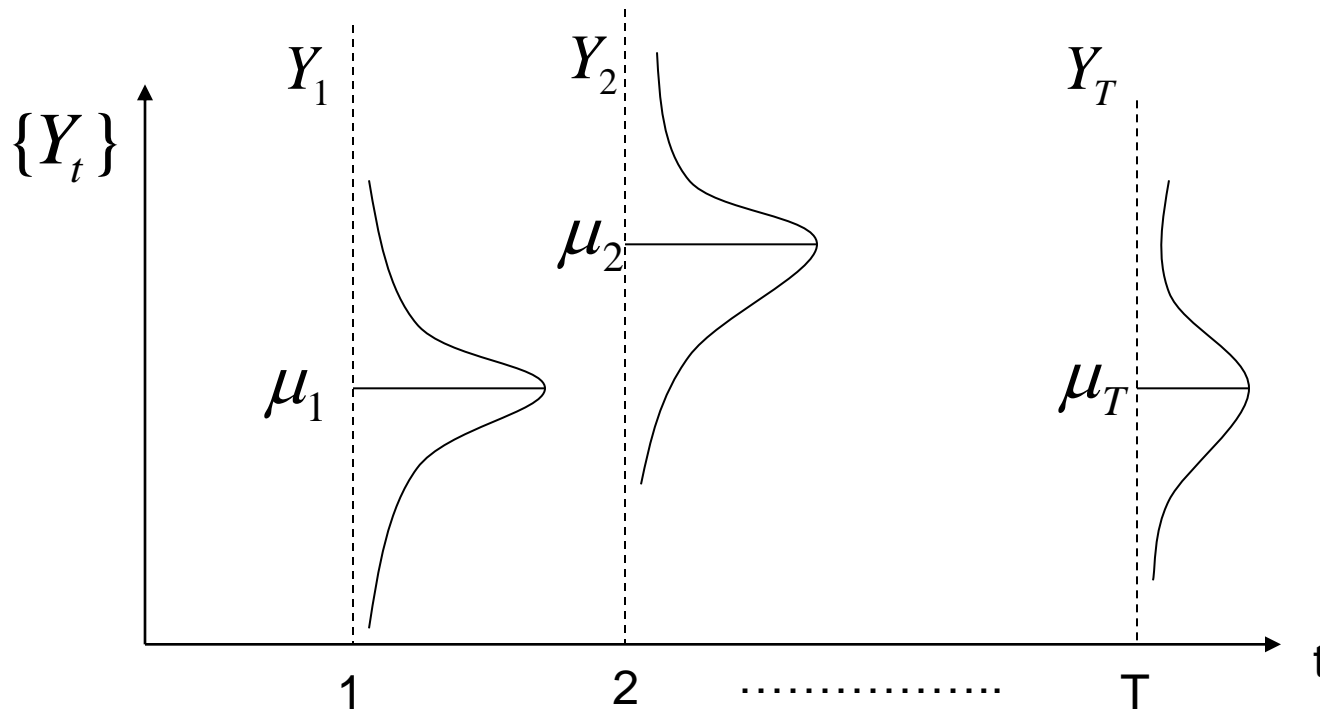


$$P(Y \leq 10) = 12\%$$

**Figure 3.2** Probability Density Function

### 3.1.1 Stochastic Process

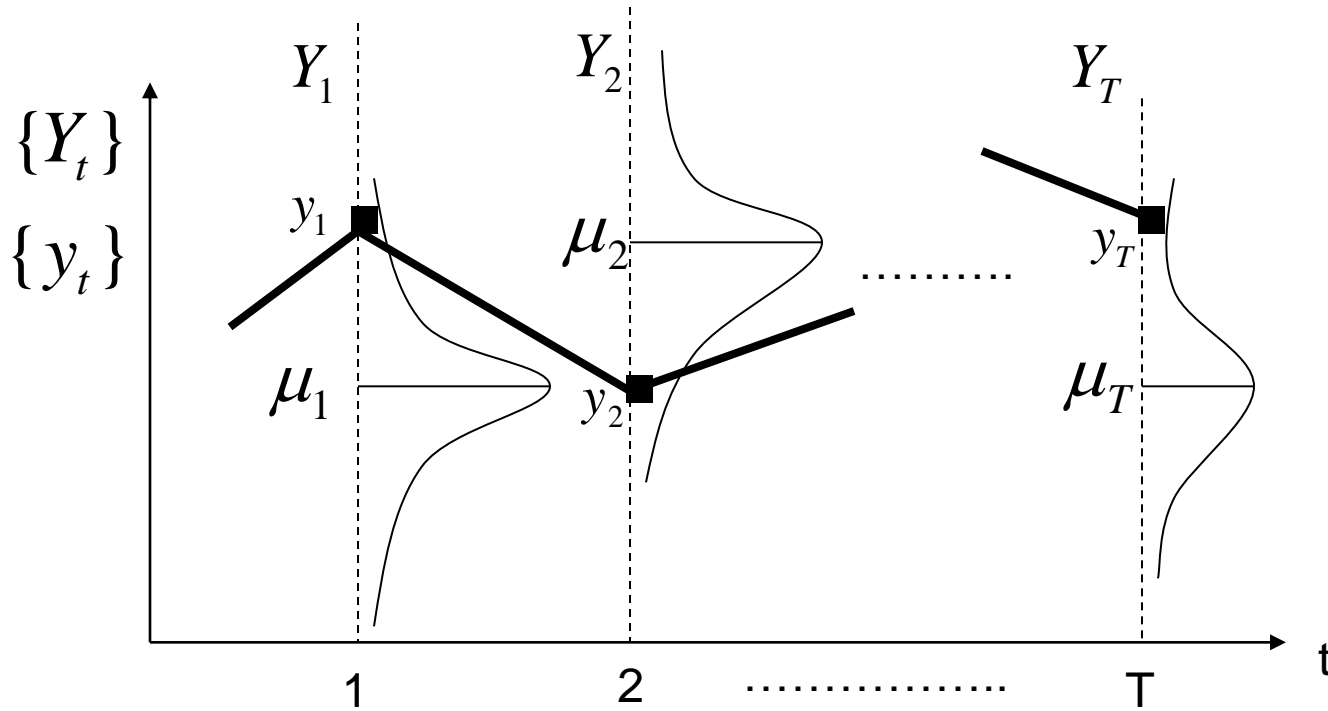
A stochastic process is a collection of random variables indexed by time.



**Figure 3.3** Graphical Representation of a Stochastic Process

### 3.1.1 Time Series

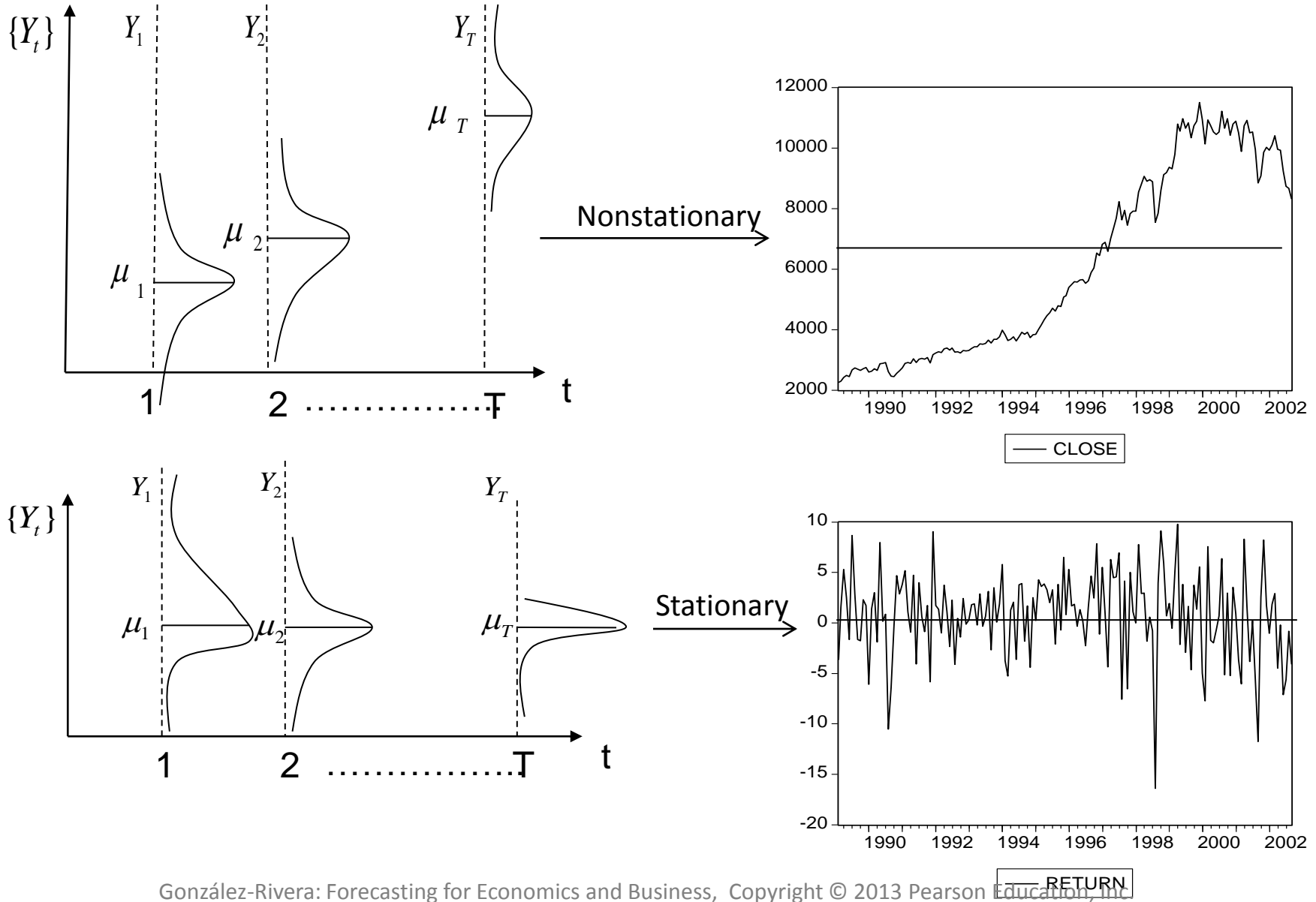
A time series is a sample realization of a stochastic process.



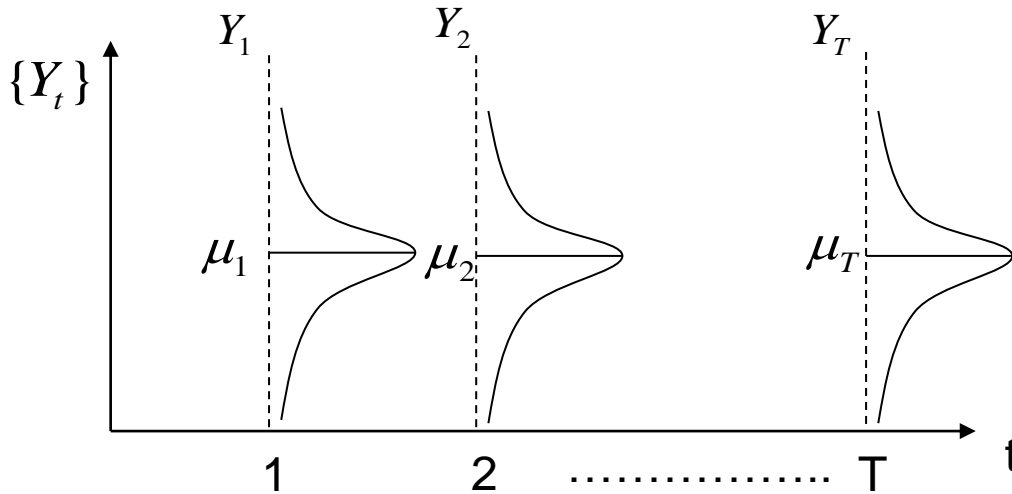
**Figure 3.4** Graphical Representation of a Stochastic Process and a Time Series (Thick Line)

### 3.2.1 Stationarity

Figure 3.5 Nonstationary and Stationary Stochastic Process



A stochastic process is said to be **first order strongly stationary** if all random variables have the **same probability mass/density function**.



**Figure 3.6** Strongly Stationary Stochastic Process

A stochastic process is said to be **first order weakly stationary** if all random variables have the same mean.

A stochastic process is said to be **second order weakly stationary** (or **covariance stationary**) if all random variables have the **same mean and the same variance and covariances do not depend on time, only on lag**.

### 3.2.2 Useful transformations of Nonstationary Processes

To transform a nonstationary series into a first-moment-stationary series, we can apply first differences :

$$\Delta y_t = (1 - L)y_t = y_t - y_{t-1}$$

↑  
Lag operator

To stabilize the variance we can use the Box-Cox transformation:  
(before taking differences)

$$y_i^{(\lambda)} = \begin{cases} \frac{y_i^\lambda - 1}{\lambda} & \text{if } \lambda \neq 0, \\ \ln y_i & \text{if } \lambda = 0, \end{cases}$$

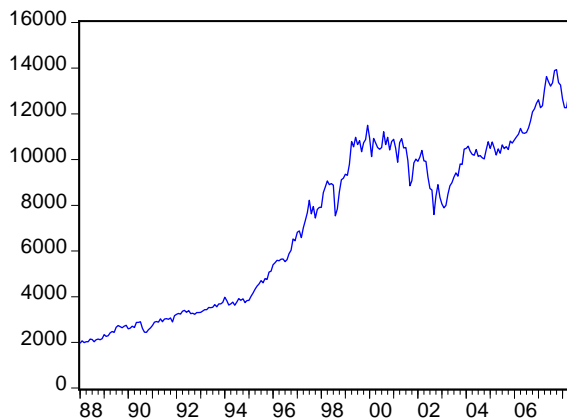
### 3.2.2 Useful transformations of Nonstationary Processes

**Table 3.1** Dow Jones Index and Returns

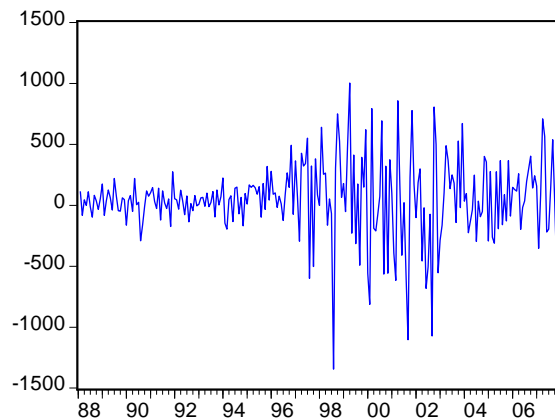
Date	$y_t$	$y_{t-1}$	$\Delta y_t$	$R_t = \frac{\Delta y_t}{y_{t-1}} \times 100$	$R_t \approx \Delta \log(y_t) \times 100$
2001:01	10887.400	10788.000	99.40000	0.921394	0.917175
2001:02	10495.300	10887.400	-392.10000	-3.601411	-3.667862
2001:03	9878.800	10495.300	-616.50000	-5.874058	-6.053649
2001:04	10735.000	9878.800	856.20000	8.667045	8.311838
2001:05	10911.900	10735.000	176.90000	1.647881	1.634451
2001:06	10502.400	10911.900	-409.50000	-3.752784	-3.825013
2001:07	10522.800	10502.400	20.40000	0.194241	0.194053
2001:08	9949.800	10522.800	-573.00000	-5.445319	-5.599188
2001:09	8847.600	9949.800	-1102.20000	-11.077610	-11.740620
2001:10	9075.100	8847.600	227.50000	2.571319	2.538816
2001:11	9851.600	9075.100	776.50000	8.556380	8.209948
2001:12	10021.600	9851.600	170.00000	1.725608	1.710889
2002:01	9920.000	10021.600	-101.60000	-1.013810	-1.018984
2002:02	10106.100	9920.000	186.10000	1.876008	1.858628
2002:03	10403.900	10106.100	297.80000	2.946735	2.904153
2002:04	9946.200	10403.900	-457.70000	-4.399312	-4.499017
2002:05	9925.300	9946.200	-20.90000	-0.210131	-0.210352
2002:06	9243.300	9925.300	-682.00000	-6.871329	-7.118809
2002:07	8736.600	9243.300	-506.70000	-5.481808	-5.637787
2002:08	8663.500	8736.600	-73.10000	-0.836710	-0.840230
2002:09	8312.690	8663.500	-350.81000	-4.049287	-4.133554



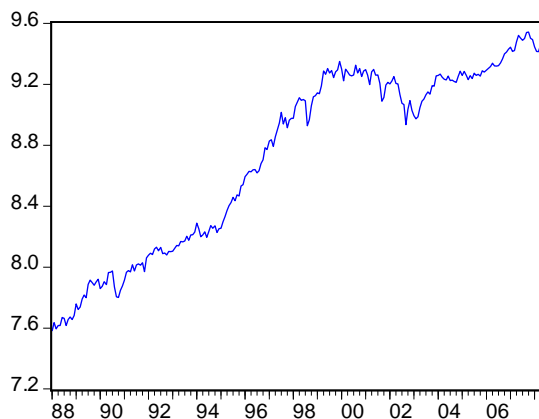
### Figure 3.7 Dow Jones Index and Its Transformation to Returns



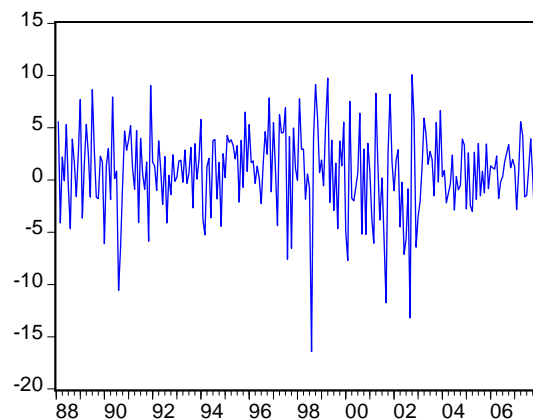
Dow Jones Index level



First difference of Index



Log Index



First difference of the log Index (returns)

### 3.3 A New Tool of Analysis: The Autocorrelation Functions

Given two random variables  $Y$  and  $X$ , the correlation coefficient is a measure of the linear association.

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)}\sqrt{\text{Var}(Y)}} \quad -1 \leq \rho_{X,Y} \leq 1$$

Autocorrelation coefficient:

$$\rho_{Y_t, Y_{t-k}} = \frac{\text{Cov}(Y_t, Y_{t-k})}{\sqrt{\text{Var}(Y_t)}\sqrt{\text{Var}(Y_{t-k})}}$$

For second order stationary processes :

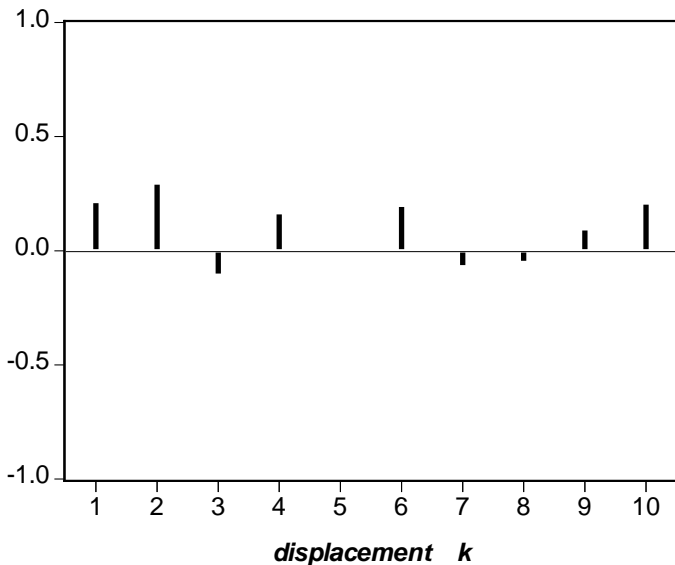
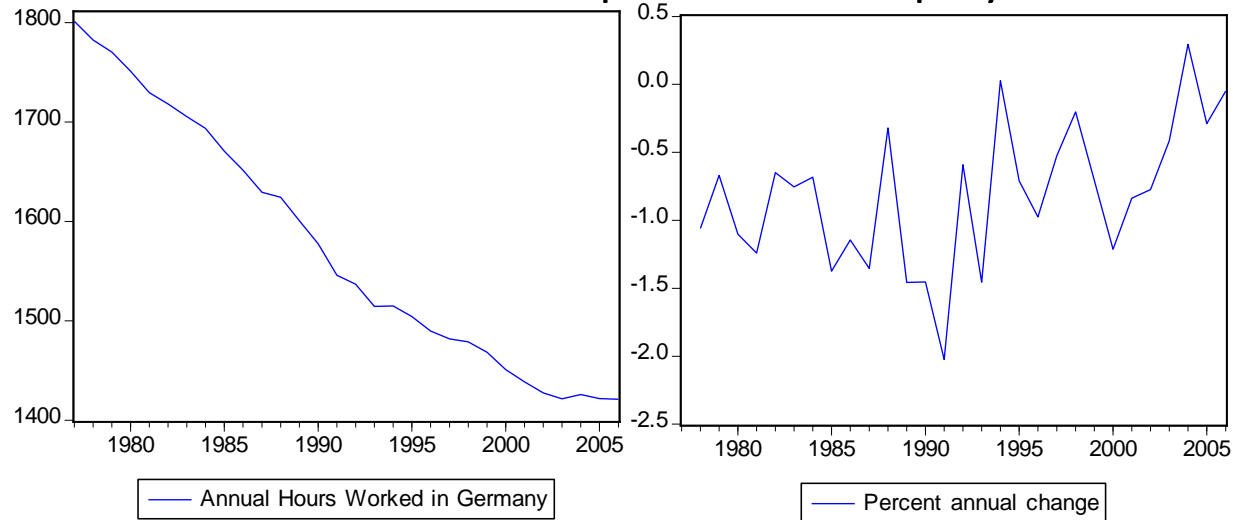
$$\rho_{Y_t, Y_{t-k}} = \rho_k = \frac{\text{Cov}(Y_t, Y_{t-k})}{\text{Var}(Y_t)} = \frac{\gamma_k}{\gamma_0} \quad \rho_k = \rho_{-k} = \rho_{|k|}$$

The **autocorrelation function** (ACF) is the function

$$\rho: k \rightarrow \rho_k$$

### 3.3 A New Tool of Analysis: The Autocorrelation Functions

**Figure 3.8** Annual Hours Worked per Person Employed in Germany

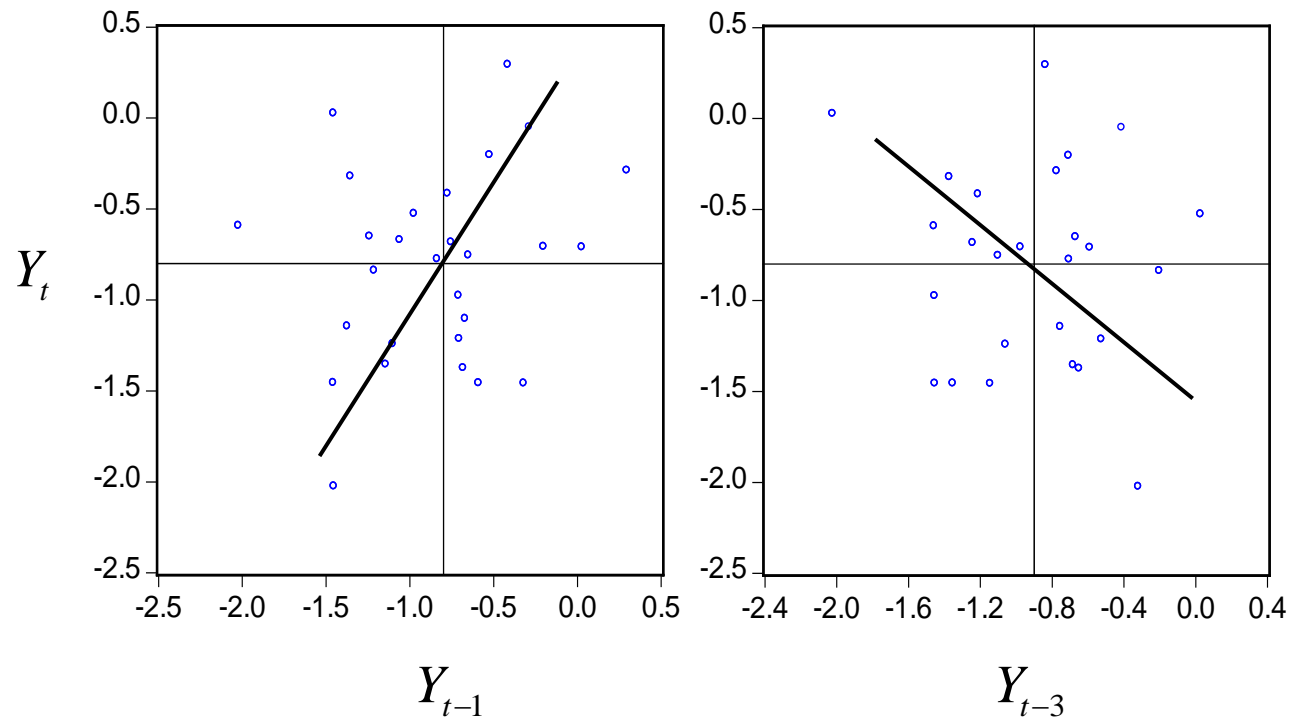


Autocorrelation function										
$k$	1	2	3	4	5	6	7	8	9	10
$\hat{\rho}_k$	.22	.29	-.10	.16	-.01	.19	-.06	-.04	.09	.20

**Table 3.2** Percentage Change in Working Hours in Germany:  
Calculation of the Autocorrelation Coefficients

	$Y_t$	$Y_{t-1}$	$Y_{t-3}$
1978	-1.0604		
1979	-0.6699	-1.0604	
1980	-1.1018	-0.6699	
1981	-1.2413	-1.1018	-1.0604
1982	-0.6497	-1.2413	-0.6699
1983	-0.7536	-0.6497	-1.1018
1984	-0.6826	-0.7536	-1.2413
1985	-1.3733	-0.6826	-0.6497
1986	-1.1438	-1.3733	-0.7536
1987	-1.3533	-1.1438	-0.6826
1988	-0.3196	-1.3533	-1.3733
1989	-1.4574	-0.3196	-1.1438
1990	-1.4536	-1.4574	-1.3533
1991	-2.0234	-1.4536	-0.3196
1992	-0.5904	-2.0234	-1.4574
1993	-1.4550	-0.5904	-1.4536
1994	0.0264	-1.4550	-2.0234
1995	-0.7087	0.0264	-0.5904
1996	-0.9752	-0.7087	-1.4550
1997	-0.5249	-0.9752	0.0264
1998	-0.2026	-0.5249	-0.7087
1999	-0.7057	-0.2026	-0.9752
2000	-1.2126	-0.7057	-0.5249
2001	-0.8375	-1.2126	-0.2026
2002	-0.7745	-0.8375	-0.7057
2003	-0.4141	-0.7745	-1.2126
2004	0.2950	-0.4141	-0.8375
2005	-0.2879	0.2950	-0.7745
2006	-0.0492	-0.2879	-0.4141
Mean: $\hat{\mu}$	-0.8026		
Variance: $\hat{\gamma}_0$	0.2905		
$\hat{\gamma}_k$ ( $k=1,3$ )		0.0651	-0.0282
$\hat{\rho}_k$ ( $k=1,3$ )		0.2240	-0.0970

**Figure 3.9** Percentage Change in Working Hours in Germany:  
Autocorrelations of Order 1 and 3



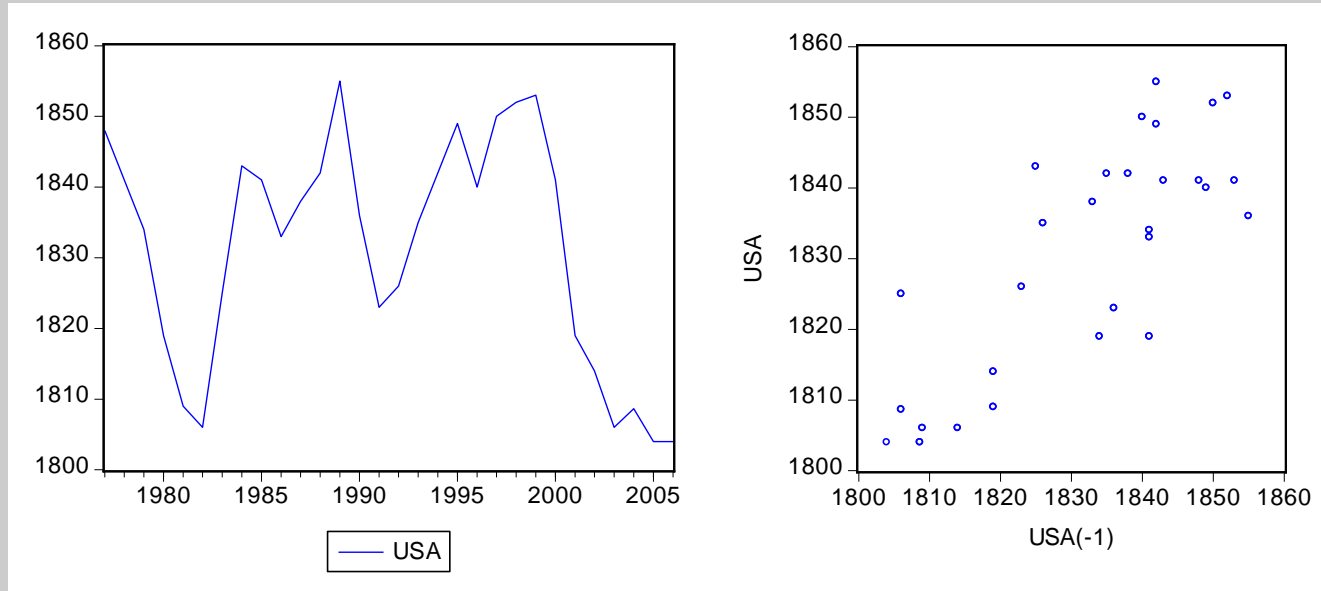
Autocorrelation between  $Y_t$  and  $Y_{t+k}$  controlling for the effect of

$Y_{t+1}, Y_{t+2}, \dots, Y_{t+k-1}$

Distance $k$	Regression	Partial autocorrelation coefficient $r_k$
1	$Y_{t+k} = \beta_0 + \beta_1 Y_{t+k-1} + \varepsilon_{t+k}$	$\beta_1$
2	$Y_{t+k} = \beta_0 + \beta_1 Y_{t+k-1} + \beta_2 Y_{t+k-2} + \varepsilon_{t+k}$	$\beta_2$
3	$Y_{t+k} = \beta_0 + \beta_1 Y_{t+k-1} + \beta_2 Y_{t+k-2} + \beta_3 Y_{t+k-3} + \varepsilon_{t+k}$	$\beta_3$
.....	.....	.....
$k$	$Y_{t+k} = \beta_0 + \beta_1 Y_{t+k-1} + \beta_2 Y_{t+k-2} + \dots + \beta_{k-1} Y_{t+1} + \beta_k Y_t + \varepsilon_{t+k}$	$\beta_k$

The **partial autocorrelation function (PACF)** is the function:  $r: k \rightarrow r_k$

**Figure 3.10** Annual Working Hours per Employee in the United States



Autocorrelation Function									
$\kappa$	1	2	3	4	5	6	7	8	9
$\hat{\rho}_\kappa$	.74	.36	.06	-.09	-.16	-.29	-.35	-.25	-.06

### 3.3.2 Statistical Tests for Autocorrelation Coefficients

$$H_0: \rho_k = 0$$

$$\hat{\rho}_k \rightarrow N(0, 1/T)$$

$$H_0: \rho_1 = \rho_2 = \dots = \rho_k = 0$$

$$Q_k = T(T+2) \sum_{j=1}^k \frac{\hat{\rho}_j^2}{T-j} \rightarrow \chi^2(k)$$

Sample: 1977 2006  
 Included observations: 30

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.737	0.737	17.987	0.000
		2 0.364	-0.392	22.537	0.000
		3 0.062	-0.058	22.676	0.000
		4 -0.086	0.039	22.951	0.000
		5 -0.162	-0.126	23.957	0.000
		6 -0.288	-0.295	27.270	0.000
		7 -0.352	0.052	32.432	0.000
		8 -0.253	0.185	35.229	0.000
		9 -0.064	0.001	35.416	0.000
		10 0.114	0.034	36.035	0.000

**Figure 3.11** Time Series: Annual Working Hours per Employee in the United States. Autocorrelation Function