

# Introduction to Time Series Analysis

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# Overview

1. Introduction to data with time dimension
2. Stationary and non-stationary time series
3. Auto-correlation function
4. Basic time series models
5. Time series analysis with Eviews

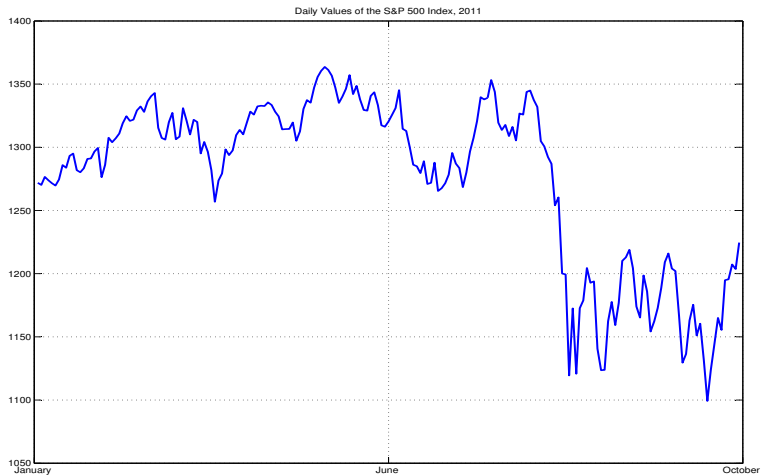
# 1. Introduction

## **What is time series?**

- ▶ Random quantity that evolves over time
- ▶ For example, river flow, stock prices or human height
- ▶ Sample at intervals to get sequence of observations
- ▶ Such sequence is a time series

# 1. Introduction

## Example: Daily Values of the S&P 500 Index



# 1. Introduction

## **What makes time series special?**

- ▶ Consider a sample of ten male students
- ▶ If students are of same age, heights are identically distributed
- ▶ If selected at random and unrelated, heights are independent
- ▶ Independent and identically-distributed (i.i.d.) sample is key
- ▶ Law of Large Numbers ensures consistent mean estimate

# 1. Introduction

## **What makes time series special?**

- ▶ Consider observing the height of one student for ten years
- ▶ Observations are no longer independent
- ▶ Most importantly, observations are not identically distributed
- ▶ Averaging out does not give true estimate of mean height

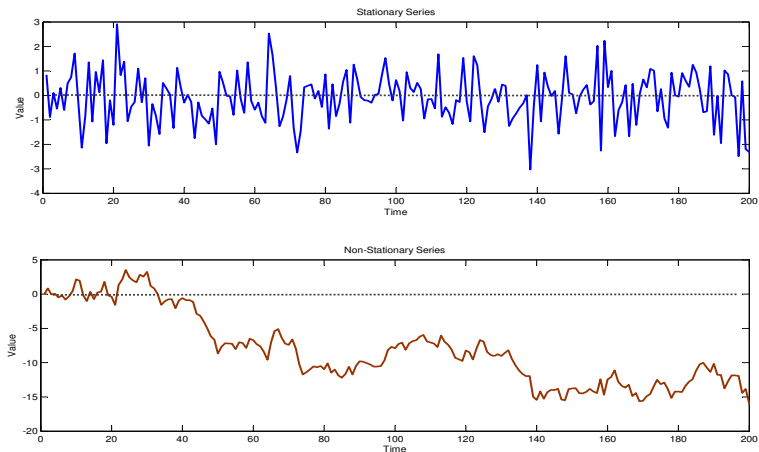
## 2. Stationarity and Non-Stationary Series

### Stationarity

- ▶ In general, let  $X_t$ ,  $t = 1, 2, \dots$  be sequence of random variables
- ▶ We get inconsistent estimates if  $F_{X_i}(x_i) \neq F_{X_j}(x_j)$
- ▶ That is if probability distribution changes over time
- ▶ In this case, time-series is **non-stationary**
- ▶ Similarly, if  $F_{X_i}(x_i) = F_{X_j}(x_j) = F_X(x_k)$ , series is **stationary**
- ▶ We may use usual inference tools with stationary time-series

## 2. Stationarity and Non-Stationary Series

### Stationary vs Non-Stationary Series





## 2. Stationarity and Non-Stationary Series

### Consequences of Non-Stationary

- ▶ Spurious regression results
- ▶ Exceptionally high  $R^2$  values and  $t$ -ratios
- ▶ No economic meaning

## 2. Stationarity and Non-Stationary Series

### Testing for Non-Stationarity

- ▶ Many time-series in social sciences are non-stationary
- ▶ Several parametric and non-parametric methods are available
- ▶ One popular method is the Wald & Wolfowitz "runs" test
- ▶ Basic idea is to split time series into several sub-series
- ▶ Check if means and standard deviations are different
- ▶ Also may use Dickey & Fuller "unit root" test

### 3. Auto-Correlation Function (ACF)

#### Correlogram and Auto-Correlations

- ▶ Before formal test, a useful "first-pass" is finding the ACF
- ▶ Auto-Correlation Function shows correlations of different lags
- ▶ For example,  $X_t$  may be correlated with  $X_{t-1}$ , but not with  $X_{t-2}$
- ▶ **Correlogram** shows ACF values at many lags
- ▶ Major problem with ACF: it only picks up linear dependence

























### 3. Auto-Correlation Function (ACF)

#### Example: Correlogram

Date: 10/17/11 Time: 15:28

Sample: 1 200

Included observations: 200

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.970	0.970	191.11	0.000
		2 0.945	0.055	373.16	0.000
		3 0.918	-0.020	546.07	0.000
		4 0.901	0.133	713.24	0.000
		5 0.883	0.015	874.84	0.000
		6 0.866	-0.000	1031.1	0.000
		7 0.846	-0.053	1180.8	0.000
		8 0.826	0.001	1324.3	0.000
		9 0.806	-0.005	1461.7	0.000
		10 0.785	-0.040	1592.9	0.000
		11 0.769	0.054	1719.2	0.000
		12 0.753	0.027	1841.2	0.000

### 3. Auto-Correlation Function (ACF)

#### **Interpreting Correlogram**

- ▶ ACF may help identify the nature of the series
- ▶ For example, long-decaying ACF may indicate non-stationarity
- ▶ Zero auto-correlations may signal random noise
- ▶ Other patterns may suggest certain types of processes

## 4. Common Time-Series Models

### **Dealing with Non-Stationarity**

- ▶ Many non-stationary series may have stationary differences
- ▶ Even if we can't work with levels, can use stationary differences
- ▶ Given that now stationary series, what are the common models?

## 4. Auto-Regressive Model

### Auto-Regressive Models

- ▶ AR( $p$ ) model is the "workhorse" of time-series econometrics
- ▶ We model variable at time  $t$  as function of its  $p$  lags
- ▶ For example, let  $Y_t$ ,  $t = 1, 2, \dots$  be stationary time series
- ▶ Basic Auto-Regressive model of order  $p$  is given by:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \dots + \alpha_p Y_{t-p} + \epsilon_t$$

## 4. Auto-Regressive Model

### AR(1) Model

- ▶ Simplest model of this form is  $AR(1)$ :

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \epsilon_t$$

- ▶ A process of this form is stationary as long as  $|\alpha_1| < 1$
- ▶ Then we can use usual least squares techniques to estimate  $\hat{\alpha}_1$
- ▶ If  $|\alpha_1| \geq 1$ , process has a **unit root** and is non-stationary
- ▶ Note that we can't use the usual  $t$ -test on  $\hat{\alpha}_1$  for  $H_0 : |\alpha_1| \geq 1$
- ▶ Under  $H_0$   $\hat{\alpha}_1$  has unknown distribution!



## 4. Auto-Regressive Model

### Testing for Unit Root in AR(1) Model

- ▶ Instead use the Dickey & Fuller test
- ▶ Rewrite model in terms of differences:

$$Y_t - Y_{t-1} = (\alpha_0 - 1)Y_{t-1} + \epsilon_t$$

- ▶ Or alternatively as

$$\Delta Y_t = \delta_0 Y_{t-1} + \epsilon_t$$

- ▶ Under  $H_0$ ,  $\delta_0 = 0$

## 4. Auto-Regressive Model

### Identifying AR(1) Process

- ▶ When to use AR(1) model?
- ▶ For AR(1) process, can show that  $E[X_t X_{t+n}] = \frac{\sigma_\epsilon^2}{1 - \alpha_1^2} \times \alpha_1^{|n|}$
- ▶ Exponential decay of auto-covariance for AR(1) process
- ▶ ACF that decays quickly may signal AR(1) model















## 4. Auto-Regressive Model

### AR(1) ACF

Date: 10/17/11 Time: 17:01

Sample: 1 200

Included observations: 200

Autocorrelation	Partial Correlation	AC
		1 0.611
		2 0.361
		3 0.154
		4 0.090
		5 0.104
		6 0.126
		7 0.098

## 4. Conditional Heteroscedasticity Models

### **General Auto-Regressive Conditional Heteroscedasticity (GARCH) Model**

- ▶ In many applications, it is useful to model variance of series
- ▶ For example, stock volatility tends to cluster
- ▶ GARCH model fits and predicts volatility clusters well

## 4. Conditional Heteroscedasticity Models

### GARCH Model

- ▶ Let  $\epsilon_t = Y_t - \alpha_0 - \alpha_1 Y_{t-1}$  be AR(1) errors
- ▶ We suspect conditional heteroscedasticity (clustering) of  $\epsilon_t$ 's
- ▶ Most basic GARCH model for  $\epsilon_t$ 's is  $\epsilon_t = \sigma_t z_t$ , there  $z_t \sim N(0, 1)$ , and  $\sigma_t$  is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \sigma_{t-2}^2 + \dots + \alpha_p \sigma_{t-p}^2$$

- ▶ We can estimate the model with least squares
- ▶ GARCH predicts financial market volatility very well

## 5. Time-series with Eviews

### **Eviews**

- ▶ One of the most popular tools for time-series analysis is Eviews
- ▶ Packages also available in STATA
- ▶ Many free tools are implemented in R statistical computing suite