FIN307 MATLAB

FINANICAL TOOLBOX CHAPTER 1 – Financial Data Analysis PART01

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Financial Toolbox

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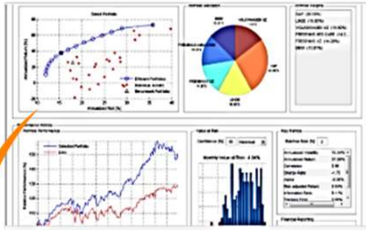
Analyze financial data and develop financial models

Financial Toolbox™ provides functions for mathematical modeling and statistical analysis of financial data. You can optimize portfolios of financial instruments, optionally taking into account turnover and transaction costs. The toolbox enables you to estimate risk, analyze interest rate levels, price equity and interest rate derivatives, and measure investment performance. Time series analysis functions let you perform transformations or regressions with missing data and convert between different trading calendars and day-count conventions.

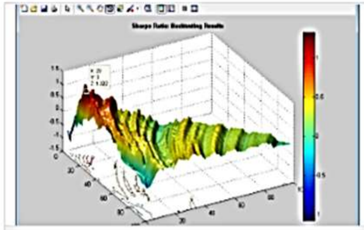
Capabilities



Asset Allocation and Portfolio Optimization

Perform capital allocation, asset allocation, and risk assessment.

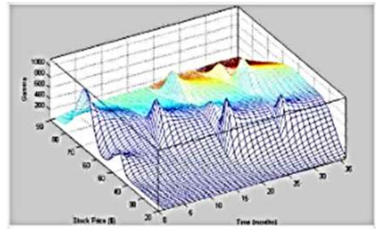
» Learn more



Risk Analysis and Investment Performance

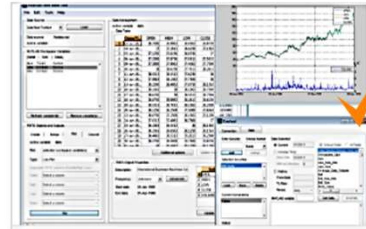
Analyze and assess risk and investment performance.

» Learn more



Fixed-Income Analysis and Option Pricing

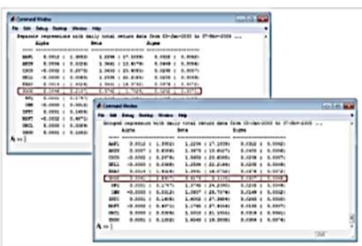
Calculate present and future values and depreciation. Determine nominal and effective internal rates of return, along with periodic interest rates.



Financial Time Series Analysis

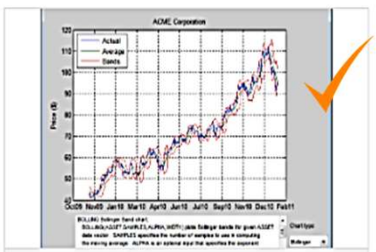
Analyze time series data in the financial markets.

» Learn more



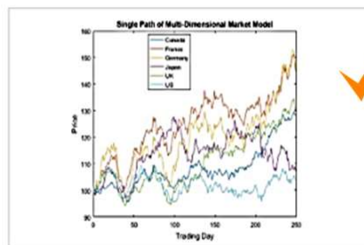
Regression and Estimation with Missing Data

Performing multivariate normal regression with or without missing data.



Technical Indicators and Financial Charts

Use well-known technical indicators, performance metrics, and specialized plots.



Monte Carlo Simulation of SDE Models

Use a variety of well-known Stochastic Differential Equation (SDE) models.

Summary: Financial time series analysis

Data

-price

-return

-volatility

Models

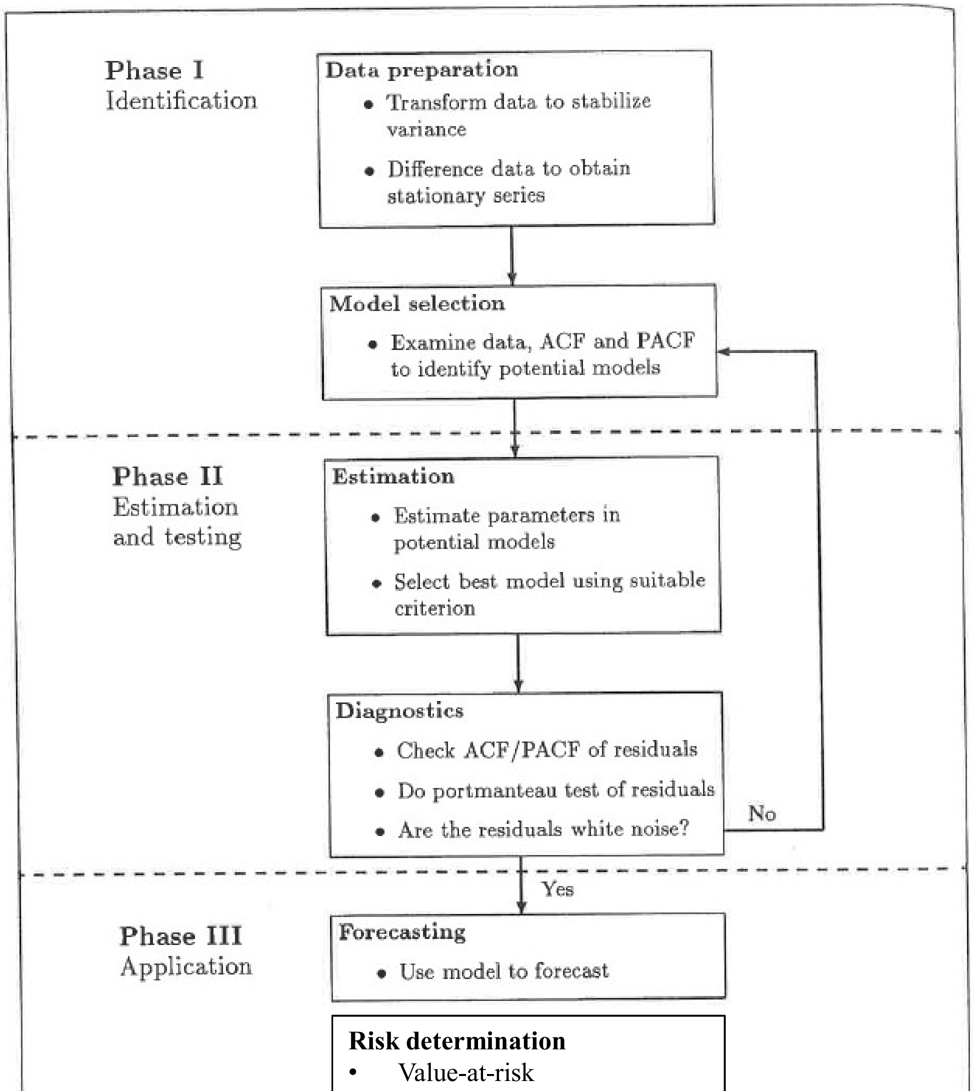
-ARMA & GARCH

Applications

-forecasting

-market risk determination

Box-Jenkins Methodology



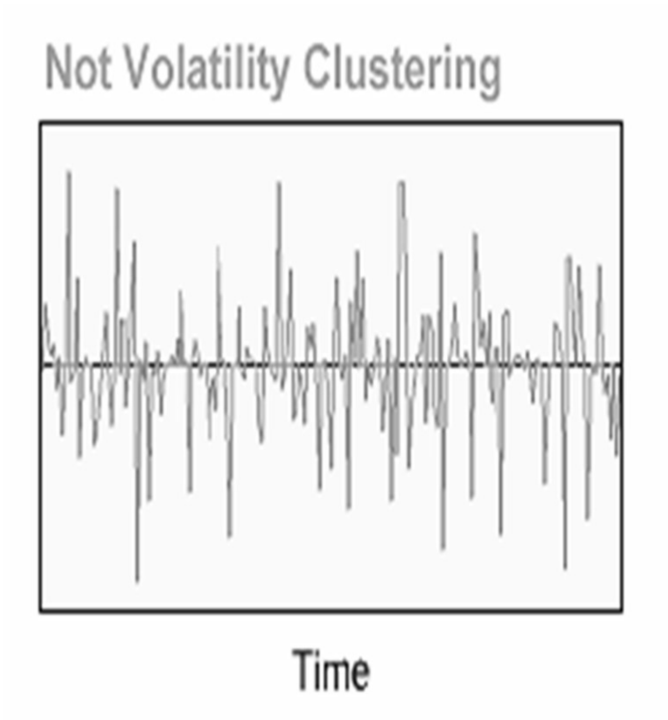
Schematic representation of the Box-Jenkins methodology for time series modeling.

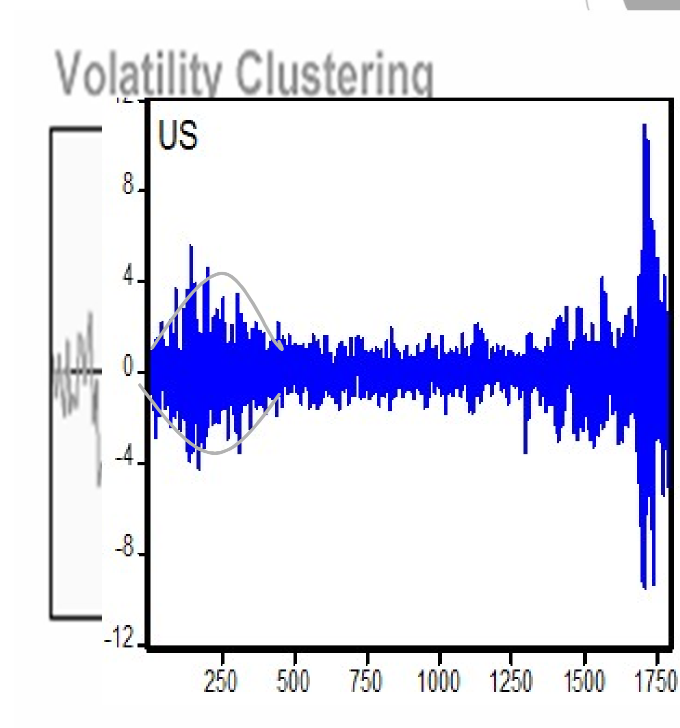
Models for financial data

Models consist 3 major characteristics

a. Trend
b. Seasonality
c. Autocorrelations

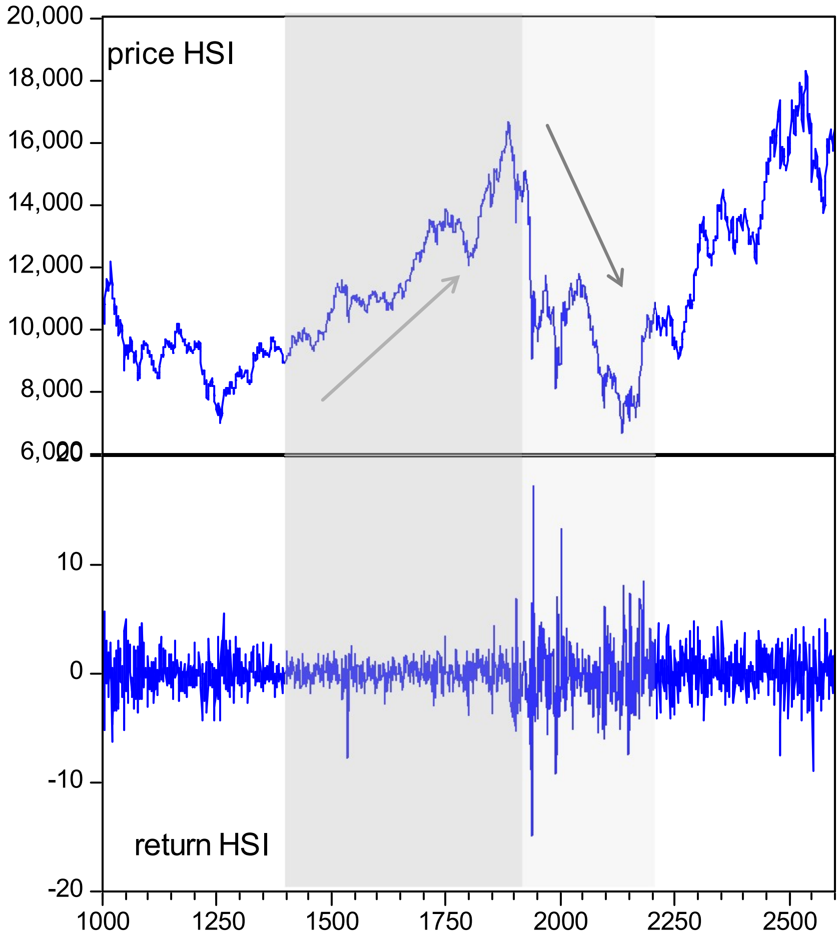
What can we observe from the data?





Details: http://www.riskglossary.com

WHAT CAN WE OBSERVED FROM THE DATA?



- "Bad news" tends to increase future market volatility more than "good news" at the same magnitude;

News ↔ **Volatility** ↔ **Risk**

Debt-Equity ratio

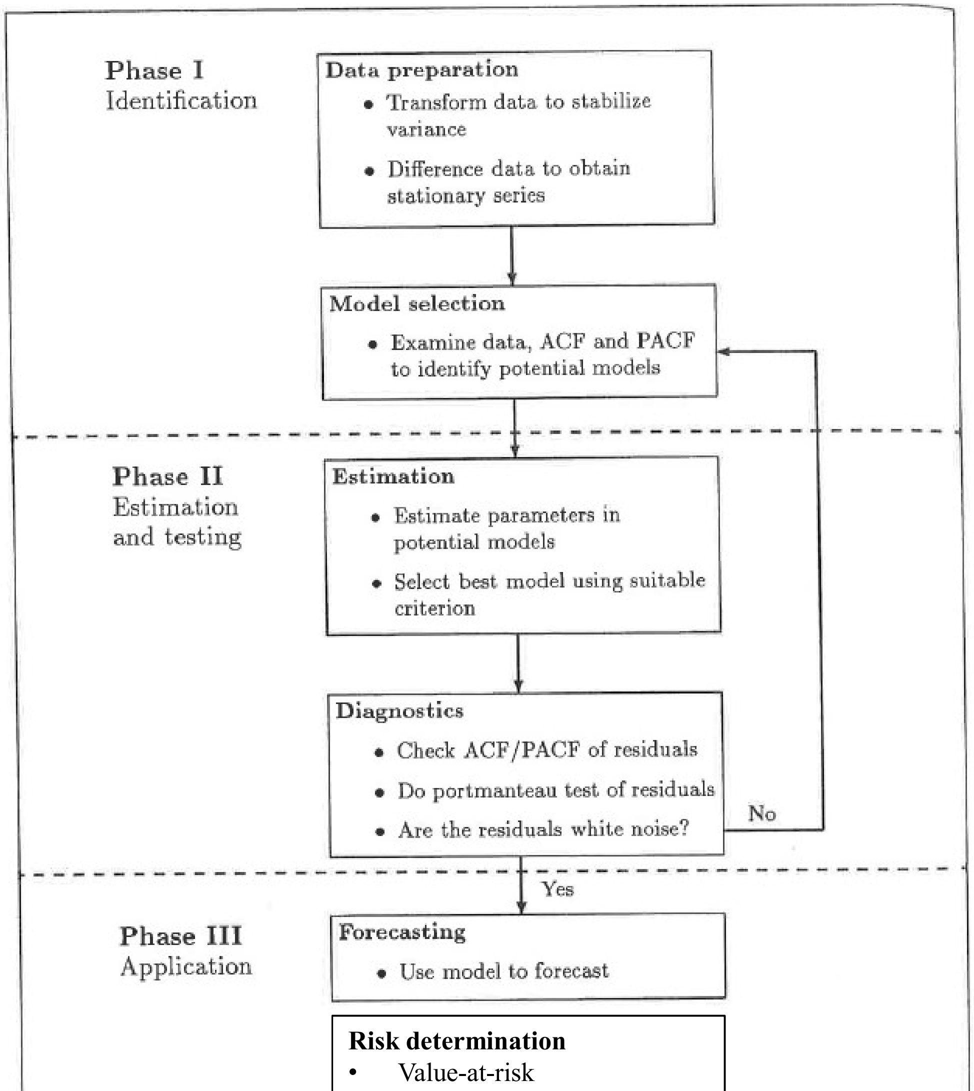
Box-Jenkins Methodology

The Box-Jenkins methodology [1] is a five-step process for identifying, selecting, and assessing conditional mean models (for discrete, univariate time series data).

1. Establish the stationarity of your time series. If your series is not stationary, successively difference your series to attain stationarity. The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of a stationary series decay exponentially (or cut off completely after a few lags).
2. Identify a (stationary) conditional mean model for your data. The sample ACF and PACF functions can help with this selection. For an autoregressive (AR) process, the sample ACF decays gradually, but the sample PACF cuts off after a few lags. Conversely, for a moving average (MA) process, the sample ACF cuts off after a few lags, but the sample PACF decays gradually. If both the ACF and PACF decay gradually, consider an ARMA model.
3. Specify the model, and estimate the model parameters. When fitting nonstationary models in Econometrics Toolbox, it is not necessary to manually difference your data and fit a stationary model. Instead, use your data on the original scale, and create an `arima` model object with the desired degree of nonseasonal and seasonal differencing. Fitting an ARIMA model directly is advantageous for forecasting: forecasts are returned on the original scale (not differenced).
4. Conduct goodness-of-fit checks to ensure the model describes your data adequately. Residuals should be uncorrelated, homoscedastic, and normally distributed with constant mean and variance. If the residuals are not normally distributed, you can change your innovation distribution to a Student's *t*.
5. After choosing a model—and checking its fit and forecasting ability—you can use the model to forecast or generate Monte Carlo simulations over a future time horizon.

References

[1] Box, G. E. P., G. M. Jenkins, and G. C. Reinsel. *Time Series Analysis: Forecasting and Control*. 3rd ed. Englewood Cliffs, NJ: Prentice Hall, 1994.



Schematic representation of the Box-Jenkins methodology for time series modeling.

Box-Jenkins Methodology

Financial Data Analysis

Three patterns:

✓Trend

✓Seasonality

✓Correlation

Time series decomposition

We shall think of the time series y_t as comprising three components: a seasonal component, a trend-cycle component (containing both trend and cycle), and a remainder component (containing anything else in the time series). For example, if we assume an additive model, then we can write

$$y_t = S_t + T_t + E_t,$$

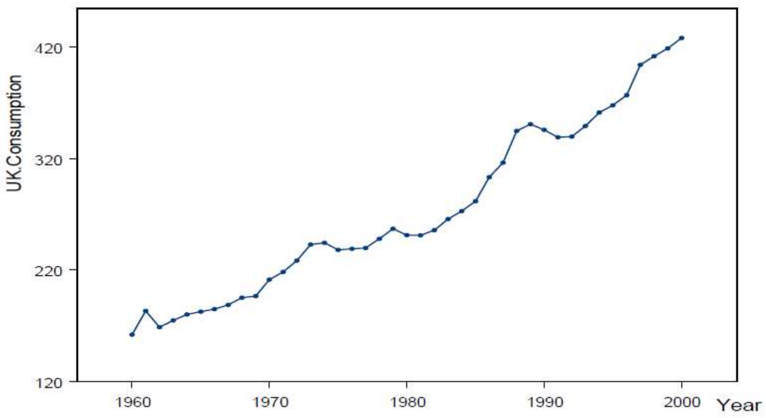
where y_t is the data at period t, S_t is the seasonal component at period t, T_t is the trend-cycle component at period t and E_t is the remainder (or irregular or error) component at period t. Alternatively, a multiplicative model would be written as

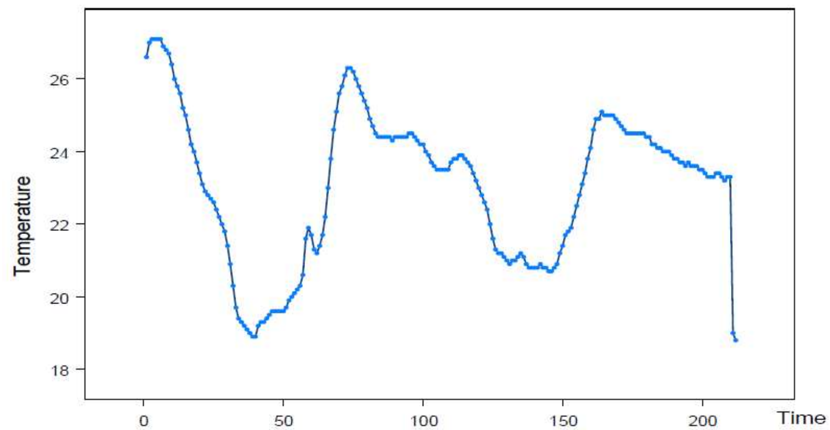
written as

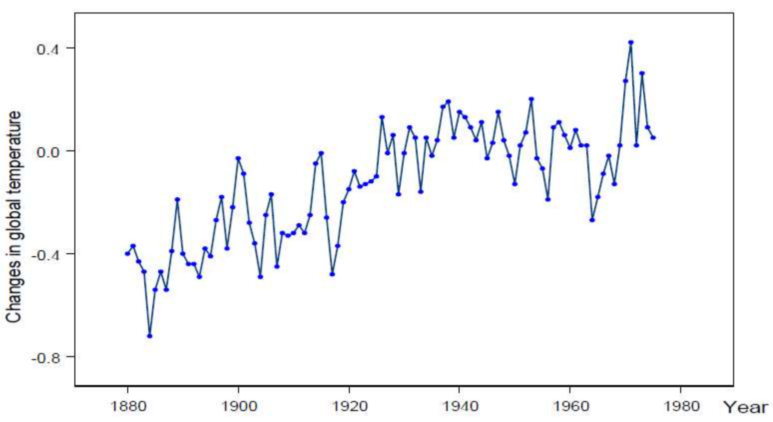
$$y_t = S_t \times T_t \times E_t.$$

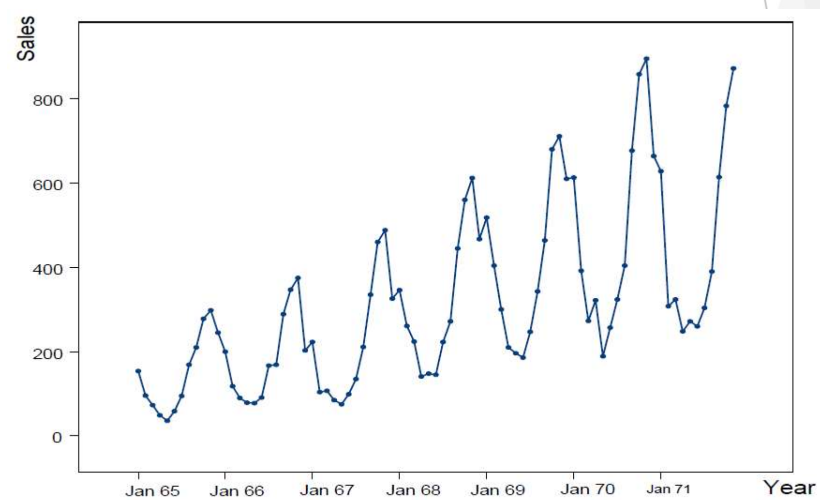
$$y_t = S_t + T_t + E_t$$

$$y_t = S_t \times T_t \times E_t$$









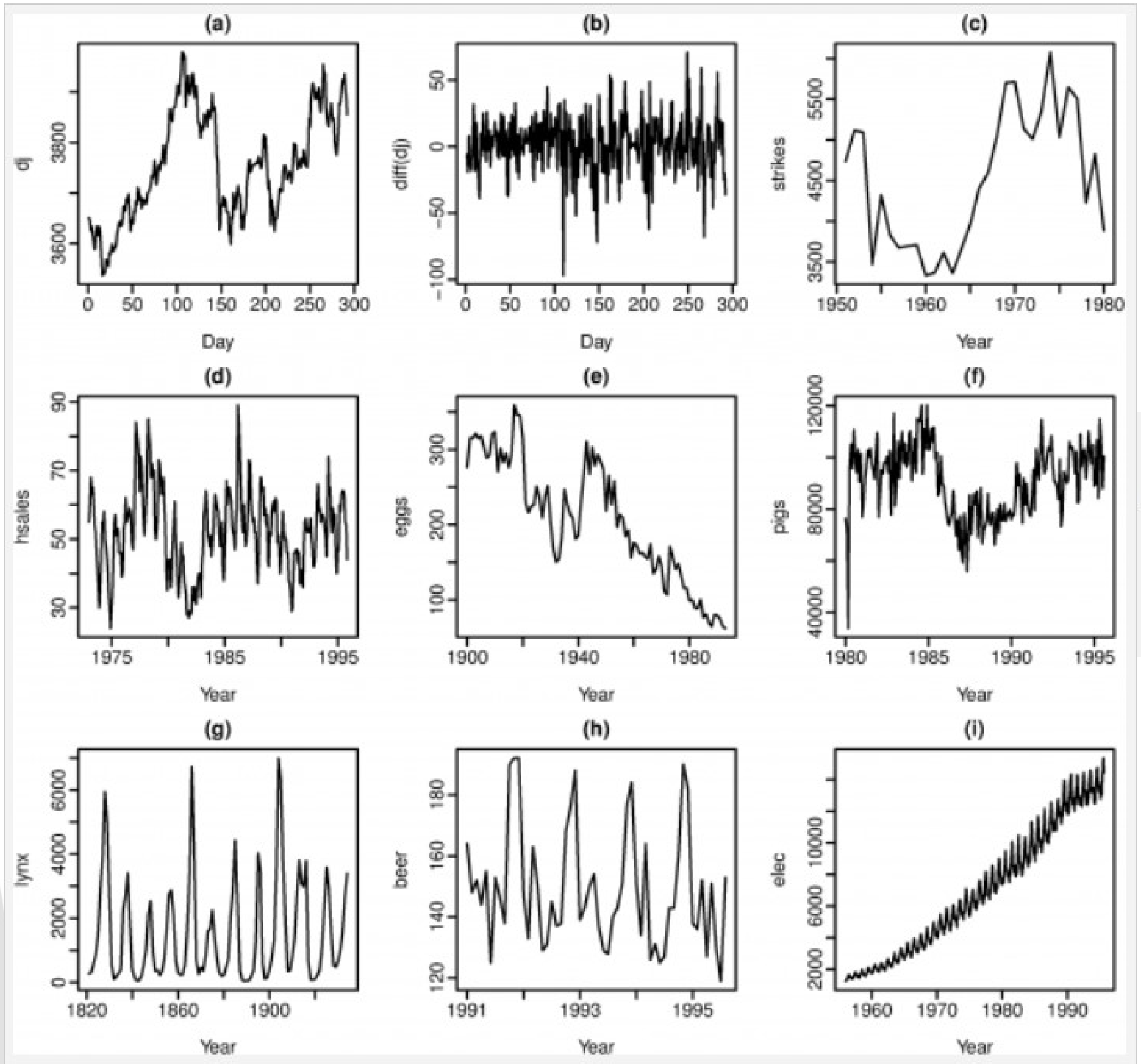


Figure 8.1: Which of these series are stationary? (a) Dow Jones index on 292 consecutive days; (b) Daily change in Dow Jones index on 292 consecutive days; (c) Annual number of strikes in the US; (d) Monthly sales of new one-family houses sold in the US; (e) Price of a dozen eggs in the US (constant dollars); (f) Monthly total of pigs slaughtered in Victoria, Australia; (g) Annual total of lynx trapped in the McKenzie River district of north-west Canada; (h) Monthly Australian beer production; (i) Monthly Australian electricity production.

Differencing

first (lag 1) difference operator by ∇

$$\nabla X_t = X_t - X_{t-1}$$

backward shift operator, usually denoted by B,

$$BX_t = X_{t-1}$$

example:

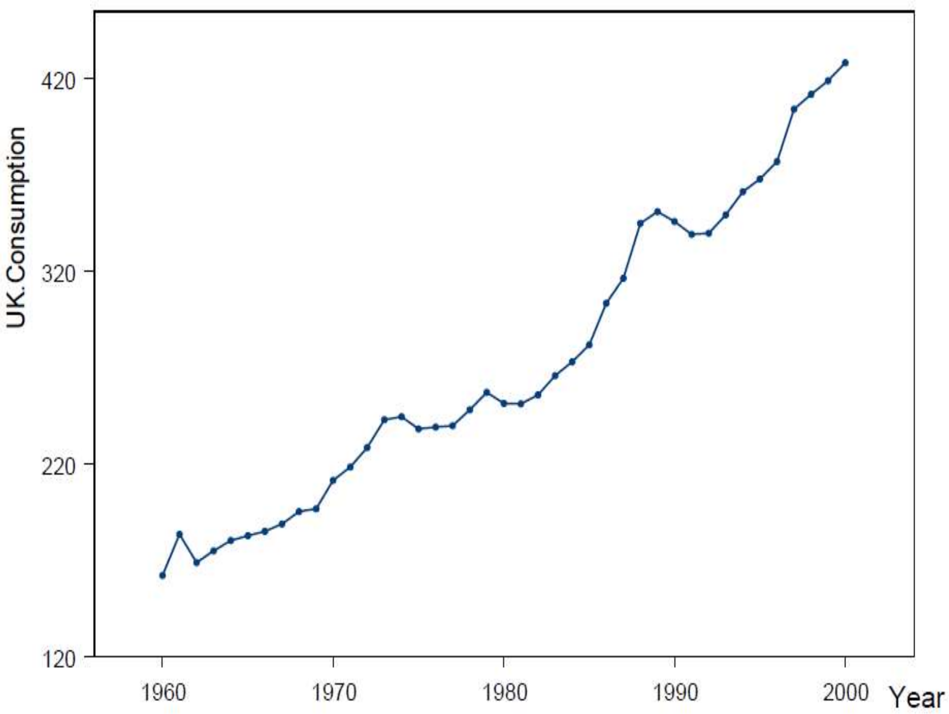
$$\nabla X_t = X_t - X_{t-1} \ = X_t - BX_t \ = (1-B)X_t.$$

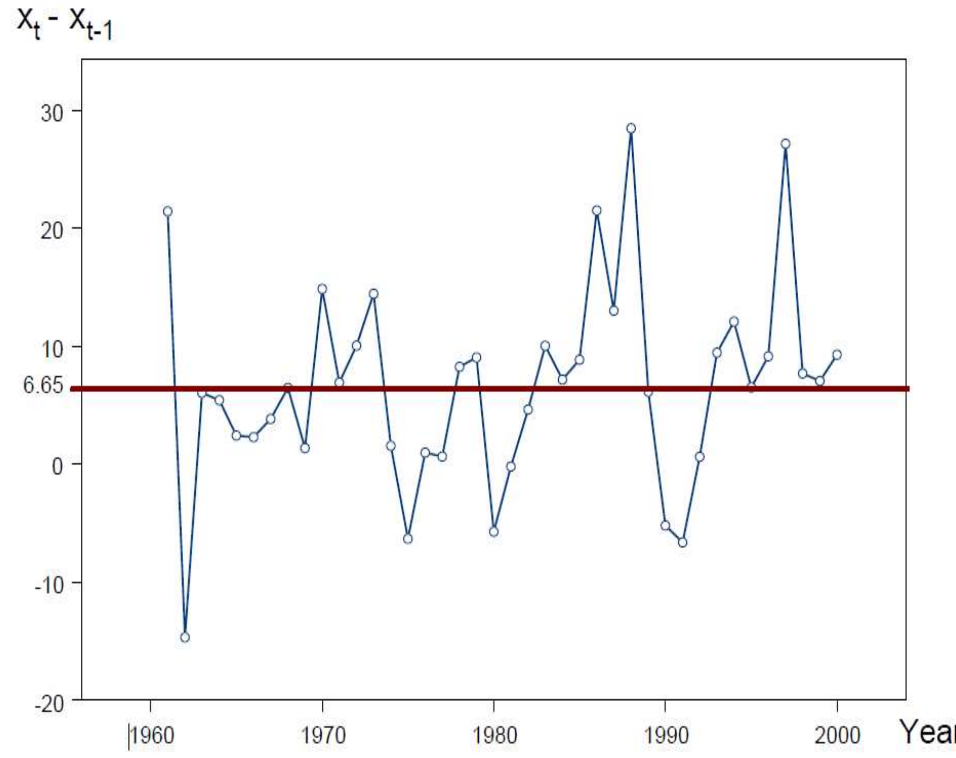
$$X_{t-2} = BX_{t-1} \ = B(BX_t) \ = B^2 X_t.$$

$$B^j X_t = X_{t-j}.$$

Example

$$X_t \rightarrow \nabla X_t = X_t - X_{t-1}$$





example:

$$\begin{aligned}\nabla^2 X_t &= \nabla(\nabla X_t) = (1-B)(1-B)X_t \\ &= (1-2B+B^2)X_t \\ &= X_t - 2X_{t-1} + X_{t-2}.\end{aligned}$$

Example

$$X_t = m_t + Y_t,$$

the trend m_t is a polynomial of degree k. Then for $k = 1$ we have $m_t = \beta_0 + \beta_1 t$

$$\begin{aligned}
\nabla X_t &= X_t - X_{t-1} \\
&= m_t + Y_t - (m_{t-1} + Y_{t-1}) \\
&= \beta_0 + \beta_1 t - [\beta_0 + \beta_1(t-1)] + \nabla Y_t \\
&= \beta_1 + \nabla Y_t.
\end{aligned}$$

Example Similarly, for $k = 2$ we obtain

$$X_t = m_t + Y_t, \qquad m_t = \beta_0 + \beta_1 t + \beta_2 t^2$$

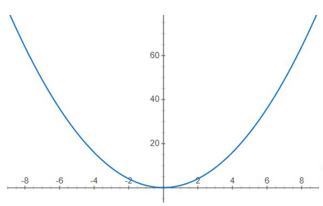
$$\nabla^2 X_t = X_t - 2X_{t-1} + X_{t-2}$$

$$= m_t + Y_t - 2(m_{t-1} + Y_{t-1}) + m_{t-2} + Y_{t-2}$$

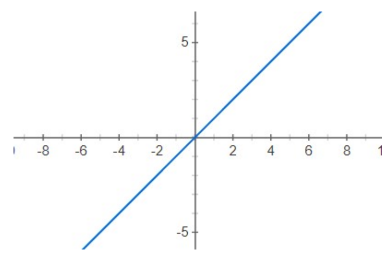
$$= \beta_0 + \beta_1 t + \beta_2 t^2 - 2[\beta_0 + \beta_1(t-1) + \beta_2(t-1)^2]$$

$$+ \beta_0 + \beta_1(t-2) + \beta_2(t-2)^2 + \nabla^2 Y_t$$

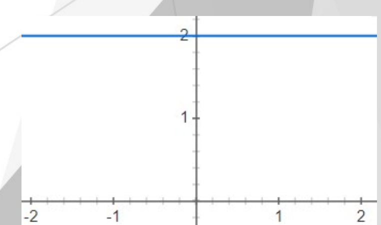
$$= 2\beta_2 + \nabla^2 Y_t.$$



$\nabla^2 X_t = X_t - 2X_{t-1} + X_{t-2}$



$\nabla X_t = X_t - X_{t-1}$



Differencing at lag d

lag-d differencing operator

$$\nabla_d X_t = X_t - X_{t-d} \;= (1 - B^d)X_t.$$

Example

$$\begin{aligned}\nabla_d X_t = X_t - X_{t-d} \;&= (m_t + s_t + Y_t) - (m_{t-d} + s_{t-d} + Y_{t-d}) \\ &= m_t - m_{t-d} \;+ Y_t - Y_{t-d}.\end{aligned}$$

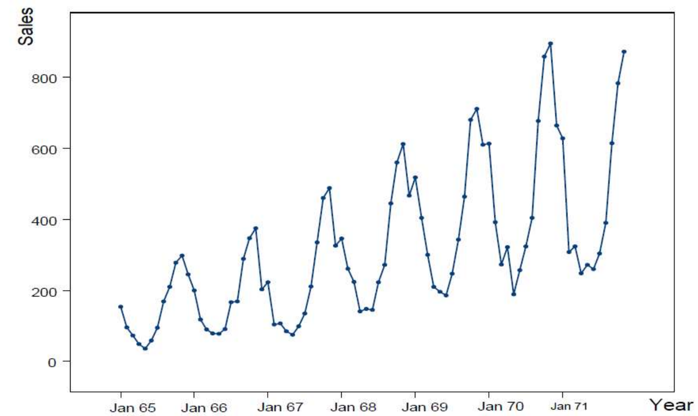


Figure : Sales of an industrial heater; monthly data starting from January 1965 till December 1971. Source: Chatfield (2004). (The last value is added for completeness).

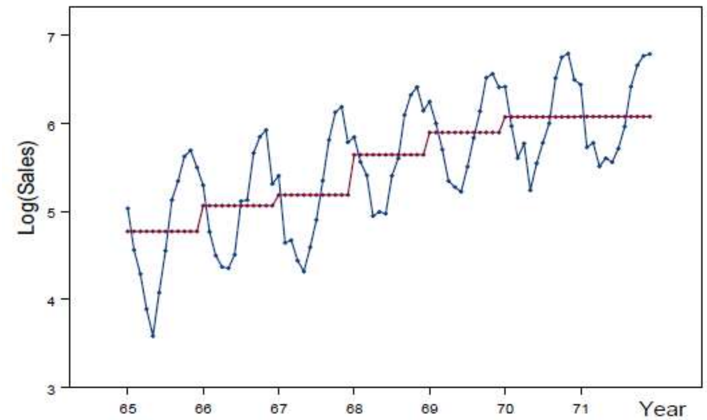


Figure : Transformed data and the Trend: Sales of an industrial heater.

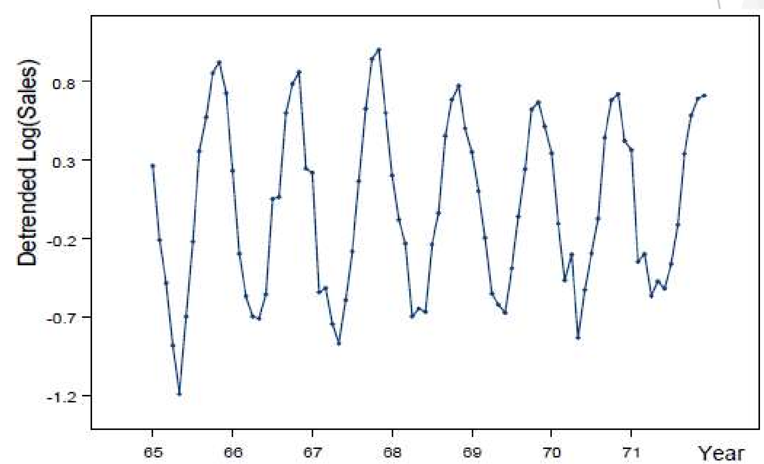


Figure : Detrended data: Sales of an industrial heater.

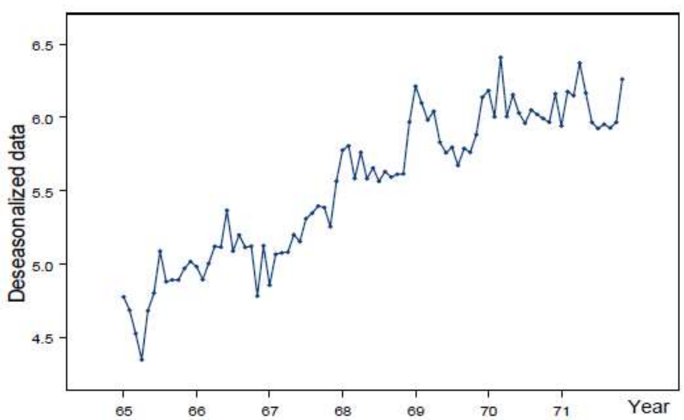


Figure : Deseasonalized data: Sales of an industrial heater.

MATLAB: Data handling

Step 1: documentation, Data sets and Examples

Step 2: Select data, example Data_EquityIdx

Step 3: Description of selected data set, example: price or index

Step 4: generate continuously compounded return

Step 5: plot the graphs

Build in functions: **load, price2ret, plot, subplot, figure**

Financial Data Analysis

Three patterns:

✓Trend

✓Seasonality

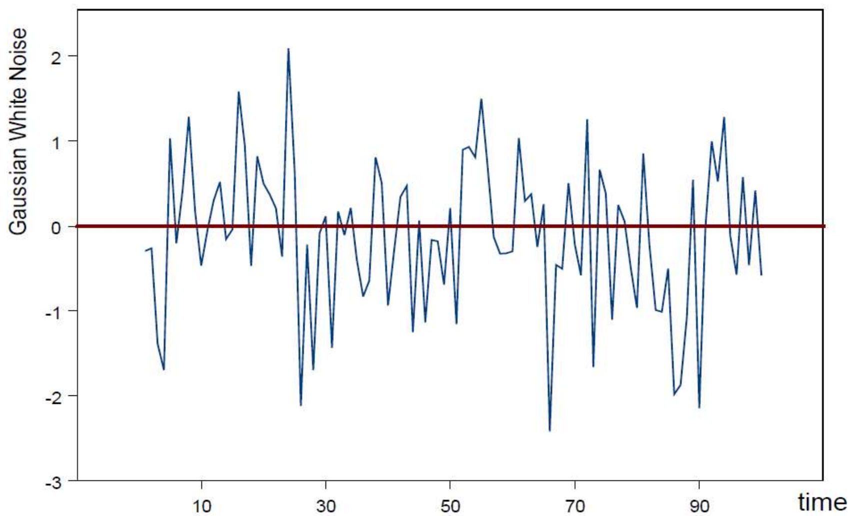
✓Correlation

Financial Data Analysis

A sequence $\{X_t\}$ of uncorrelated r.vs, each with zero mean and variance σ^2 is called **white noise**. It is denoted by

$$\{X_t\} \sim WN(0, \sigma^2).$$

The name 'white' comes from the analogy with white light and indicates that all possible periodic oscillations are present with equal strength.



Simulated Gaussian White Noise Time Series

Moving Average Process $Z_t \sim WN(0, \sigma^2)$

MA(1) process $X_t = Z_t + \theta Z_{t-1}, \quad t = 0, \pm 1, \pm 2, \ldots,$

MA(2) process $X_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2}$

Autoregressive Processes $Z_t \sim WN(0, \sigma^2)$ and ϕ is a constant

AR(1) $X_t = \phi X_{t-1} + Z_t$

AR(2) $X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + Z_t$

AR(1): $X_t = \phi X_{t-1} + Z_t$

MA(1): $X_t = Z_t + \theta Z_{t-1}$

ARMA(1,1): $X_t - \phi X_{t-1} = Z_t + \theta Z_{t-1}$

Autoregressive Moving Average Model ARMA(1,1)

ARMA(1,1) process

$X_t - \phi X_{t-1} = Z_t + \theta Z_{t-1}$ *for every* t, *where* $\{Z_t\} \sim WN(0, \sigma^2)$ *and* $\phi + \theta \neq 0$.

MATLAB: simulation

Simulation

- Simulate MA(1), MA(2), AR(1), AR(2), ARMA(1,1)

MA(1) process $\quad X_t = Z_t + \theta Z_{t-1}, \quad t = 0, \pm 1, \pm 2, \ldots,$

MA(2) process $\quad X_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2}$

Build in functions: **arima, rng, simulate, plot, title, subplot**

MATLAB: simulation

Simulation

- Simulate MA(1), MA(2), AR(1), AR(2), ARMA(1,1)

AR(1) $$X_t = \phi X_{t-1} + Z_t$$

AR(2) $$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + Z_t,$$

Build in functions: **arima, rng, simulate, plot, title, subplot**

MATLAB: simulation

Simulation

- Simulate MA(1), MA(2), AR(1), AR(2), ARMA(1,1)

$$X_t - \phi X_{t-1} = Z_t + \theta Z_{t-1} \quad \textit{for every } t,$$

$$\textit{where } \{Z_t\} \sim WN(0, \sigma^2) \textit{ and } \phi + \theta \neq 0.$$

Build in functions: **arima, rng, simulate, plot, title, subplot**


THE
END