

Applied Financial Econometrics

Lecturer: Axel A. Araneda, Ph.D.

About the course (1/2)

– Time table:

- Lectures: Friday 10:00-11:50 (P106)
- Seminars: Friday 14:00-15:50 (VT105)

– Course Rules:

- Attendance is highly recommended but not compulsory.
- The final grade of the course is established as:
 - Tasks on seminars (50%). The best 8 grades become the tasks grade.
 - Final Term or Exam (50%)

About the course (2/2)

– Contact

- Anytime by email: axelaraneda@mail.muni.cz

– Consultation (office) hours:

- Wednesday (11:00-12:00 hrs) and Friday (13:00-14:00 hrs).
- Preferable an email in advance.
- Office: 408.
- Other consultation hours (physically or virtually) per agreement by email.

About the lecturer

- Axel A. Araneda, Ph.D.
 - Native of Chile.
 - B.Sc. Physics and B.Eng. Engineering Physics.
 - Ph.D. in Complex Systems.
 - Former postdoc at FIAS and MUNI.
 - Current position: Assistant Professor, Department of Finance, MUNI.
 - Research line:
 - Quantitative Finance
 - Econophysics
 - Economic Modelling
 - Financial Econometrics

Outline of the course

1. Introduction to financial econometrics.
2. Predictability of market returns.
3. Time-series econometric models, AR (p), MA (p), ARMA (p, q), ARIMA (p, q).
4. Unit Root Tests and invertibility.
5. ARDL models – estimation, autocorrelation tests, HAC standard errors.
6. ARCH/GARCH models.
7. Value-at-Risk models.
8. Expected shortfall.
9. Market event study – design of a market event study.
10. News driven market movements.
11. Capital asset pricing model, Fama and French model.
12. Asset allocation (portfolio).



Lecture 1

Introduction to Financial Econometrics

- Introduction to financial markets and econometrics analysis using R.

Some Basics

- Time series: Sequence of successive observed points. Data indexed in time order.

$$X_{-1}, X_0, X_1, X_2, \dots, X_t, \dots X_n$$

```
library(quantmod)
getSymbols('^GSPC',src='yahoo', from="2010-01-01") # S&P500 since 2010
SP500=GSPC$GSPC.Adjusted # adjusted closing price
plot(SP500)
```



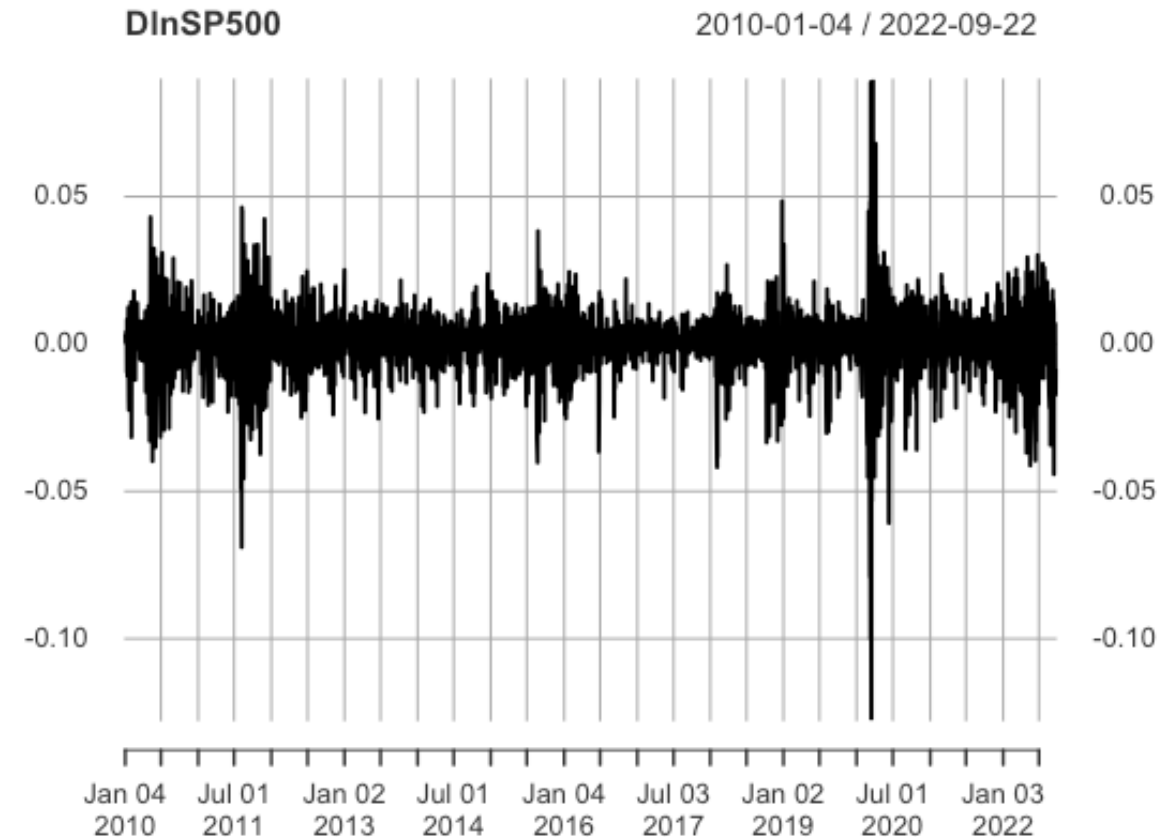
Some Basics

– Simple return: $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$

– Log-return:

$$r_t = \ln \left(\frac{P_t}{P_{t-1}} \right) = \ln(P_t) - \ln(P_{t-1})$$

```
#log_returns  
lnSP500<-log(SP500) # Natural log of SP500  
DlnSP500<-diff(lnSP500) # First difference of lnSP500  
plot(DlnSP500) |
```



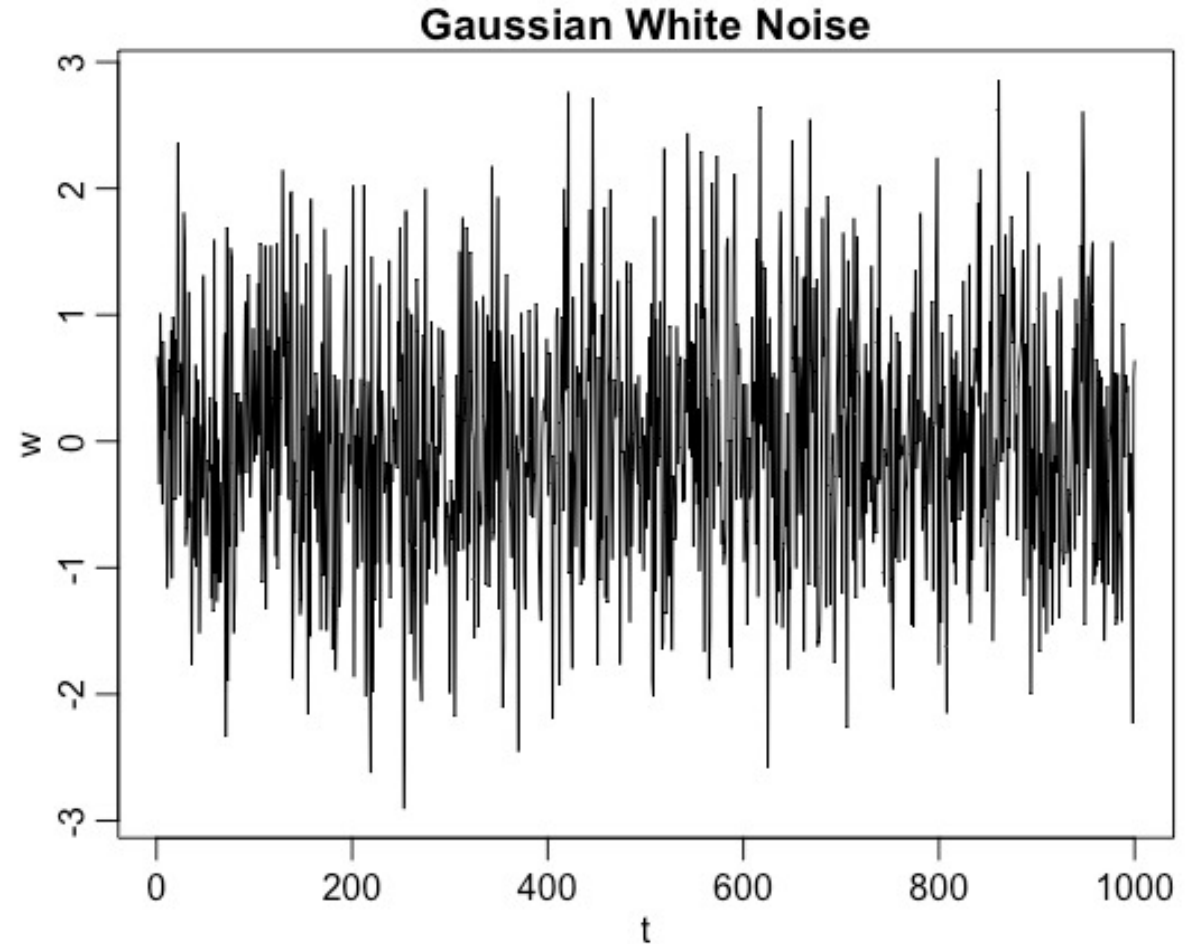
Some Basics

– White noise: Random variable u_t with zero unconditional mean, constant variance, and uncorrelated.

- $\mathbb{E}(u_t) = 0$
- $\text{Var}(u_t) = \sigma^2$
- $\text{Cov}(u_s, u_t) = 0$

– In case $u_t \sim N(0, \sigma^2)$: Gaussian WN

```
set.seed(120)
w=rnorm(1000,0,1)
plot(w,type="l", main = 'Gaussian White Noise',xlab='t')
```



Time-series decomposition

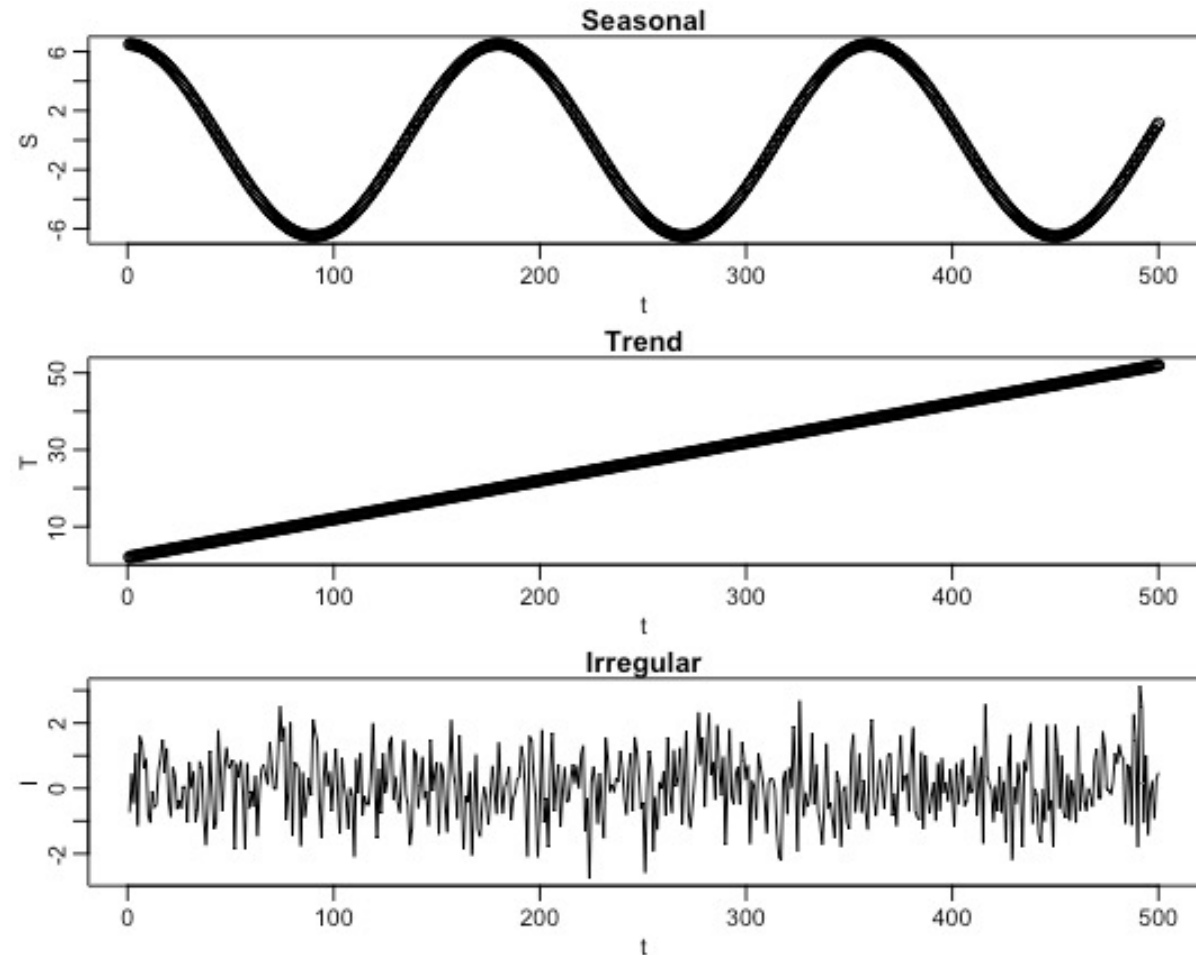
– Time-series are usually decomposed into:

- a) A trend T_t
- b) A seasonal component S_t
- c) An irregular element I_t

– For example:

$$T_t = 2 + 0.1t; S_t = \cos\left(\pi \frac{t}{90}\right); I_t \sim N(0, 1)$$

```
t<-seq(1,500)
T<-2+0.1*t
S<-6.5*cos(pi*t/90)
I<-rnorm(500,0,1)
par(mfrow=c(3,1))
plot(S,xlab='t',main='Seasonal')
plot(T,xlab='t',main='Trend')
plot(I,type='l',xlab='t',main='Irregular')
par(mfrow=c(1,1))
plot.ts(S + T + I)
```



Time-series decomposition

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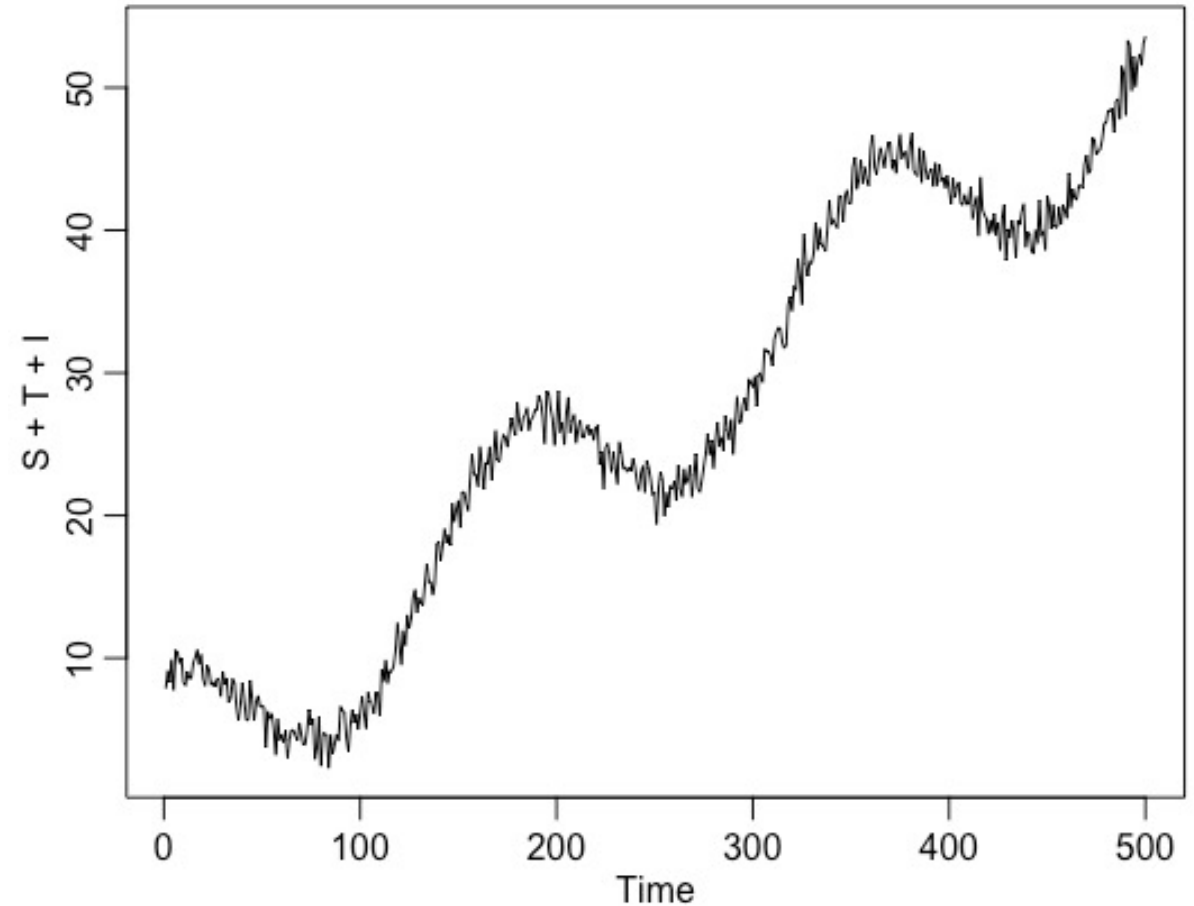
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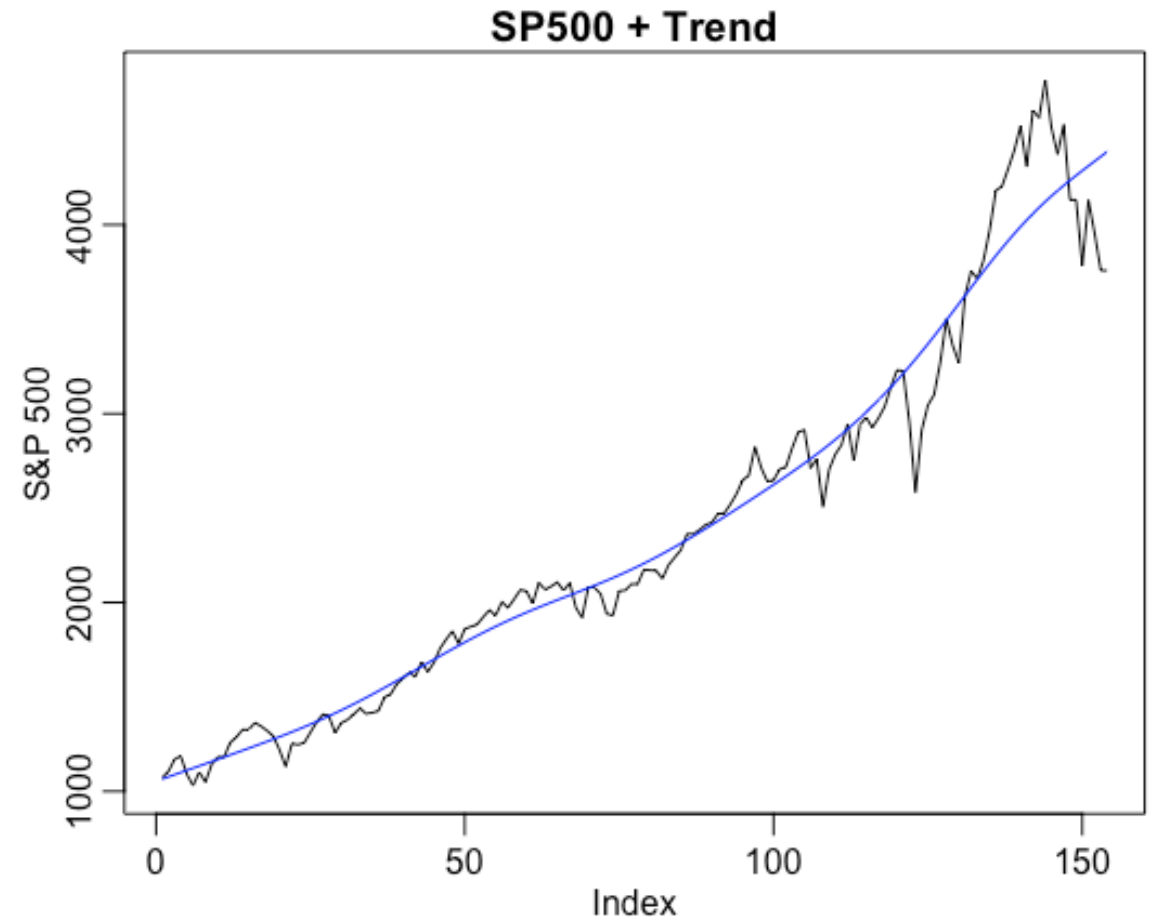
```
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par(mfrow=c(1,1))
plot.ts(S + T + I)
```



Time-series decomposition: Hodrick-Prescott Filter

- The Hodrick-Prescott (HP) filter allows to separate the trend and cyclic components for x_t .

```
#install.packages("mFilter")  
library(mFilter)  
HPF<-hpfilter(SP500, freq=14400, type="lambda")  
plot(HPF$cycle, type = 'l')  
plot(HPF$trend, type = 'l')  
plot(HPF$x, type = 'l', ylab='S&P 500', main='SP500 + Trend')  
lines(HPF$trend, col='blue')
```



Time-series differences

– First difference:

$$\Delta x_t = x_t - x_{t-1}$$

– Second difference:

$$\Delta^2 x_t = (x_t - x_{t-1}) - (x_{t-1} - x_{t-2})$$

Difference transformations are used to capture the seasonal component of the series

Dummy variables

- D is a binary variable such that:
 - $D=1$ if the observation has specific characteristics.
 - $D=0$ if it does not have them.

– For example: $x_t = \beta_0 + \beta_1 z_t + \beta_2 D + \beta_3 D z_t$

$$D = 1 \Rightarrow x_t = (\beta_0 + \beta_2) + (\beta_1 + \beta_3) z_t$$

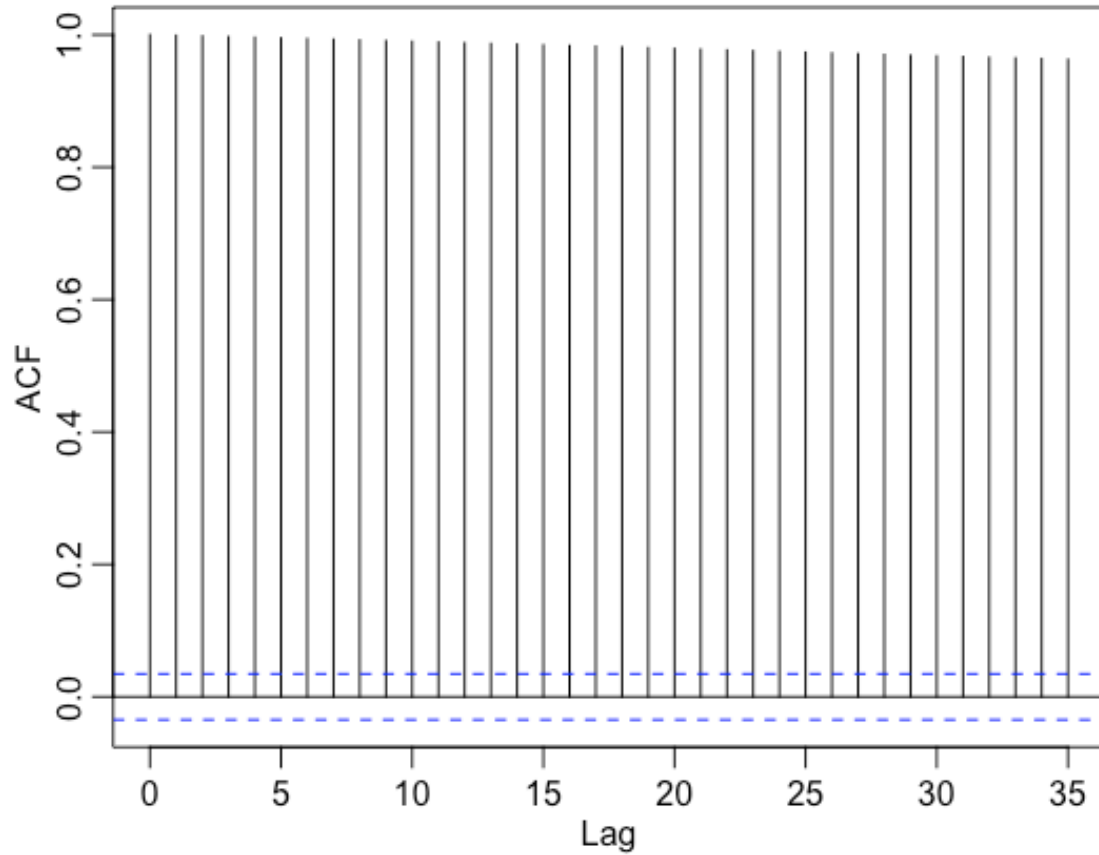
$$D = 0 \Rightarrow x_t = \beta_0 + \beta_1 z_t$$

Dummy variables can be used to change the slope and/or intercept in a linear model, which allows capturing seasonality namely (quarter or season)

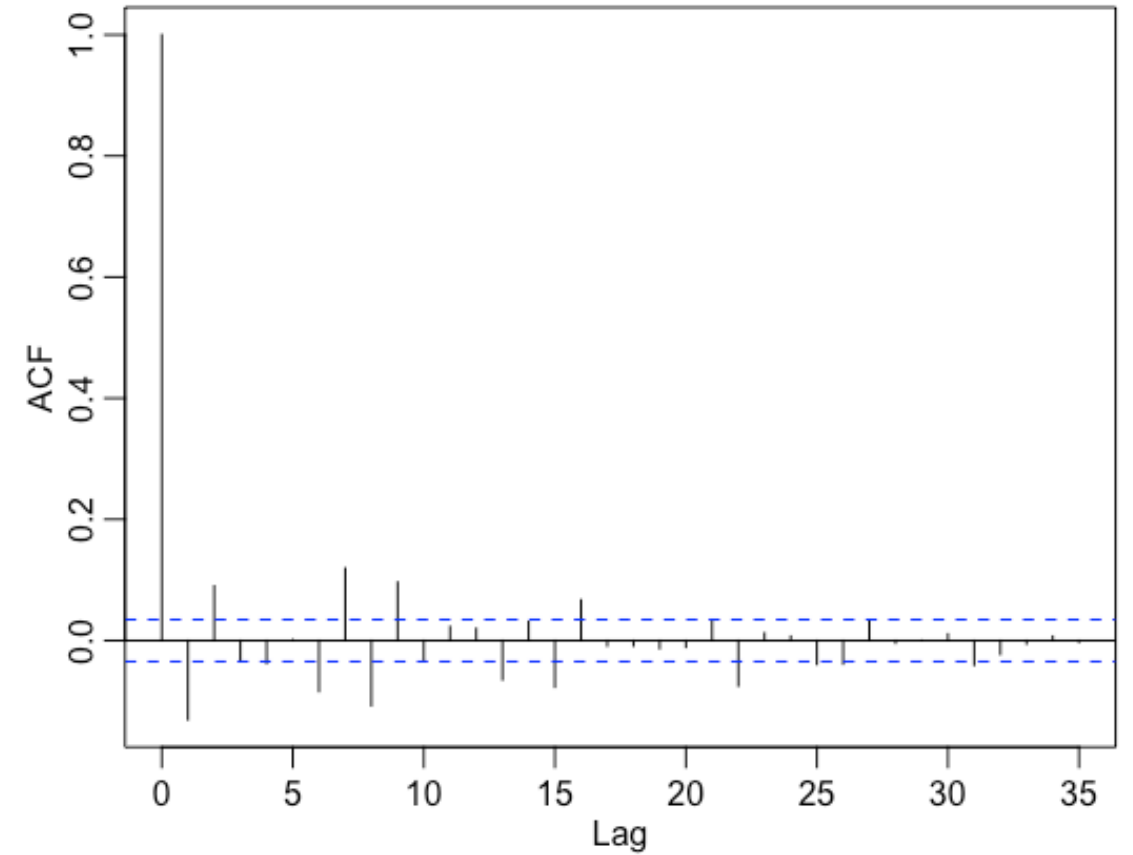
Statistics and dependency measures

- Mean:
$$\mu_x = \mathbb{E}(x_t) = \int_{-\infty}^{\infty} x f(x_t) dx$$
- Autocovariance:
$$\gamma_x(s, t) = \text{COV}(x_t, x_s) = \mathbb{E}(x_t - \mu_{x_t}, x_s - \mu_{x_s})$$
- Autocorrelation:
$$-1 \leq \rho(s, t) = \frac{\gamma(s, t)}{\sqrt{\gamma(s, s) \gamma(t, t)}} \leq 1$$

ACF, measures the linear predictability of the series at time t ; i.e., we predict x_t using only the value x_s .



```
acf(SP500,na.rm = TRUE,na.action = na.pass)
```



```
acf(DlnSP500,na.rm = TRUE,na.action = na.pass)
```