

# Seminar 5 Solutions

## *Stationarity and Time Series Properties*

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# Roadmap

## Exercise 1: True/False

- Gauss-Markov Assumptions

- Trending Variables

- Seasonality

## Exercise 3: Stationarity

- Stochastic Processes

- Weakly Stationary Process

## Exercise 4: Stationarity

- Setup

- Expected Value and Variance

- Autocovariance

- Autocorrelation

## Exercise 6: Stock Return Predictability

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# Disclaimer

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Full solutions are available on my.wbs. All exercises are examinable material, not just the ones we covered in the seminars.

# Exercise 1

## *Gauss-Markov Assumptions*

**Q:** The OLS estimator in a time-series setting is unbiased under the first three Gauss-Markov assumptions.

# Exercise 1

## *Gauss-Markov Assumptions*

**Q:** The OLS estimator in a time-series setting is unbiased under the first three Gauss-Markov assumptions.

1. TS.1: Linearity in parameters
2. TS.2: No perfect collinearity
3. TS.3: Strict exogeneity / Zero conditional mean

When we add the following two assumptions, the OLS estimator is also BLUE.

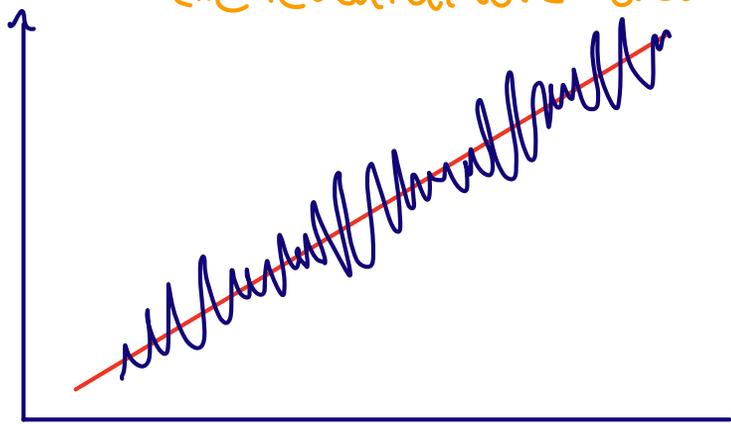
4. TS.4: Homoskedasticity
5. TS.5: No serial correlation

# Exercise 1

## Trending Variables

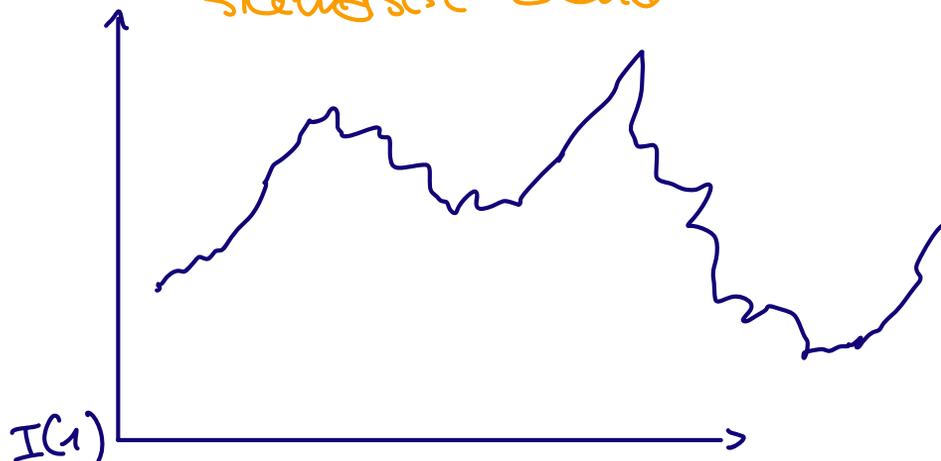
**Q:** A trending variable cannot be used as a dependent variable in the multiple linear regression model.

deterministic trend



$$y_t = \beta_0 + \beta_1 x_t + \alpha t + u_t$$

stochastic trend



$I(1)$   
as RW:  $\underline{x}_t = x_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2)$

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

$I(0) \quad \Delta x_t = \varepsilon_t$

# Exercise 1

## *Trending Variables*

**Q:** A trending variable cannot be used as a dependent variable in the multiple linear regression model.

- Trending variables *can* be used as dependent variables in a linear regression model.
- However, be cautious when interpreting the results:
  - spurious relationship between  $y_t$  and trending explanatory variables.
- Including a time trend in the regression is advisable when dependent and/or independent variables are trending.
- The usual  $R^2$  measure can be misleading when the dependent variable is trending.

# Exercise 1

## *Seasonality*

**Q:** Seasonality is not an issue when using annual time-series observations.

# Exercise 1

## *Seasonality*

**Q:** Seasonality is not an issue when using annual time-series observations.

- Each period represents a year and this is not associated with any season.

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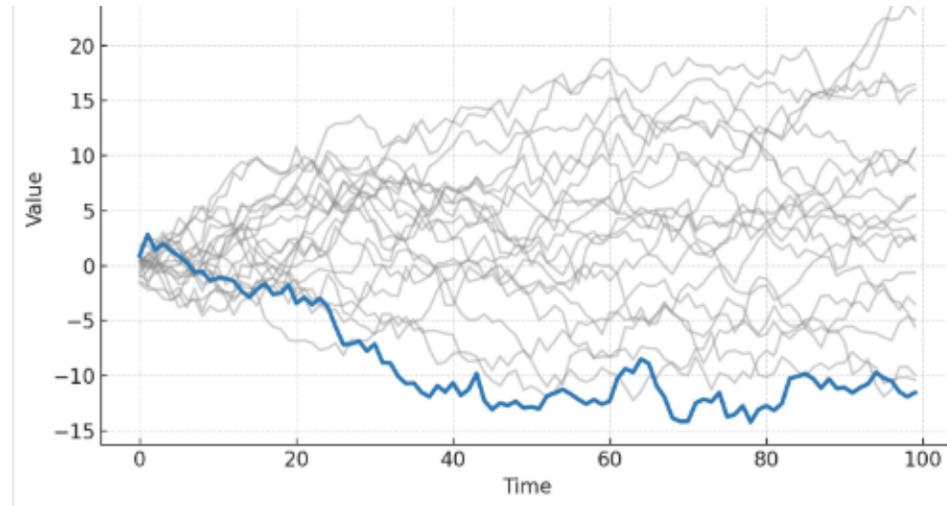
Autocorrelation

## Exercise 6: Stock Return Predictability

# Exercise 3

## *Stochastic Processes*

We model time series as a sequence of **random variables**. A collection of random variables indexed by time is called a **stochastic process**



- We observe only one realization of the process
- But all the grey paths were equally likely to have happened
- We want to make inference about the **whole process**, and we see only one path

# Exercise 3

## Weakly Stationary Process: Correlation

Let  $\{x_t : t = 1, 2, \dots, T\}$  be a weakly stationary process.

Define  $\gamma_h = \text{Cov}(x_t, x_{t+h})$  for  $h \geq 0$ . Then  $\gamma_0 = \text{Var}(x_t)$ . Show that

$$\text{Corr}(x_t, x_{t+h}) = \frac{\gamma_h}{\gamma_0}.$$

## Weak (or covariance) Stationarity

A stochastic process  $\{x_t : t = 1, 2, \dots\}$  is said to be weakly stationary if:

$$\mathbb{E}(x_t) = \mu, \quad \text{Var}(x_t) = \sigma^2, \quad \text{Cov}(x_t, x_{t+h}) = f(h).$$

A weakly stationary process is uniquely determined by its mean, variance, and autocovariance function.

X 1980

X 1985

X 2015

X 2020

### Exercise 3

$$\text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

Derivation

$$\gamma_h = \text{cov}(x_t, x_{t+h})$$

$$h=0 \quad \underline{\underline{\gamma_0}} = \text{cov}(x_t, x_{t+0}) = \text{cov}(x_t, x_t) = \text{var}(x_t)$$

$$\text{corr}(x_t, x_{t+h}) = \frac{\text{cov}(x_t, x_{t+h})}{\sqrt{\text{var}(x_t)} \sqrt{\text{var}(x_{t+h})}} = \frac{\gamma_h}{\gamma_0}$$

$$\text{var}(x_t) = \text{var}(x_{t+1}) = \dots = \text{var}(x_{t+h}) = \gamma_0$$

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# Exercise 4

## Setup

Suppose that a time-series process  $\{x_t : t = 1, 2, \dots, T\}$  is given by

$$x_t = z + \epsilon_t,$$

for all  $t = 1, 2, \dots, T$ , where  $\epsilon_t$  is an i.i.d. sequence with mean zero and variance  $\sigma_\epsilon^2$ . The random variable  $z$  is constant over time, and it has mean zero and variance  $\sigma_z^2$ .

Furthermore, assume that  $\epsilon_t$  is uncorrelated with  $z$ .

$$\begin{aligned} \epsilon_t &\overset{\text{iid}}{\sim} (0, \underbrace{\sigma_\epsilon^2}_{\text{var}}) \\ z &\sim (\underbrace{0}_{\text{mean}}, \underbrace{\sigma_z^2}_{\text{var}}) \end{aligned} \quad \text{COV}(\epsilon_t, z) = 0$$

# Exercise 4

Expected Value and Variance

$$x_t = z + \varepsilon_t$$

**Q:** Find the expected value and variance of  $x_t$ . Do your answers depend on  $t$ ?

$$E[x_t] = E[z + \varepsilon_t] = E[z] + E[\varepsilon_t] \quad E[x_{t+u}] = 0$$

$\downarrow \quad \leftarrow \quad \downarrow$   
 $0 \quad \leftarrow \quad \textcircled{\forall t}$

$$\text{var}(x_t) = \text{var}(z + \varepsilon_t) = \text{var}(z) + \text{var}(\varepsilon_t) + \underbrace{2\text{cov}(z, \varepsilon_t)}_0$$

$\downarrow \quad \downarrow \quad \downarrow$   
 $= \sigma_z^2 + \sigma_\varepsilon^2 \quad \forall t$

$$\text{cov}(\varepsilon_t, z) = E[\varepsilon_t z]$$

$$E[x_t] = 0$$

# Exercise 4

$$\text{COV}(X, Y) = \boxed{E[XY]} - \cancel{E[X]E[Y]}$$

↑  $C$

$$\leftarrow E[\varepsilon_t] = 0$$

## Autocovariance

**Q:** Find  $\text{Cov}(x_t, x_{t+h})$  for any  $t$  and  $h$ . Is  $x_t$  a weakly stationary process?

$$\begin{aligned} \text{COV}(x_t, x_{t+h}) &= E[x_t x_{t+h}] - E[x_t] E[x_{t+h}] \\ &= E[x_t x_{t+h}] \\ &= E[(z + \varepsilon_t)(z + \varepsilon_{t+h})] \end{aligned}$$

$h=1$   $\text{COV}(x_t, x_{t+1}) = E[(z + \varepsilon_t)(z + \varepsilon_{t+1})]$

$h=2$   $= E[z^2 + \varepsilon_t z + z \varepsilon_{t+1} + \varepsilon_t \varepsilon_{t+1}]$

$$= E[z^2] + \underbrace{E[\varepsilon_t z]}_0 + E[z \varepsilon_{t+1}] + E[\varepsilon_t \varepsilon_{t+1}]$$

$\leftarrow \text{COV}(\varepsilon_t, z)$

## Exercise 4

### Autocorrelation

**Q:** Show that  $\text{Corr}(x_t, x_{t+h}) = \frac{\sigma_z^2}{\sigma_z^2 + \sigma_\epsilon^2}$  for any  $t$  and  $h$ .

$$\text{COV}(x_t, x_{t+h}) = \frac{1}{h} \sigma_z^2$$

$$= \sigma_z^2 \quad \forall t \equiv \text{constant}$$

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# Exercise 6

## Predictive Model – Regression Output

Model:

$$\text{Return}_t = \beta_0 + \beta_1 \text{Return}_{t-1} + u_t, \quad u_t \sim N(0, \sigma^2).$$

Source	SS	df	MS	Number of obs =	689
Model	10.6866231	1	10.6866231	F( 1, 687) =	2.40
Residual	3059.73817	687	4.45376735	Prob > F =	0.1218
Total	3070.42479	688	4.46282673	R-squared =	0.0035
				Adj R-squared =	0.0020
				Root MSE =	2.1104

return	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
return_1	.0588984	.0380231	1.55	0.122	-.0157569 .1335538
_cons	.179634	.0807419	2.22	0.026	.0211034 .3381646

**Q:** Compute the unconditional mean and variance of the returns.

# Exercise 6

## Unconditional Mean and Variance

- AR(1) model:  $\text{Return}_t = \beta_0 + \beta_1 \text{Return}_{t-1} + u_t$ .
- Unconditional mean:

$$E(\text{Return}_t) = \frac{\beta_0}{1 - \beta_1} = \frac{0.179}{1 - 0.058} = 0.19.$$

- Unconditional variance of returns is

$$\text{Var}(\text{Return}_t) = \frac{\sigma^2}{1 - \beta_1^2} = \frac{4.45}{1 - 0.058^2} = 4.465.$$

- where the error variance is computed from the residuals as

$$\hat{\sigma}^2 = \frac{\hat{u}'\hat{u}}{T - k - 1} = \frac{3059}{687} = 4.45.$$

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## *Expectations Hypothesis – Setup*

Let  $hy6_t$  denote the three-month holding-period yield (in percent) from buying a six-month T-bill at time  $(t - 1)$  and selling it at time  $t$  (three months later) as a three-month T-bill. Let  $hy3_{t-1}$  be the three-month holding-period yield from buying a three-month T-bill at time  $(t - 1)$ .

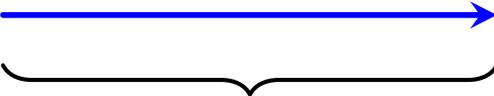
An implication of the EH is that no other variable dated as  $t - 1$  or earlier should help explain  $hy6_t$  once  $hy3_{t-1}$  has been controlled for. Including one lag of the spread between the 6-month and 3-month T-bills rates yields

$$hy6_t = \beta_0 + \beta_1 hy3_{t-1} + \beta_2 (r6_{t-1} - r3_{t-1}) + u_t$$

# Exercise 1

## Visual Representation



- 3-month T-bill   
 $hy3_{t-1}$  known at  $t - 1$

- 6-month T-bill   
 $hy6_t$  unknown at  $t - 1$

# Exercise 1

## Estimation Results

Source	SS	df	MS			
Model	86.8264477	2	43.4132238	Number of obs =	123	
Residual	11.2905482	120	.094087901	F( 2, 120) =	461.41	
Total	98.1169958	122	.804237671	Prob > F =	0.0000	
				R-squared =	0.8849	
				Adj R-squared =	0.8830	
				Root MSE =	.30674	

hy6	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
hy3_1	1.053483	.0385001	27.36	0.000	
spr63_1	.4799728	.1085678	4.42	0.000	
_cons	-.1229242	.066781	-1.84	0.068	

Q: Is  $\beta_1$  statistically different from one?

# Exercise 1

## Computing the $t$ -Statistic

- The OLS estimate of  $\beta_1$  is  $\hat{\beta}_1 = 1.053$ .
- Compute the  $t$ -statistic for testing  $H_0 : \beta_1 = 1$ :

$$t_{\hat{\beta}_1} = \frac{\hat{\beta}_1 - 1}{\text{se}(\hat{\beta}_1)} = \frac{1.053 - 1}{0.038} = \frac{0.053}{0.038} = 1.39.$$

- Since  $1.39 < c$ , fail to reject  $H_0$ : the estimate is not statistically different from 1 at usual significance levels.

# Exercise 1

## *Lagged Spread Significance*

**Q:** Is the lagged spread term significant? Should we invest in six-month or three-month T-bills if  $r_6$  is above  $r_3$  at time  $t - 1$ ?

- The lagged spread is clearly significant, as the p-value is 0.000.
- Therefore, we reject the null hypothesis  $H_0 : \beta_2 = 0$  at the 1% significance level.
- For the buying strategy when  $r_6 > r_3$ , the three-month holding-period yield from buying a six-month T-bill is higher than what is implied by the Expectations Hypothesis (EH).
- As a result, it is more favorable to invest in a six-month T-bill.

# Exercise 1

## Time Trend

Suppose you estimate a linear time trend model on the three-month holding-period yield from buying a six-month T-bill:

$$hy6_t = \alpha_0 + \alpha_1 t + u_t$$

Source	SS	df	MS	Number of obs =	123
Model	34.8025748	1	34.8025748	F( 1, 121) =	66.51
Residual	63.314421	121	.523259678	Prob > F =	0.0000
Total	98.1169958	122	.804237671	R-squared =	0.3547
				Adj R-squared =	0.3494
				Root MSE =	.72337

hy6	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
t	.0149814	.001837	8.16	0.000	.0113446 .0186182
_cons	.770868	.1328443	5.80	0.000	.5078677 1.033868

- We can clearly reject the null hypothesis  $H_0 : \alpha_1 = 0$  (p-value = 0.000).