



Norwegian University of
Science and Technology

Department of Economics

Examination paper for FIN3006 Applied Time Series Econometrics

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Formelsamling:

Knut Sydsæter, Arne Strøm og Peter Berck (2006): Matematisk formelsamling for økonomer, 4utg. Gyldendal akademiske.

Knut Sydsæter, Arne Strøm, og Peter Berck (2005): Economists' mathematical manual, Berlin.

Calculator:

Casio fx-82ES PLUS, Casio fx-82EX Citizen SR-270x, SR-270X College or HP 30S.

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Informasjon om trykking av eksamensoppgave

Originalen er:

1-sidig **2-sidig**

sort/hvit **farger**

skal ha flervalgskjema

Checked by:

Date

Signature

Instructions

The exam consists of Question 1 and Question 2, each one presenting a number of subquestions. On page 6 and page 7 you will find the Stata commands (do-file) and output (log-file) relative to Question 1. On page 10 and page 11 you will find the Stata commands (do-file) and output (log-file) relative to Question 2. Read carefully the text. Answer all questions. Good luck!

Question 1

This question is largely based on Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3-6.

"The analysis of Bitcoin has recently received much attention. This can be attributed to its innovative features, simplicity, transparency and its increasing popularity (Urquhart, 2016), while since its introduction it has posed great challenges and opportunities for policy makers, economists, entrepreneurs, and consumers (Dyhrberg, 2016b). Bitcoin is probably the most successful - and probably most controversial - virtual currency scheme to date (ECB, 2012 p. 21), representing about 41% of the total estimated cryptocurrency capitalisation at present¹. However, recent fluctuations in Bitcoin prices (see Figure 1) have resulted in periods of high volatility. In fact, as Bitcoin is mainly used as an asset rather than a currency (Glaser et al., 2014; Baek and Elbeck, 2015; Dyhrberg, 2016a), the Bitcoin market is currently highly speculative, and more volatile and susceptible to speculative bubbles than other currencies (Grinberg, 2011; Cheah and Fry, 2015). Bitcoin has therefore a place in the financial markets and in portfolio management (Dyhrberg, 2016a), and examining its volatility is crucial. Moreover, the presence of long memory and persistent volatility (Bariviera et al., 2017) justifies the application of GARCH-type models. [...]

Most of the previous studies of the Bitcoin price volatility have used a single conditional heteroskedasticity model, a question that remains unanswered is which conditional heteroskedasticity model can better explain the Bitcoin data. [...]

The data used are the daily closing prices for the Bitcoin Coindesk Index from 18th July 2010 (as the earliest date available) to 1st October 2016, which corresponds to a total of 2267 observations.

The returns are calculated by taking the natural logarithm of the ratio of two consecutive prices. Figure illustrates both the Bitcoin prices and price returns." (Katsiampa, 2017, p.3)

The returns are called *return* in the do-file and log-file. On page 6 and page 7 you will find the Stata commands (do-file) and output (log-file) relative to this question.

¹coinmarketcap.com accessed on Jun 12th 2017

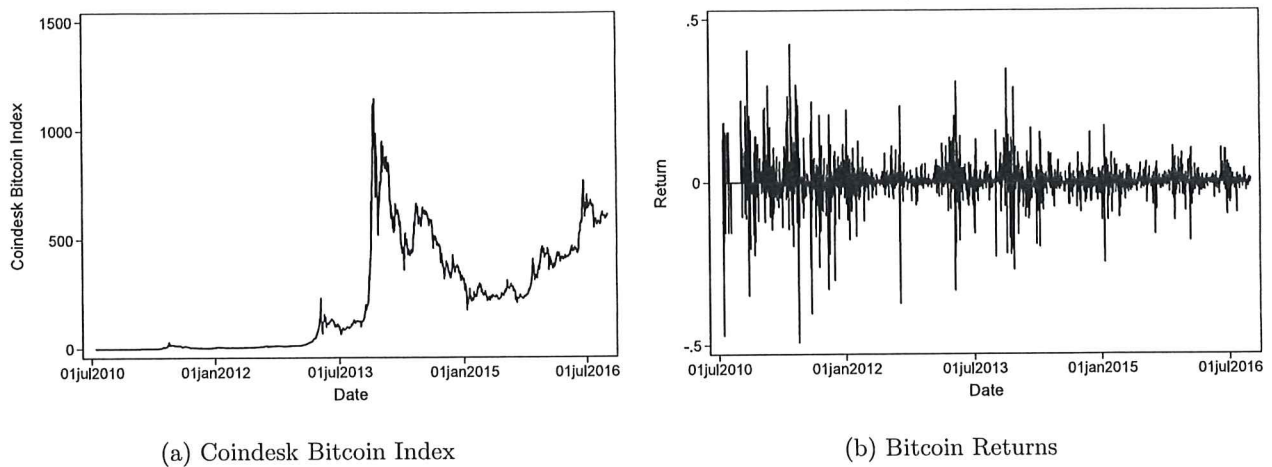


Figure 1: Daily closing prices and price returns of the Coindesk Bitcoin Index (US Dollars)

- (a) Before starting with her analysis, the author writes on p. 4 of the paper: “The value of the test for conditional heteroskedasticity confirms that there exist ARCH effects in the returns of the Bitcoin price index, suggesting that the Autoregressive model for the conditional mean needs to be expanded to include an Autoregressive Conditional Heteroskedasticity model for the conditional variance.” Explain this sentence. In particular: 1) Define the two models that the author is comparing and 2) Present one test that the author has possibly performed to distinguish between the two models.
- (b) Consider now the estimation of Model 1 presented on line 22-27 in the do-file and line 15-20 in the log-file. Define the Q-statistic and its purpose in this analysis.
- (c) Consider now the two different GARCH models estimated. Present them and explain the results.
- (d) Which model would you choose between the two estimated? Which implications do the models have for investors? Explain, justifying your choices.
- (e) Suppose you wanted to compare the two models based on their forecasting performance of the conditional variance, and subsequently choose the best performing model. Explain a test based on which you could make this decision.

Focus now solely on the bitcoin price, shown in Figure 1(a). An article published in Forbes on 10 December 2013² states:

After a summer lull of relatively stability, the crypto-currency started making headlines again as the latest investment vehicle. Babin Tremblay said the coin's latest parabolic rise started in early October as a result of Chinese demand. The demand in November was so high that some prices quoted on Chinese exchanges were almost double compared to exchanges outside the country, he said. "The rest of the world has been buying bitcoins to try and sell them to Chinese consumers because there is so much demand there," he said. He added that the country's growing middle class are attracted to the crypto-currency because of the lack of other alternatives. "Essentially you have the perfect storm in China," he said. "It's very difficult for Chinese people to invest overseas. They have a real estate bubble, they have a stock market bubble and they have one of the highest saving rates in the world."

Chinese demand for bitcoins cooled significantly since hitting its November high, after the Chinese government announced that it was cracking down on the currency. On Dec. 5 China's central bank barred banks from handling bitcoin transactions."

- (f) A financial analyst suspects that international events such as the one presented above have a significant permanent impact on data-generating process of the bitcoin price. Looking at Figure 1(a), present an adequate model that would account for this feature.

²Excerpt from <https://www.forbes.com/sites/kitconews/2013/12/10/2013-year-of-the-bitcoin>, last retrieved on 30 November 2018

Question 2

Arms races have long been a central area of interest in the field of international relations. Beginning with the seminal work of the political scientist Lewis Richardson, scholars have been interested in the dynamics of whether, when, and to what extent states match their rivals' spending on military weapons. The question was particularly important during the Cold War, when numerous scholars examined the dynamics of the U.S.-Soviet arms race. Although the arms race literature has faded in importance in the field of international relations with the end of the Cold War, there are still important rivalries around the world that maintain the competitive dynamics that could lead states to spend heavily on weapons to match their competitors.

One intense non-superpower rivalry that has garnered some attention in the arms race literature is that between India and Pakistan. Figure 2 shows both countries' defense spending over the 1949-2001 period, when the rivalry was at its most intense. (Box-Steffensmeier, Janet M., et al. Time series analysis for the social sciences. Cambridge University Press, 2014, p.166-167)



Figure 2: India and Pakistan Defense Spending, 1948-2001

Note that the analysis in point (a) to (d) is performed for the years 1948 to 1990. In the do-file and log-file, *pakds* indicates Pakistani Defense Spending, while *indds* indicates Indian defense spending, both in millions of U.S. dollars. On page 10 and page 11 you will find the Stata commands (do-file) and output (log-file) relative to this question.

- (a) Present the test for nonstationarity performed on lines 22-23 in the do-file and lines 15-16 of the log file, and discuss the findings.

- (b) “Because we have confirmed nonstationarity in both series, the next step is to investigate the possibility of cointegration.” Explain whether you agree with this statement.
- (c) Discuss the analysis presented on lines 31-34 of the do-file and lines 28-31 of the log-file. In particular, discuss whether: 1) you find evidence of cointegration and 2) whether you agree with the use of the Dickey-Fuller test as produced by Stata.
- (d) Discuss the results from the estimation of the model on line 36 of the do-file and lines 33 of the log-file. What can you conclude about the relationship between Indian and Pakistani defense spending?
- (e) A young econometrician knows that the methodology discussed up to now presents a number of limitations. Hence, she decides to follow a different testing strategy to check for cointegration. In addition, she decides to extend the estimation period to 2001. The analysis is shown on line 43 of the do-file and line 40 of the log-file. Discuss the test performed and its findings, emphasizing what they imply for the relationship between Indian and Pakistani defense spending.
- (f) What could explain the different results in point (c) and (e)?

```

1 *****
2 *****
3 * Question 1
4 *****
5 *****
6
7 log using FIN3006exam_h18_question1_log.smcl, replace nomsg
8
9 *****
10 ** Log-file - QUESTION 1
11 *****
12 clear all
13 use bitcoin_final.dta
14 tsset time
15
16 *****
17
18 ** Estimation - Model 1
19
20 *****
21
22 arch return, ar(1) arch(1) garch(1) nolog
23 estat ic
24 predict h_garch, variance
25 predict res_garch, res
26 gen std_res_garch=res_garch/sqrt(h_garch)
27 wntestq std_res_garch, lag(10)
28
29
30
31 *****
32
33 ** Estimation - Model 2
34
35 *****
36 arch return, ar(1) arch(1) garch(1) tarch(1) nolog
37 estat ic
38 predict h_tgarch, variance
39 predict res_tgarch, res
40 gen std_res_tgarch=res_tgarch/sqrt(h_tgarch)
41 wntestq std_res_tgarch, lag(10)
42
43 log close
44

```

```

1 .
2 . *****
3 . ** Log-file - QUESTION 1
4 . *****
5 . clear all

6 . use bitcoin_final.dta

7 . tsset time
   time variable:  time, 1 to 2268
   delta: 1 unit

8 .
9 . *****
10 .
11 . ** Estimation - Model 1
12 .
13 . *****
14 .
15 . arch return, ar(1) arch(1) garch(1) nolog

```

ARCH family regression -- AR disturbances

```

Sample: 2 - 2268           Number of obs   =       2,267
Distribution: Gaussian     Wald chi2(1)   =         9.29
Log likelihood = 3829.551  Prob > chi2    =         0.0023

```

returns	OPG		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
returns						
_cons	.0018001	.0007294	2.47	0.014	.0003705	.0032296
ARMA						
ar						
L1.	.0760451	.0249435	3.05	0.002	.0271567	.1249336
ARCH						
arch						
L1.	.2681125	.0115737	23.17	0.000	.2454285	.2907964
garch						
L1.	.7539281	.0065832	114.52	0.000	.7410253	.7668309
_cons	.0001004	3.43e-06	29.32	0.000	.0000937	.0001071

16 . estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	2,267	.	3829.551	5	-7649.103	-7620.472

Note: N=Obs used in calculating BIC; see [\[R\] BIC note](#).

17 . predict h_garch, variance

18 . predict res_garch, res
(1 missing value generated)

19 . gen std_res_garch=res_garch/sqrt(h_garch)
(1 missing value generated)

20 . wntestq std_res_garch, lag(10)

Portmanteau test for white noise

Portmanteau (Q) statistic = 35.6062
 Prob > chi2(10) = 0.0001

21 .

22 .

23 .

24 . *****

25 .

26 . ** Estimation - Model 2

27 .

28 . *****

29 . arch return, ar(1) arch(1) garch(1) tarch(1) nolog

ARCH family regression -- AR disturbances

Sample: 2 - 2268	Number of obs =	2,267
Distribution: Gaussian	Wald chi2(1) =	8.75
Log likelihood = 3830.912	Prob > chi2 =	0.0031

returns	OPG				[95% Conf. Interval]
	Coef.	Std. Err.	z	P> z	
returns					
_cons	.0020553	.0007649	2.69	0.007	.0005561 .0035544

ARMA							
	ar						
	L1.	.0733922	.0248088	2.96	0.003	.0247678	.1220166
ARCH							
	arch						
	L1.	.238068	.0119247	19.96	0.000	.214696	.26144
	tarch						
	L1.	.0557199	.0207454	2.69	0.007	.0150596	.0963802
	garch						
	L1.	.7549076	.0068933	109.51	0.000	.741397	.7684182
	_cons	.0001003	3.55e-06	28.26	0.000	.0000934	.0001073

30 . estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	2,267	.	3830.912	6	-7649.825	-7615.468

Note: N=Obs used in calculating BIC; see [R] BIC note.

31 . predict h_tgarch, variance

32 . predict res_tgarch, res
(1 missing value generated)

33 . gen std_res_tgarch=res_tgarch/sqrt(h_tgarch)
(1 missing value generated)

34 . wntestq std_res_tgarch, lag(10)

Portmanteau test for white noise

Portmanteau (Q) statistic =	34.5271
Prob > chi2(10) =	0.0002

35 .

36 . log close

```

1 *****
2 *****
3 * Question 2
4 *****
5 *****
6
7 log using FIN3006exam_h18_question2_log.smcl, replace nomsg
8
9 *****
10 ** Log-file - QUESTION 2
11 *****
12 clear all
13 use indipaki.dta
14 tsset year
15
16
17 *****
18
19 ** Identification
20
21 *****
22 dfuller pakds if year<1991, drift
23 dfuller indds if year<1991, drift
24
25
26 *****
27
28 ** Estimation - Only up to 1990
29
30 *****
31 reg indds pakds if year<1991
32 predict residuals if year<1991, res
33
34 dfuller residuals, drift
35
36 var d.indds d.pakds if year<1991, exog(l.residuals) lags(1/3)
37
38 *****
39
40 ** Alternative Estimation - Full sample
41
42 *****
43 vecrank indds pakds
44
45
46 log close
47

```

```

1 .
2 . *****
3 . ** Log-file - QUESTION 2
4 . *****
5 . clear all

6 . use indipaki.dta

7 . tsset year
   time variable: year, 1948 to 2001
   delta: 1 unit

8 .
9 .
10 . *****
11 .
12 . ** Identification
13 .
14 . *****
15 . dfuller pakds if year<1991, drift

```

Dickey-Fuller test for unit root Number of obs = 42

Test Statistic	Z(t) has t-distribution		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.423	-1.684	-1.303

p-value for Z(t) = 0.9592

```
16 . dfuller indds if year<1991, drift
```

Dickey-Fuller test for unit root Number of obs = 42

Test Statistic	Z(t) has t-distribution		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.423	-1.684	-1.303

p-value for Z(t) = 0.9857

```

17 .
18 .
19 .
20 .
21 .

```

22 .
 23 . *****
 24 .
 25 . ** Estimation - Only up to 1990
 26 .
 27 . *****
 28 . reg indds pakds if year<1991

Source	SS	df	MS	Number of obs	=	
Model	3.4435e+14	1	3.4435e+14	F(1, 41)	=	985.35
Residual	1.4328e+13	41	3.4947e+11	Prob > F	=	0.0000
Total	3.5867e+14	42	8.5398e+12	R-squared	=	0.9601
				Adj R-squared	=	0.9591
				Root MSE	=	5.9e+05

indds	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
pakds	3.403981	.1084408	31.39	0.000	3.184981	3.622982
_cons	-62240.45	130591.3	-0.48	0.636	-325974.9	201494

29 . predict residuals if year<1991, res
 (11 missing values generated)

30 .
 31 . dfuller residuals, drift

Dickey-Fuller test for unit root Number of obs = 42

Test Statistic	Z(t) has t-distribution		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.438	-2.423	-1.684

p-value for Z(t) = 0.0007

32 .
 33 . var d.indds d.pakds if year<1991, exog(l.residuals) lags(1/3)

Vector autoregression

Sample: 1952 - 1990	Number of obs	=	39
Log likelihood = -1065.934	AIC	=	55.48379
FPE = 4.33e+21	HQIC	=	55.72866
Det(Sigma_ml) = 1.88e+21	SBIC	=	56.16627

Equation	Parms	RMSE	R-sq	chi2	P>chi2
----------	-------	------	------	------	--------

D_indds	8	398376	0.4722	34.89672	0.0000
D_pakds	8	147609	0.2969	16.46623	0.0212

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
D_indds						
indds						
LD.	.4200342	.171752	2.45	0.014	.0834065	.7566619
L2D.	-.0363878	.1616146	-0.23	0.822	-.3531465	.280371
L3D.	.7486132	.1597915	4.68	0.000	.4354276	1.061799
pakds						
LD.	-.3540278	.5340671	-0.66	0.507	-1.40078	.6927246
L2D.	-.2626064	.5284725	-0.50	0.619	-1.298393	.7731808
L3D.	-1.92713	.4957406	-3.89	0.000	-2.898764	-.9554965
residuals						
L1.	-.4260569	.1445496	-2.95	0.003	-.709369	-.1427449
_cons	144885.6	77198.19	1.88	0.061	-6420.085	296191.2
D_pakds						
indds						
LD.	.0075642	.0636388	0.12	0.905	-.1171656	.1322939
L2D.	-.0359262	.0598826	-0.60	0.549	-.1532939	.0814416
L3D.	.1731291	.0592071	2.92	0.003	.0570853	.2891729
pakds						
LD.	-.0320751	.1978864	-0.16	0.871	-.4199254	.3557752
L2D.	.0502077	.1958135	0.26	0.798	-.3335797	.4339951
L3D.	-.0593546	.1836854	-0.32	0.747	-.4193714	.3006622
residuals						
L1.	.0536739	.0535596	1.00	0.316	-.051301	.1586488
_cons	36204.53	28604.03	1.27	0.206	-19858.35	92267.4

```

34 .
35 . *****
36 .
37 . ** Alternative Estimation - Full sample
38 .
39 . *****
40 . vecrank indds pakds

```

Johansen tests for cointegration

Trend: constant Number of obs = **52**
 Sample: 1950 - 2001 Lags = **2**

				5%	
maximum				trace	critical
rank	parms	LL	eigenvalue	statistic	value
0	6	-1488.5299	.	12.8106*	15.41
1	9	-1482.614	0.20351	0.9787	3.76
2	10	-1482.1246	0.01865		

41 . log close