Outlined Solutions FIN3006 Exam - Fall 2018

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Instructions

The exam consists of Question 1 and Question 2, each one presenting a number of subquestions. On page 9 and page 10 you will find the Stata commands (do-file) and output (log-file) relative to Question 1. On page 13 and page 14 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 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 present[1]. However, recent fluctuations in Bitcoin prices (see Figure) 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 specu- lative 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. [...]

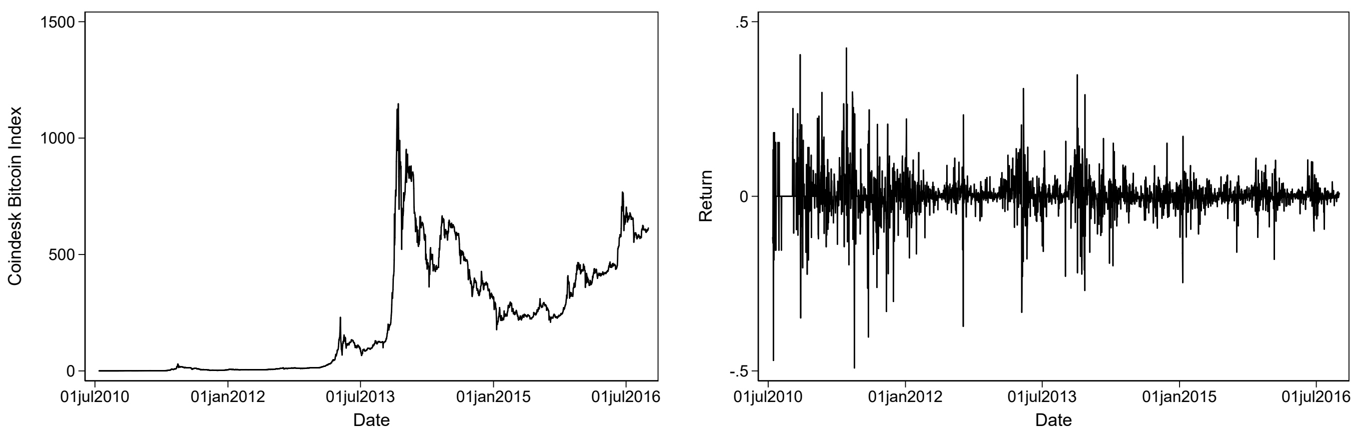
[1] coinmarketcap.com accessed on Jun 12th 2017

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.



(a) Coindesk Bitcoin Index

(b) Bitcoin Returns

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.

Solution. We have discussed a LM test in class. Note that using variable labels that relate to the question rather than generic y or z is preferred. The key elements that one should explain are:

- An AR model
- An ARCH model
- The LM test, where residuals from the AR model are regressed on their past values. Students should emphasize that the statistic must be large enough to reject H0. See textbook on p. 137.

(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.

Solution. The Q-statistic is one of the first concepts introduced in the course. It checks the statistical significance of autocorrelation terms. Here the students should:

- Define the Q-statistic. With a large number of autocorrelatons some will exceed two standard deviations due to pure chance. It is important to test whether the correlations are jointly significant. See p.68.
- Explain the Q-statistic is applied to standardized residuals. Through standardization the error term in the GARCH should behave as a white noise. See textbook applications on p.138.

(c) Consider now the two different GARCH models estimated. Present them and explain the results.

Solution. Here the students should present the GARCH (1,1) and TGARCH(1,1) models. Emphasis on:

- Non-negativity constraints in GARCH terms are satisfied. Constraints in the TGARCH model are also satisfied.

- Results suggest that negative shocks have larger impact on volatility than positive shocks.

(d) Which model would you choose between the two estimated? Which implications do the models have for investors? Explain, justifying your choices.

Solution. AIC very close, BIC selects GARCH, magnitude of the dummy in TGARCH economically small albeit statistically significant. The answer should include:

- Explanation of the two criteria. Note that they are likelihood-based in this context.
- A good reply should point to the fact that the Q-statistic indicates that serial correlation is still present in the models so extra effort should be put in analyzing the dynamics of volatility.
- Presence of leverage effects points to the fact that rising bitcoin prices are accompanied by declining volatility, but also vice versa. This model is in principle not favored by the two criteria, so investors should not expect leverage effect. However, it is important to point out that the persistence of volatility effects from residual analysis cast doubts on the validity of this analysis.

(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.

Solution. Students should present the Diebold-Mariano test. See p.86.

Focus now solely on the bitcoin price shown in Figure 1(a). An article published in Forbes on 10 December 2013[2] states:

After a summer lull of relatively stability, the crypto-currency started making headlines again as the latest investment vehicle. BabinTremblay 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."

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

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) An analyst suspects that international events such as the one presented above have a significant impact on data-generating process of the bitcoin price. Looking at Figure 11a, present an adequate model that would account for this feature.

Solution. Setting aside concerns of integration about the variable, one could present a TAR model. Looking at the Figure, there seems to have been 3 phases. A good answer should therefore briefly point to the issue of choosing break points or multiple breaks in a serie.

Question 2

Arms races have long been a central area of interest in the field of international relations. Beginning with the seminal work of weatherman-turned-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 1949-1990 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.

(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.

Solution. This requires discussion of a standard Dickey-Fuller test. The null, alternative hypothesis, test statistic and rejection regions should be reported. The test fails to reject H0 hence suggesting the presence of a unit root.

(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.

Solution. By definition, cointegration necessitates two variables to be integrated of the same order. Hence one would need to test the order of integration of each variable. The test is suggesting at least one unit root but the two variables could still have different orders of cointegration. It would be more appropriate to test also the presence of unit roots in the differenced variables.

(c) Discus 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.

Solution. The students should present here the Engle-Granger methodology. One important caveat (that the code does not account for) is that it is not possible to use the Dickey-Fuller usual test tables, as the residuals are estimated quantities and thus the procedure is prejudiced toward finding a stationary error process.

(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?

Solution. India seem to respond to Pakistani changes in defense spending, not the other way around. Speed of adjustments should be discussed and, hence, the answer should focus on the short-run vs long-run response of the variables.

(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.

Solution. A discussion of the trace test is expected. See p. 378. The results indicate zero cointegrating vectors. This would suggest that the two variables are not cointegrated, hence they do not have any long term relationship.

(f) What could drive the results at point (e) compared with what you found at point (c)?

Solution. Here students should carefully look at Figure 2. As shown, after the 1990s the two processes seem to have experienced a break. Structural breaks tend to invalidate the Dickey Fuller test. Hence it could be that: 1) at point (c) the incorrect critical values for the test were reported by Stata, hence the finding of cointegration could be invalid; 2) the presence of a structural break in the 1990s is leading the Johansen's procedure towards finding unit roots even where there are not.

```
*****************************************************************
*****************************************************************
* Question 1
*****************************************************************
*****************************************************************

log using FIN3006exam_h18_question1_log.smcl, replace nomsg

************************************************
** Log-file - QUESTION 1
************************************************
clear all
use bitcoin_final.dta
tsset time

************************************************

**  Estimation - Model 1

************************************************

arch return, ar(1) arch(1) garch(1)  nolog
estat ic
predict h_garch, variance
predict res_garch, res
gen std_res_garch=res_garch/sqrt(h_garch)
wntestq std_res_garch, lag(10)



************************************************

** Estimation - Model 2

************************************************
arch return, ar(1)  arch(1) garch(1)  tarch(1) nolog
estat ic
predict h_tgarch, variance
predict res_tgarch, res
gen std_res_tgarch=res_tgarch/sqrt(h_tgarch)
wntestq std_res_tgarch, lag(10)

log close

```

```
.
. *********************************************
. ** Log-file - QUESTION 1
. *********************************************
. clear all

. use bitcoin_final.dta

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

.
. *********************************************
.
. **  Estimation - Model 1
.
. *********************************************
.
. 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

------------------------------------------------------------------------------
             |                 OPG
     returns |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
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
------------------------------------------------------------------------------
```

```
. 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.

. predict h_garch, variance

. predict res_garch, res
(1 missing value generated)

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

. wntestq std_res_garch, lag(10)

Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    35.6062
 Prob > chi2(10)           =     0.0001

.
.
.
. ***********************************************
.
. ** Estimation - Model 2
.
. ***********************************************
. 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

------------------------------------------------------------------------------
             |                 OPG
     returns |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
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
```

```
*******************************************************************
*******************************************************************
* Question 2
*******************************************************************
*******************************************************************

log using FIN3006exam_h18_question2_log.smcl, replace nomsg

*************************************************
** Log-file - QUESTION 2
*************************************************
clear all
use indipaki.dta
tsset year


*************************************************

**  Identification

*************************************************
dfuller pakds if year<1991, drift
dfuller indds if year<1991, drift


*************************************************

**  Estimation - Only up to 1990

*************************************************
reg indds pakds if year<1991
predict residuals if year<1991, res

dfuller residuals, drift

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

*************************************************

**  Alternative Estimation - Full sample

*************************************************
vecrank  indds pakds


log close
```

```
 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

                               ---------- Z(t) has t-distribution ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)              1.786            -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

                               ---------- Z(t) has t-distribution ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)              2.270            -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   =        43
-------------+----------------------------------   F(1, 41)        =    985.35
       Model |  3.4435e+14         1  3.4435e+14   Prob > F        =    0.0000
    Residual |  1.4328e+13        41  3.4947e+11   R-squared       =    0.9601
-------------+----------------------------------   Adj R-squared   =    0.9591
       Total |  3.5867e+14        42  8.5398e+12   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

                               ---------- Z(t) has t-distribution ----------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.438            -2.423            -1.684            -1.303
------------------------------------------------------------------------------
   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

```
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. ************************************************
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. **  Alternative Estimation - Full sample
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. ************************************************
. vecrank  indds pakds
```

Johansen tests for cointegration

Trend: constant　　　Number of obs = **52**

Sample: **1950 - 2001**　　　Lags = **2**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical 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