

**Practical 4**  
**Note for Eview 9**

**Yung-Lin Wang**

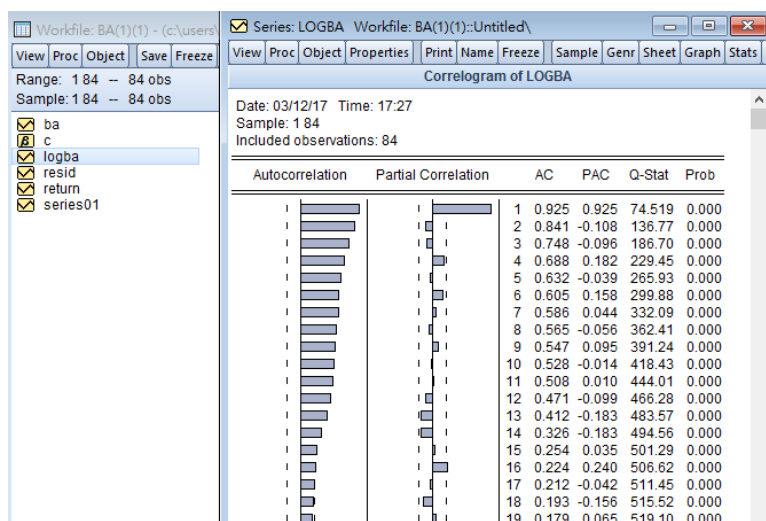
**Financial Modelling and  
Business Forecasting  
2016/2017**

## AR Modelling (Dataset: BA)

### 1. Can Graphics Function suggest a preferred model for the price of British Airways?



Now we look at ACF/PACF plot.



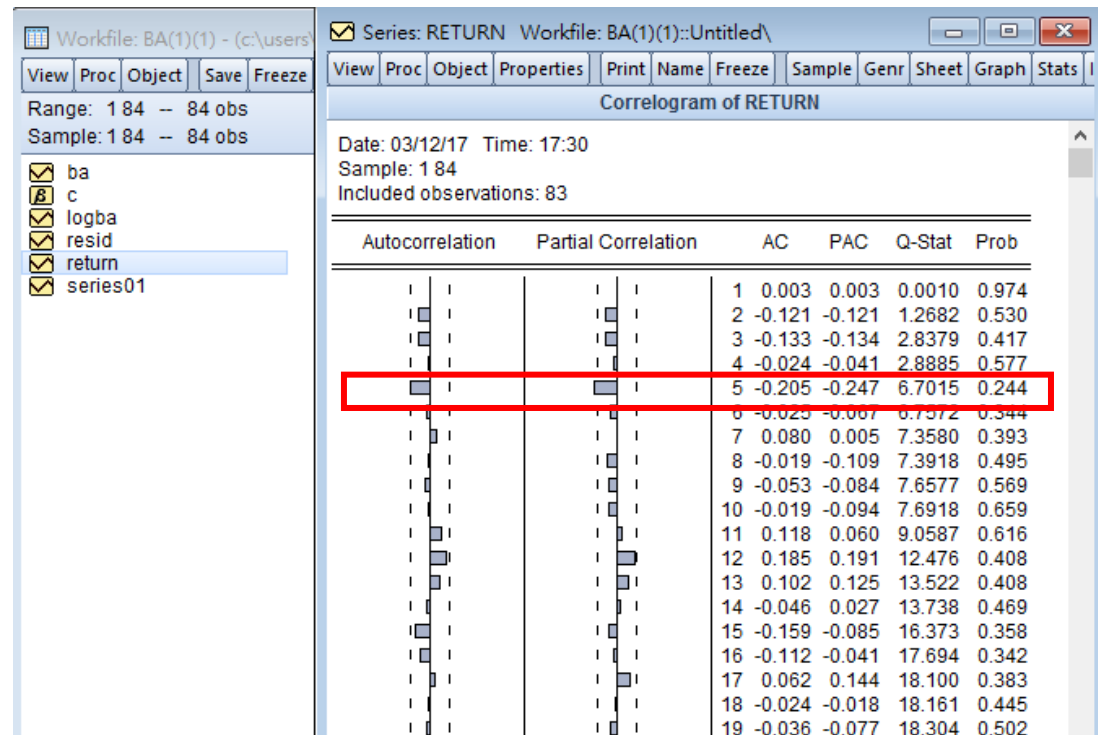
MA( $\infty$ ), AR(1)  $\rightarrow$  Non-stationary

## 2. Constructing the model for price of BA.

Using **Box-Jenkins** approach

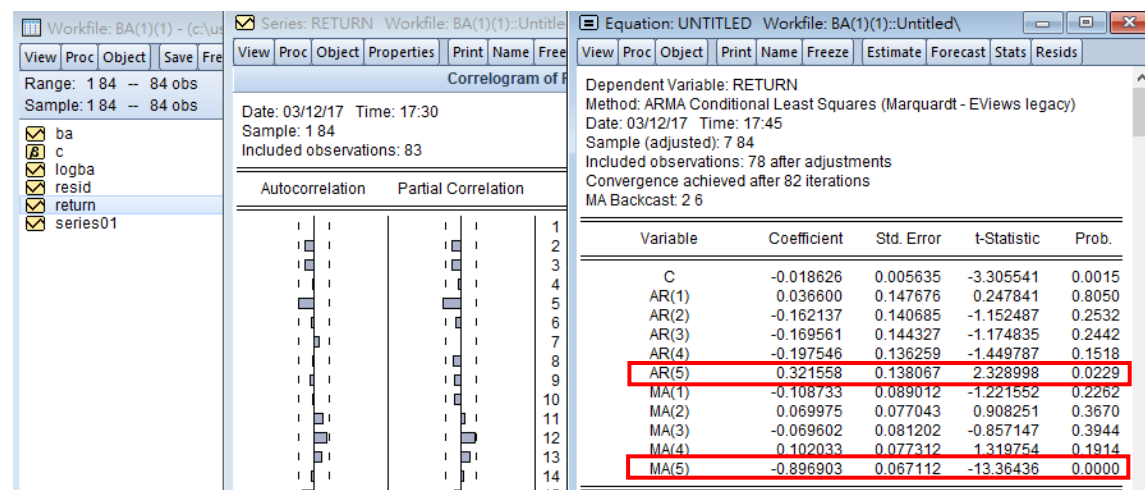
The first step is **Identification**

Now we look at return



We guess the appropriate model is ARMA(5, 5).

The second step is **Estimation**.



### 3. Process the diagnostic steps to test the fitness of the model built up in question 2

Using **Wald test**

Workfile: BA(1)(1) - (c:\u

Equation: UNTITLED Workfile: BA(1)(1)::Untitled\

View Proc Object Print Name Freeze Estimate Forecast Stats R

Range: 1 84 -- 84 obs  
Sample: 1 84 -- 84 obs

☒ ba  
☒ c  
☒ logba  
☒ resid  
☒ return  
☒ series01

Wald Test:  
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	1.616887	(8, 67)	0.1366
Chi-square	12.93510	8	0.1141

Null Hypothesis: C(2)=C(3)=C(4)=C(5)=C(7)=C(8)=C(9)=C(10)=0  
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2)	0.036600	0.147676
C(3)	-0.162137	0.140685
C(4)	-0.169561	0.144327
C(5)	-0.197546	0.136259
C(7)	-0.108733	0.089012
C(8)	0.069975	0.077043
C(9)	-0.069602	0.081202
C(10)	0.102033	0.077312

Restrictions are linear in coefficients.

Workfile: BA(1)(1) - (c:\u

Equation: UNTITLED Workfile: BA(1)(1)::Untitled\

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Range: 1 84 -- 84 obs  
Sample: 1 84 -- 84 obs

☒ ba  
☒ c  
☒ logba  
☒ resid  
☒ return  
☒ series01

Dependent Variable: RETURN  
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)  
Date: 03/12/17 Time: 18:07  
Sample (adjusted): 7 84  
Included observations: 78 after adjustments  
Convergence achieved after 17 iterations  
MA Backcast: 2 6

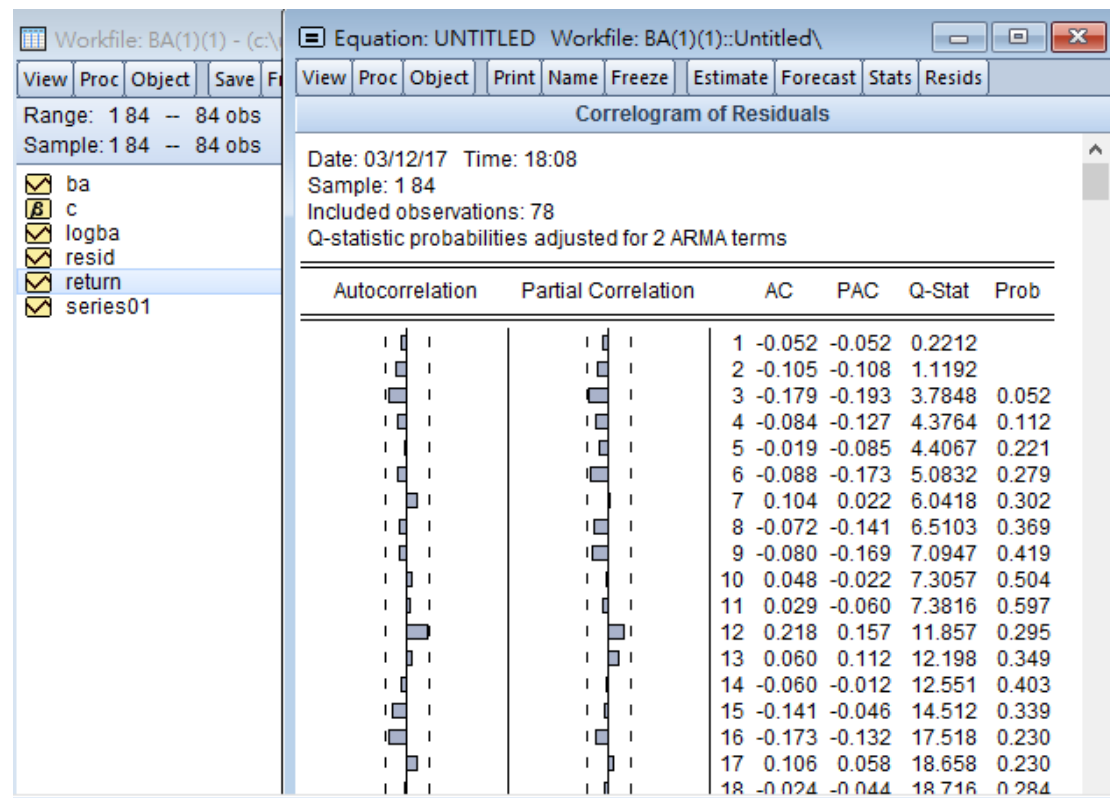
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.020196	0.007778	-2.596672	0.0113
AR(5)	0.497996	0.146083	3.408980	0.0011
MA(5)	-0.878905	0.079681	-11.03031	0.0000

R-squared 0.165244 Mean dependent var -0.015147  
Adjusted R-squared 0.142984 S.D. dependent var 0.150255  
S.E. of regression 0.139098 Akaike info criterion -1.069567  
Sum squared resid 1.451129 Schwarz criterion -0.978924  
Log likelihood 44.71310 Hannan-Quinn criter. -1.033281  
F-statistic 7.423332 Durbin-Watson stat 2.082547  
Prob(F-statistic) 0.001144

Inverted AR Roots .87 .27-.83i .27+.83i -.70+.51i  
Inverted MA Roots .97 .30-.93i .30+.93i -.79+.57i

Now we are sure return is ARMA(5,5). Actually, without first difference, it is ARIMA(5, 1, 5). Why?

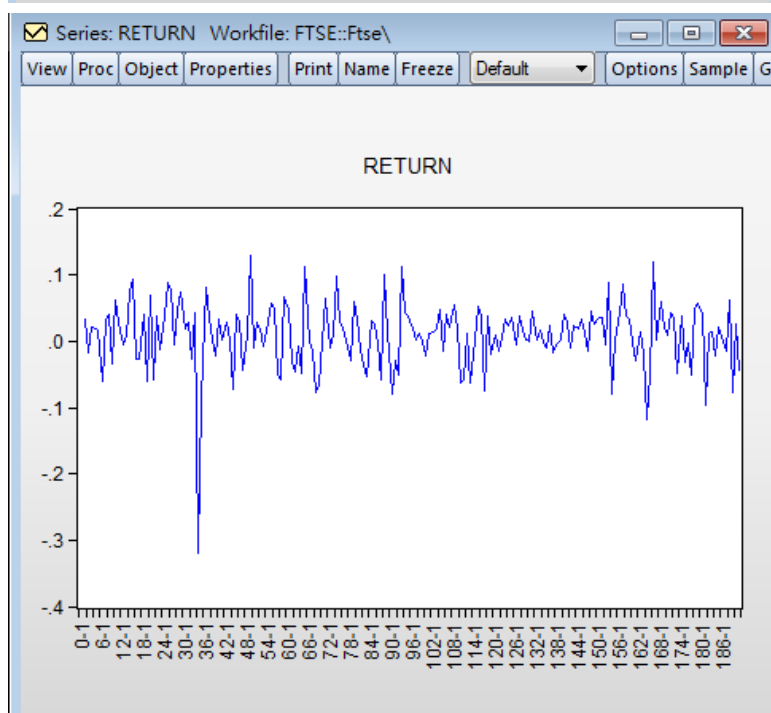
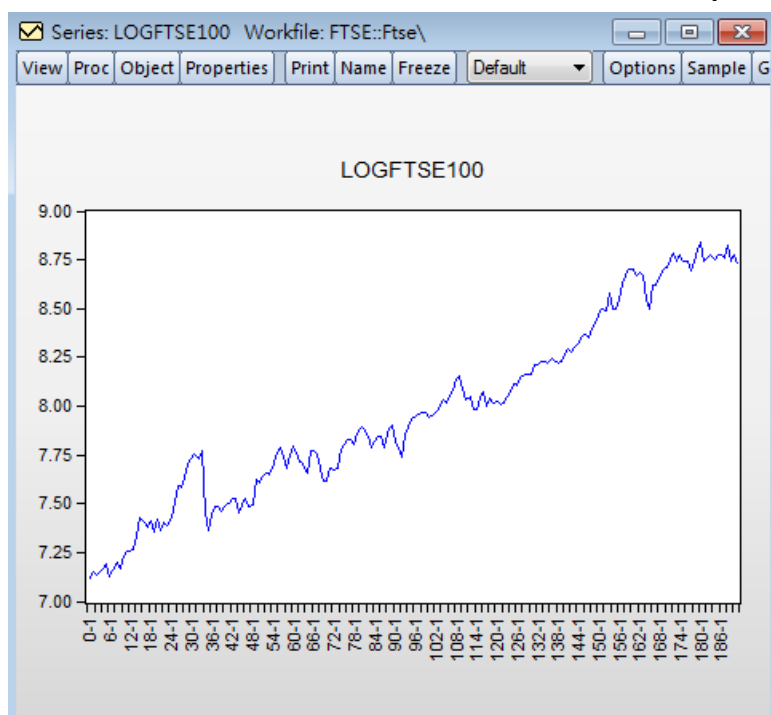
The third step is **Diagnostic checking**.



Residual diagnostics refers to checking whether the residuals are free from autocorrelation. The model is adequate, if autocorrelations of residuals are zero.

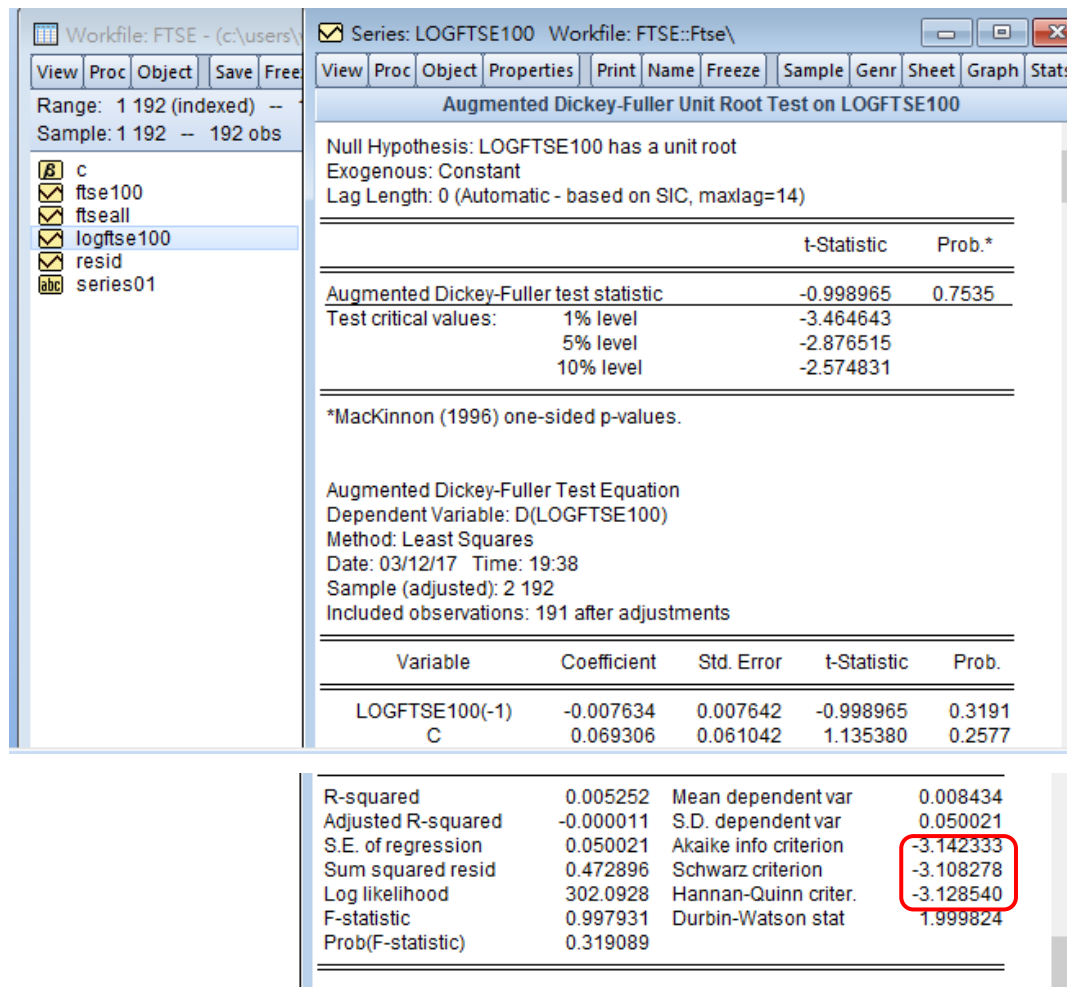
## Unit root test (Dataset: FTSE)

### 4. Manual unit root test on the variable FTSE100 and explain the result.



## 5. Automated unit root testing on FTSE100 and explain the result.

Let's look to LOGFTSE100



Unit Root Test

Test type  
Augmented Dickey-Fuller

Test for unit root in  
☒ Level  
☐ 1st difference  
☐ 2nd difference

Include in test equation  
☒ Intercept  
☐ Trend and intercept  
☐ None

Lag length  
☒ Automatic selection:  
 Schwarz Info Criterion  
 Maximum lags: 14  
☐ User specified: 4

OK Cancel

Include in test equation → choose your exogenous regressor.

After we taking difference, there is still a trend in graph, then we need to do de-trend(option 2)

Let's look at D(LOGFTSE100)

Workfile: FTSE - (c:\users\...)

Series: LOGFTSE100 Workfile: FTSE::Ftse\

View Proc Object Save Free

Range: 1 192 (indexed) --  
Sample: 1 192 -- 192 obs

☒ c  
☒ ftse100  
☒ ftseall  
☒ logftse100  
☒ resid  
☒ series01

Augmented Dickey-Fuller Unit Root Test on D(LOGFTSE100)

Null Hypothesis: D(LOGFTSE100) has a unit root  
Exogenous: Constant  
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-13.75894	0.0000
Test critical values:		
1% level	-3.464827	
5% level	-2.876595	
10% level	-2.574874	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation  
Dependent Variable: D(LOGFTSE100,2)  
Method: Least Squares  
Date: 03/12/17 Time: 19:39  
Sample (adjusted): 3 192  
Included observations: 190 after adjustments

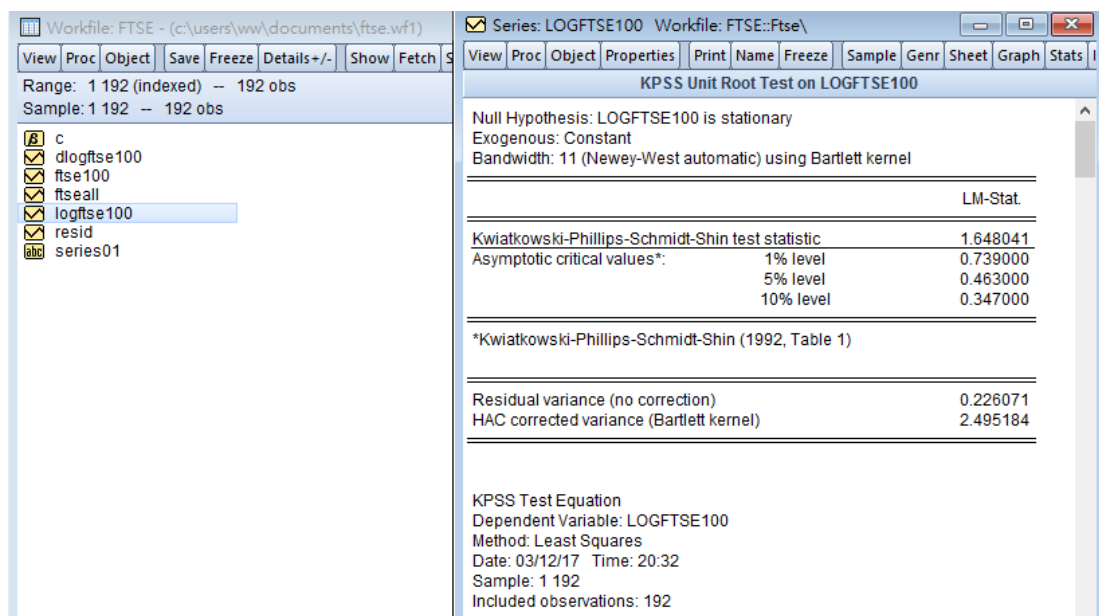
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOGFTSE100(-1))	-1.005952	0.073113	-13.75894	0.0000
C	0.008361	0.003701	2.258973	0.0250

R-squared	0.501734	Mean dependent var	-0.000409
Adjusted R-squared	0.499084	S.D. dependent var	0.071006
S.E. of regression	0.050255	Akaike info criterion	-3.132944
Sum squared resid	0.474806	Schwarz criterion	-3.098765
Log likelihood	299.6297	Hannan-Quinn criter.	-3.119099
F-statistic	189.3085	Durbin-Watson stat	1.991373
Prob(F-statistic)	0.000000		

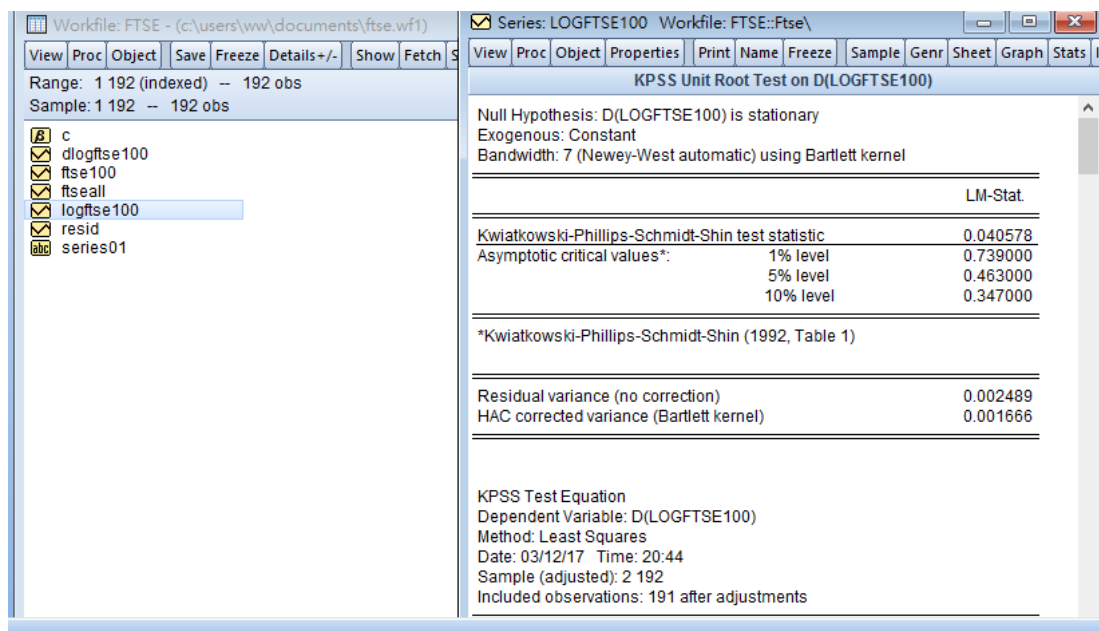
< > Ftse New Page



Using KPSS here



$1.68 > 0.73(1\%) > 0.46(5\%)$ , so reject Null Hypothesis. This means LOGFTSE100 is non-stationary.

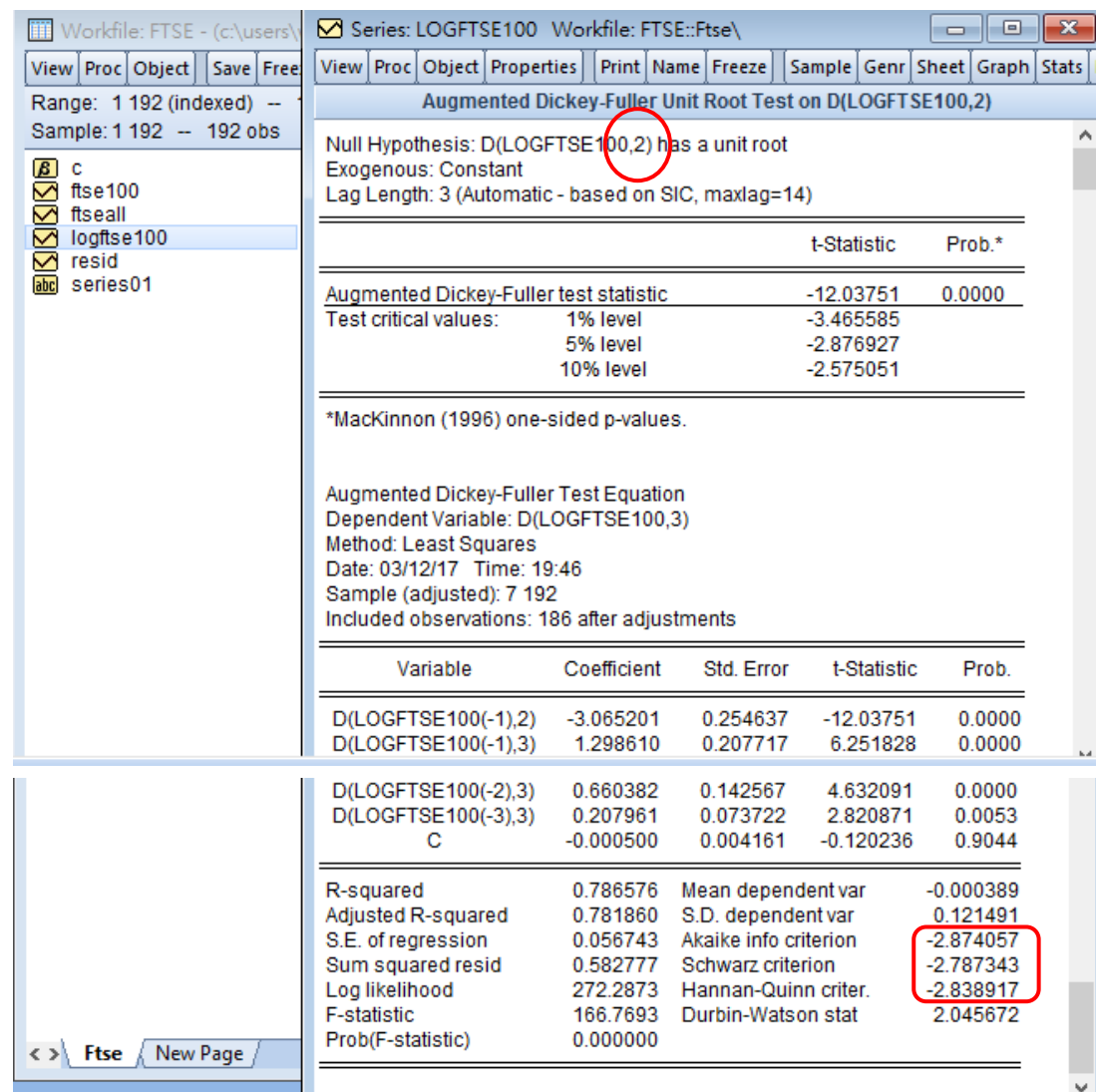


$0.73(1\%) > 0.46(5\%) > 0.040578$ , so do not reject Null Hypothesis. This means DLOGFTSE100 is stationary. If you have conflicting results between ADF and KPSS, refer to literature.

**6. If appropriate, test for the presence of I(2) for FTSE100 series.**

ADF and KPSS give us the same information, so we just focus on ADF.

Let's look at D(LOGFTSE100,2)



Therefore, we can use I(1) or I(2).

But I(1) is better, if we look at AIC, SBIC, and HQIC (smaller is better).

## Cointegration-EG test (Dataset: FTSE)

### 7. Does cointegration exist between FTSE100 and FTSEALL?

Generate the residuals of the cointegration and ensure the residuals are  $I(0)$

Workfile: FTSE - (c:\users\ww\d\Documents\Workfile: FTSE::Ftse\)

Range: 1 192 (indexed) -- 192 obs  
Sample: 1 192 -- 192 obs

Equation: UNTITLED

Dependent Variable: LOGFTSE100  
Method: Least Squares  
Date: 03/12/17 Time: 20:56  
Sample: 1 192  
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.455849	0.030437	14.97670	0.0000
LOGFTSEALL	1.035888	0.004184	247.6030	0.0000

R-squared	0.996910	Mean dependent var	7.977222
Adjusted R-squared	0.996894	S.D. dependent var	0.476712
S.E. of regression	0.026567	Akaike info criterion	-4.407920
Sum squared resid	0.134105	Schwarz criterion	-4.373987
Log likelihood	425.1603	Hannan-Quinn criter.	-4.394177
F-statistic	61307.26	Durbin-Watson stat	0.067852
Prob(F-statistic)	0.000000		

$R^2$  is high. So we consider cointegration.

Proc>Make Residual Series

Conduct unit root test for residuals to examine whether they are  $I(0)$ , using ADF.

Workfile: FTSE - (c:\users\ww\d\Documents\Workfile: FTSE::Ftse\)

Range: 1 192 (indexed) -- 192 obs  
Sample: 1 192 -- 192 obs

Equation: UNTITLED

Dependent Variable: LOGFTSE100  
Method: Least Squares  
Date: 03/12/17 Time: 20:56  
Sample: 1 192  
Included observations: 192

Variable	Coefficient
C	0.455849
LOGFTSEALL	1.035888

R-squared	0.996910
Adjusted R-squared	0.996894
S.E. of regression	0.026567
Sum squared resid	0.134105
Log likelihood	425.1603
F-statistic	61307.26
Prob(F-statistic)	0.000000

Series: RESIDUALS

Augmented Dickey-Fuller Unit Root Test on RESIDUALS

Null Hypothesis: RESIDUALS has a unit root  
Exogenous: Constant  
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.469949	0.1245
Test critical values:		
1% level	-3.464827	
5% level	-2.876595	
10% level	-2.574874	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation  
Dependent Variable: D(RESIDUALS)  
Method: Least Squares  
Date: 03/12/17 Time: 20:59  
Sample (adjusted): 3 192  
Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDUALS(-1)	-0.046336	0.018760	-2.469949	0.0144
D(RESIDUALS(-1))	0.169796	0.071481	2.375409	0.0185

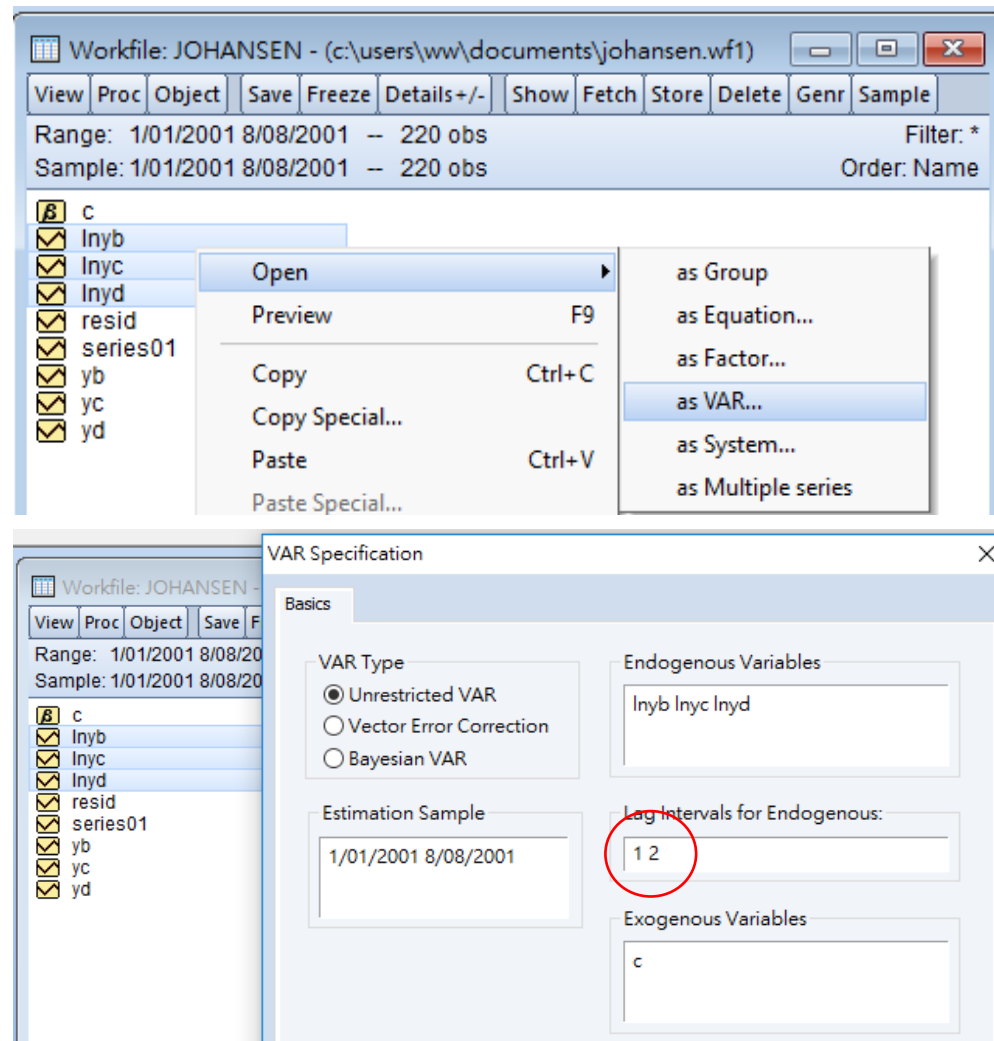
Residuals has a unit root, implying residuals series is non-stationary.

So there is not cointegration relation.

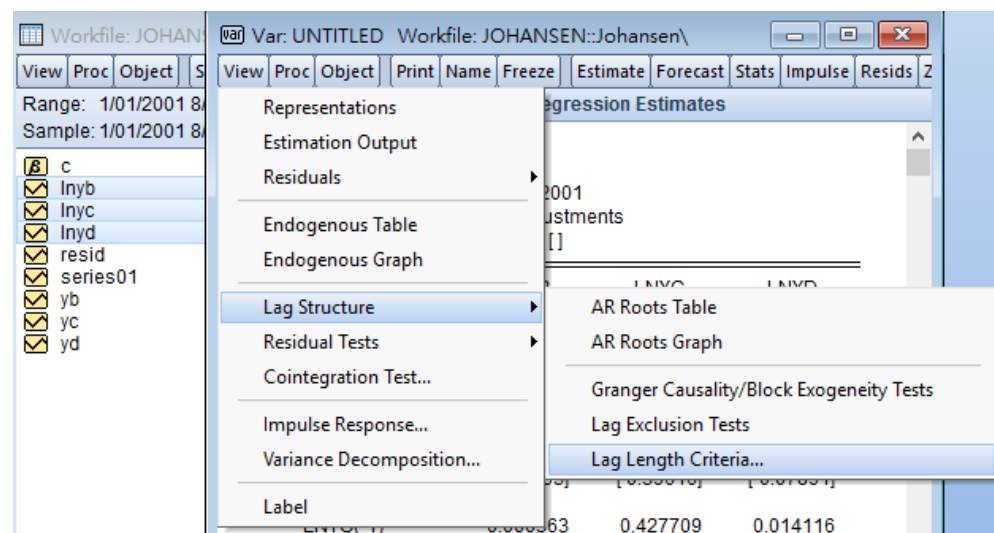
## Cointegration-Johansen test (Dataset: Johansen)

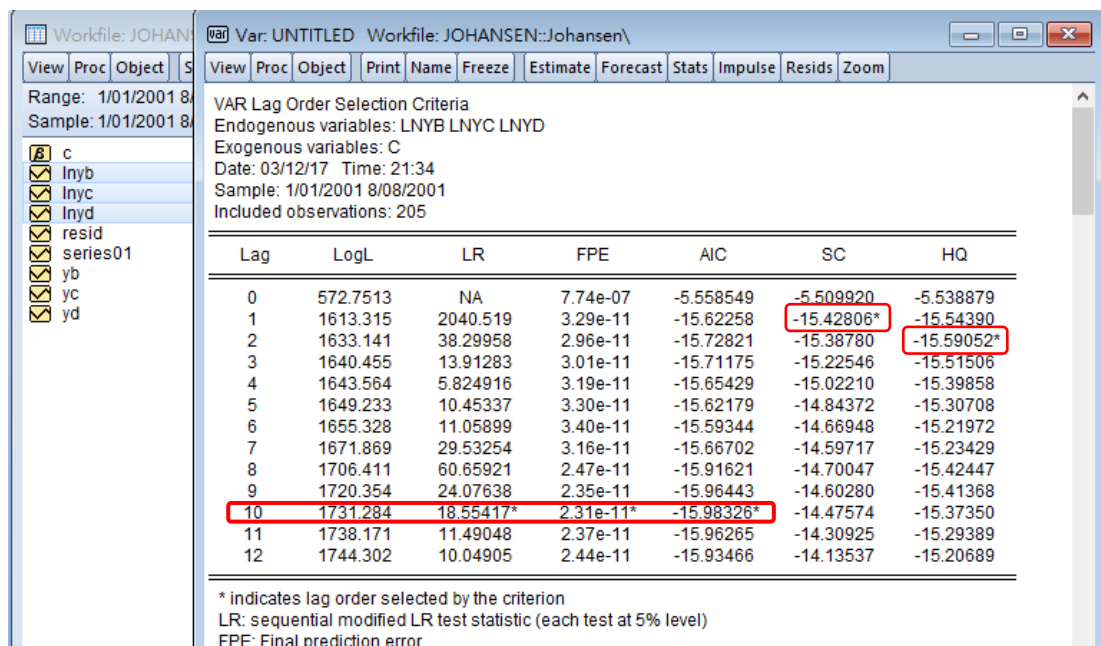
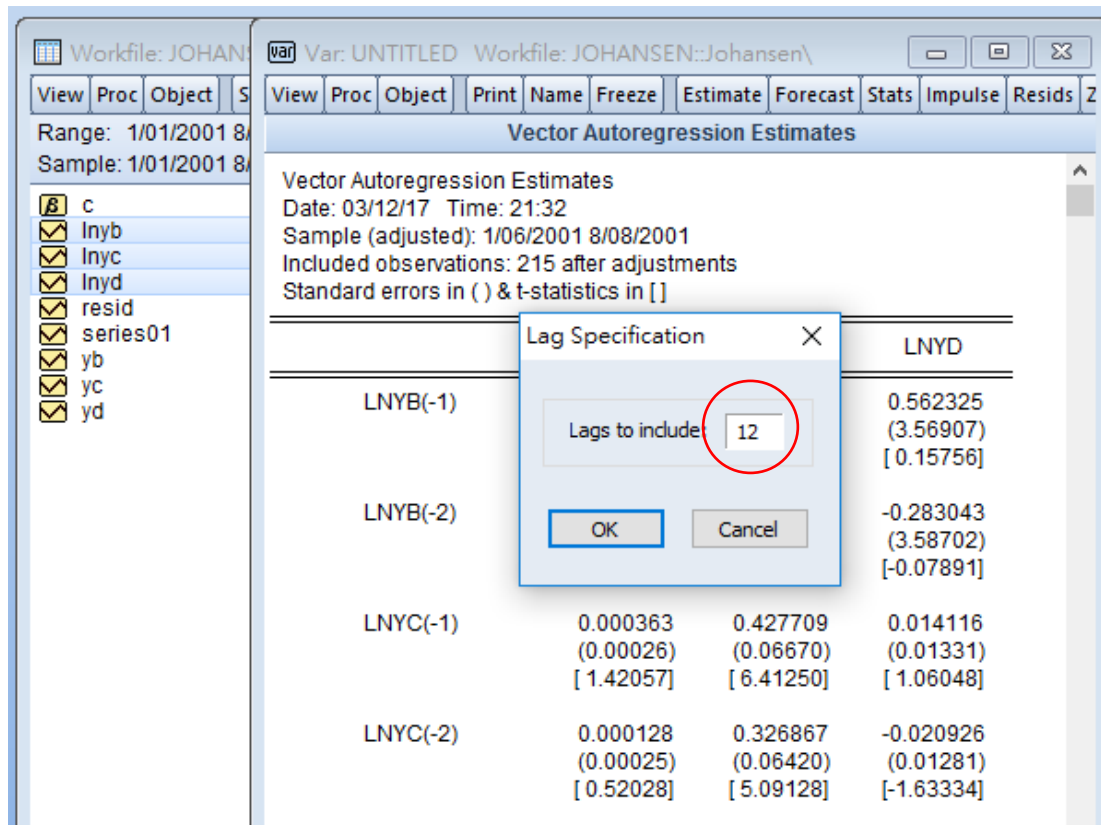
8. Detect cointegration and find out the relationship among Yb Yc Yd.

How to choose the optimal lag?



Eviews suggests us to use 2 lags.

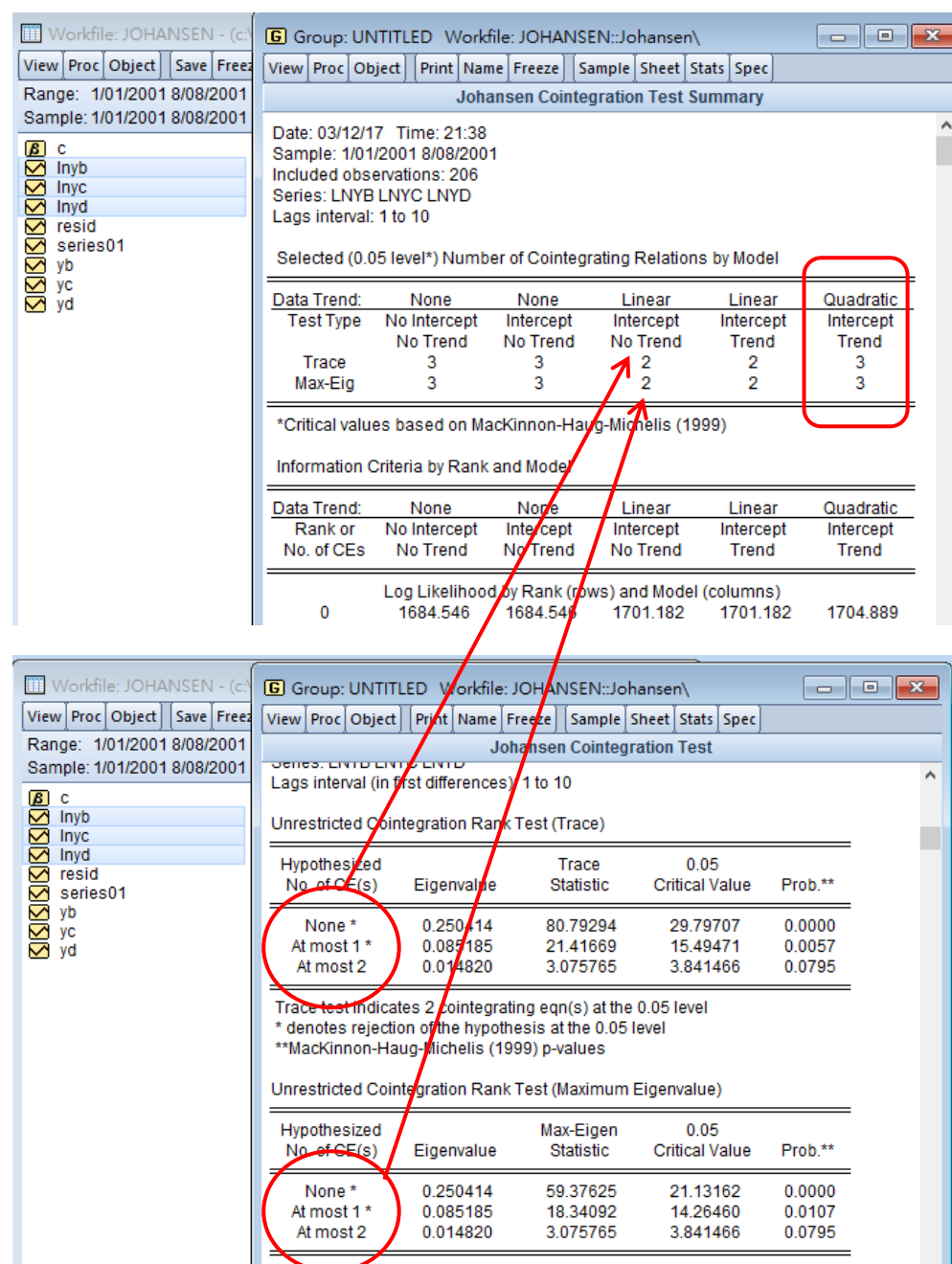




There is no unique way to decide the optimal lag, we could follow Eviews here, using

2.

We choose option 6 that summarize all 5 sets of assumptions to examine whether the results are sensitive to the type of specification used.



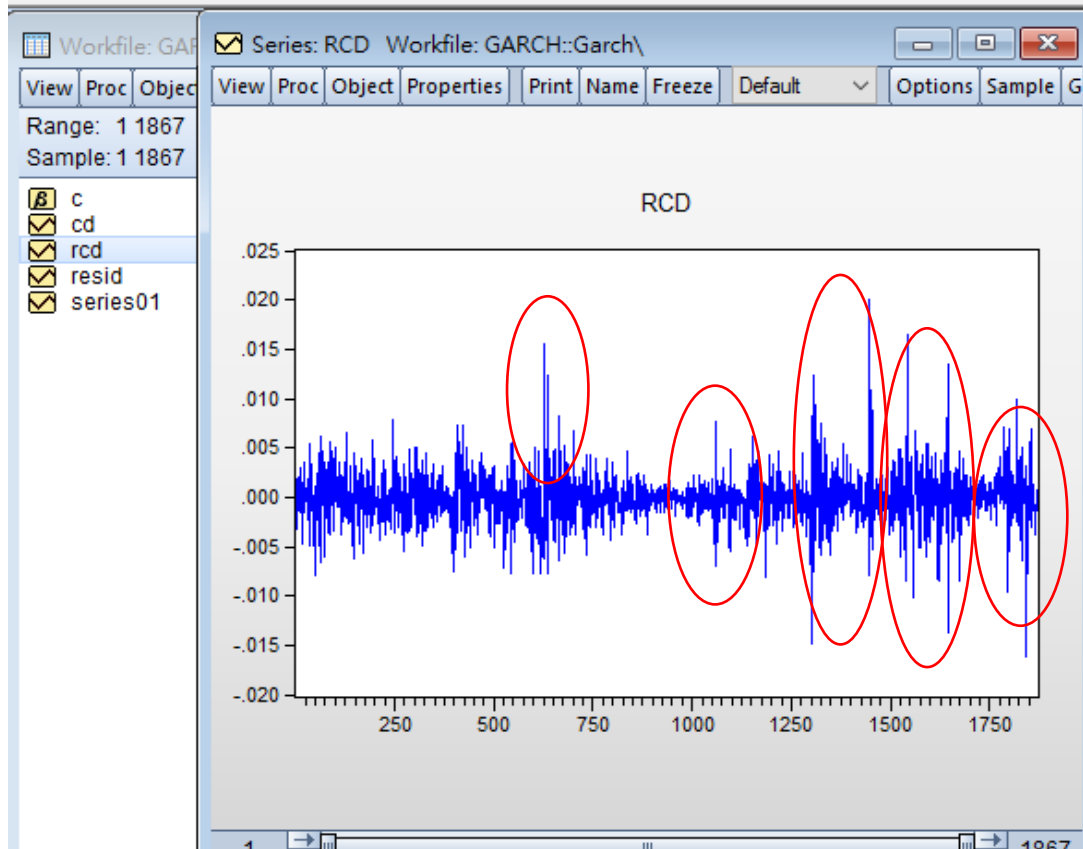
Trace test may have conflicting results from Max-Eig, Johansen and Juselius (1990) suggests using Max-Eig results.

In my understanding: If there is variable with  $I(0)$ , it is not appropriate to do cointegration test since cointegration is conducted when we have non-stationarity data. We can just proceed with VAR system by taking the first difference for the  $I(1)$  variable. With this situation, look at these two papers: Toda, Hiro Y., and Taku Yamamoto (1995) and Pesaran, M. Hashem, Yongcheol Shin and Richard J. Smith (2001)

## ARCH and GARCH modelling (Dataset: GARCH)

9. Build up a proper model for the series of exchange rate of Canadian Dollar (variable CD in the dataset) and explain why the model you obtain should be a preferred model.

Let's look at the graph of rcd first



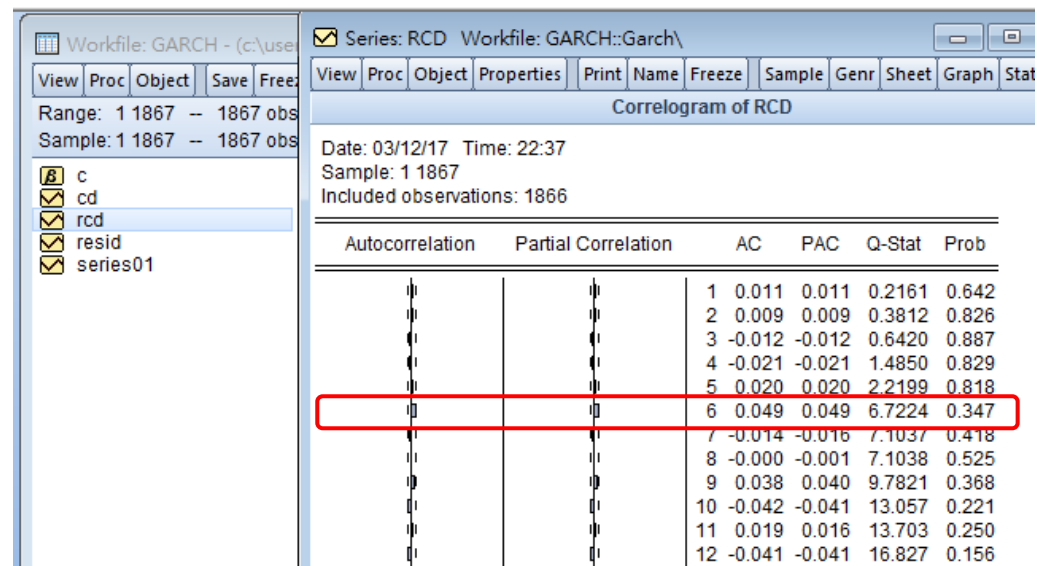
We can see few periods with large increase and decrease.

Volatility Clustering



Identify an appropriate ARMA model by following the Box-Jenkins methodology

The first step: Identification



The second step: estimation

Included observations: 1860 after adjustments  
Convergence achieved after 24 iterations  
MA Backcast: 2 7

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.98E-05	6.39E-05	-1.248501	0.2120
AR(1)	-0.302083	0.166322	-1.816258	0.0695
AR(2)	0.414158	0.164630	2.515687	0.0120
AR(3)	0.505727	0.190767	2.651014	0.0081
AR(4)	-0.086245	0.193586	-0.445516	0.6560
AR(5)	-0.380005	0.153154	-2.481196	0.0132
AR(6)	-0.658308	0.161637	-4.072756	0.0000
MA(1)	0.309184	0.156077	1.980975	0.0477
MA(2)	-0.396589	0.154868	-2.560815	0.0105
MA(3)	-0.522212	0.181593	-2.875724	0.0041
MA(4)	0.064197	0.184077	0.348752	0.7273
MA(5)	0.279078	0.148240	2.557107	0.0106
MA(6)	0.729590	0.155347	4.696520	0.0000

R-squared 0.015949 Mean dependent var -7.82E-05  
Adjusted R-squared 0.009556 S.D. dependent var 0.002668

	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	0.011	0.011	0.2161	0.642		
2	0.009	0.009	0.3812	0.826		
3	-0.012	-0.012	0.6420	0.887		
4	-0.021	-0.021	1.4850	0.829		
5	0.020	0.020	2.2199	0.818		
6	0.049	0.049	6.7224	0.347		
7	-0.014	-0.016	7.1037	0.418		
8	-0.000	-0.001	7.1038	0.525		
9	0.038	0.040	9.7821	0.368		
10	-0.042	-0.041	13.057	0.221		
11	0.019	0.016	13.703	0.250		
12	-0.041	-0.041	16.827	0.156		
13	0.023	0.026	17.824	0.164		
14	-0.004	-0.007	17.856	0.213		
15	0.012	0.010	18.146	0.255		
16	-0.005	-0.002	18.194	0.313		
17	-0.052	-0.053	23.331	0.139		
18	0.019	0.023	24.019	0.154		
19	-0.009	-0.008	24.158	0.190		

Other variables are also significant, but combining with ACF/PACF plot, let's do ARMA(6,6). So in estimate equation window, type in rcd c ar(6) ma(6)

Equation: UNTITLED Workfile: GARCH::Garch\

Dependent Variable: RCD  
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)  
Date: 03/12/17 Time: 23:01  
Sample (adjusted): 8 1867  
Included observations: 1860 after adjustments  
Convergence achieved after 27 iterations  
MA Backcast: 2 7

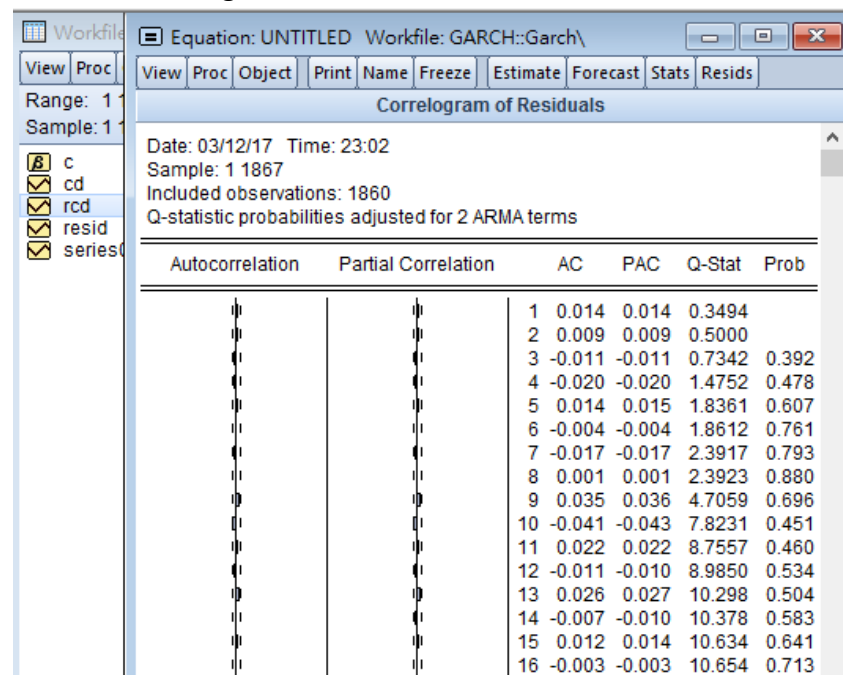
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.74E-05	6.40E-05	-1.210211	0.2264
AR(6)	-0.539302	0.203705	-2.647465	0.0082
MA(6)	0.594835	0.194429	3.059390	0.0022

R-squared 0.004600 Mean dependent var -7.82E-05  
Adjusted R-squared 0.003528 S.D. dependent var 0.002668  
S.E. of regression 0.002664 Akaike info criterion -9.016592  
Sum squared resid 0.013176 Schwarz criterion -9.007676  
Log likelihood 8388.431 Hannan-Quinn criter. -9.013306  
F-statistic 4.290489 Durbin-Watson stat 1.972465  
Prob(F-statistic) 0.013834

	Inverted AR Roots			
	.78+.45i	.78-.45i	.00-.90i	-.00+.90i
	-.78+.45i	-.78-.45i		
	.79+.46i	.79-.46i	.00+.92i	-.00-.92i
	-.79-.46i	-.79+.46i		

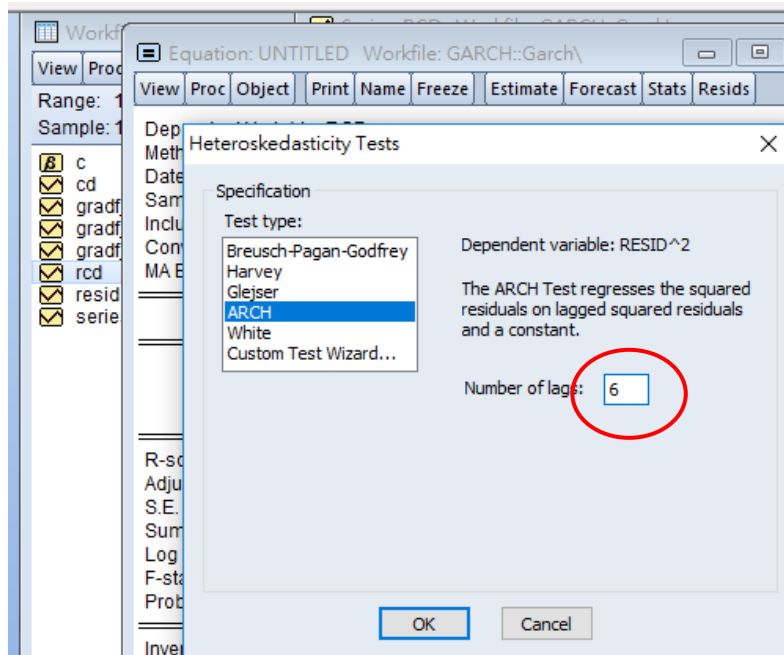
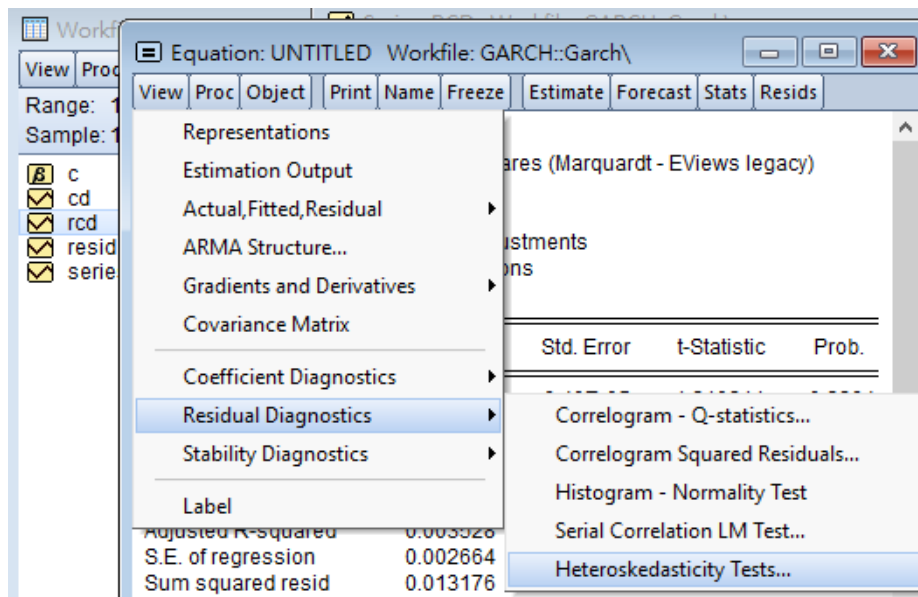


And residual diagnostic

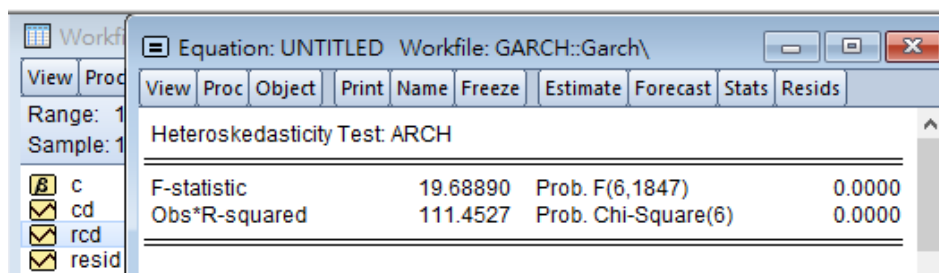


Residual diagnostics refers to checking whether the residuals are free from autocorrelation. The model is adequate, if autocorrelations of residuals are zero.

Now, let's look at ARCH effect



Choose 6, because of AR(6). Eviews suggests us to use 6, so we look at 6 in ACF/PACF plot.



There is ARCH effect.

Estimating ARCH/GARCH models. We look at ARCH first.

Workfile: GARCH::Garch\

Equation: UNTITLED

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Range: 1 1867  
Sample: 1 1867

Dependent Variable: RCD  
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)  
Date: 03/12/17 Time: 23:18  
Sample (adjusted): 2 1867  
Included observations: 1866 after adjustments  
Convergence achieved after 48 iterations  
Presample variance: backcast (parameter = 0.7)  
GARCH = C(4) + C(5)\*RESID(-1)^2 + C(6)\*RESID(-2)^2 + C(7)\*RESID(-3)^2 + C(8)\*RESID(-4)^2 + C(9)\*RESID(-5)^2 + C(10)\*RESID(-6)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-9.13E-05	4.99E-05	-1.829942	0.0673
AR(6)	-0.565594	0.177114	-3.193388	0.0014
MA(6)	0.623353	0.163865	3.804070	0.0001

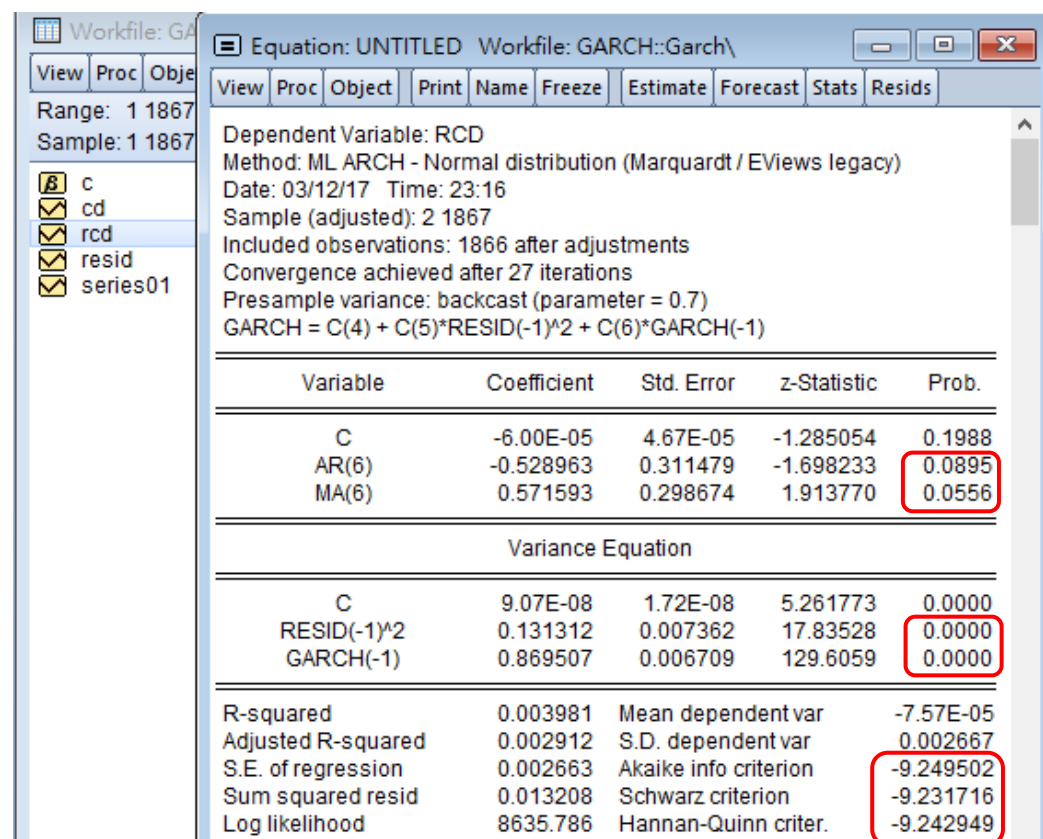
Variance Equation

	Coefficient	Std. Error	z-Statistic	Prob.
C	2.33E-06	1.25E-07	18.67124	0.0000
RESID(-1)^2	0.280908	0.026899	10.44319	0.0000
RESID(-2)^2	0.100757	0.020707	4.865885	0.0000
RESID(-3)^2	0.087083	0.022181	3.925957	0.0001
RESID(-4)^2	0.124773	0.022820	5.467695	0.0000
RESID(-5)^2	0.098174	0.023397	4.195943	0.0000
RESID(-6)^2	0.050133	0.020640	2.428905	0.0151

R-squared	0.004023	Mean dependent var	-7.57E-05
Adjusted R-squared	0.002954	S.D. dependent var	0.002667
S.E. of regression	0.002663	Akaike info criterion	-9.205481
Sum squared resid	0.013207	Schwarz criterion	-9.175837
Log likelihood	8598.714	Hannan-Quinn criter.	-9.194558
Durbin-Watson stat	1.972435		

Inverted AR Roots	.79+.45i	.79-.45i	.00-.91i	-.00+.91i
	-.79+.45i	-.79-.45i		
Inverted MA Roots	.80-.46i	.80+.46i	.00+.92i	-.00-.92i
	-.80-.46i	-.80+.46i		

Then, GARCH(1,1)



We can see the AR(6) and MA(6) becomes less significant. ARCH and GARCH effect are significant. Comparing with ARCH(6), We can use fewer variables with GARCH(1,1).

## GJR-GARCH

Note:

Due to Glosten, Jaganathan and Runkle

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

where  $I_{t-1} = 1$  if  $u_{t-1} < 0$

= 0 otherwise

For a leverage effect, we would see  $\gamma > 0$

We require  $\alpha_1 + \gamma \geq 0$  and  $\alpha_1 \geq 0$  for non-negativity.

Equation: UNTITLED Workfile: GARCH::Garch\

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Sample (adjusted): 2 1866  
Included observations: 1866 after adjustments  
Convergence achieved after 31 iterations  
Presample variance: backcast (parameter = 0.7)  
GARCH = C(4) + C(5)\*RESID(-1)^2 + C(6)\*RESID(-1)^2\*(RESID(-1)<0) + C(7)\*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000124	4.88E-05	-2.542853	0.0110
AR(6)	-0.524149	0.285453	-1.836201	0.0663
MA(6)	0.570710	0.272475	2.094537	0.0362

Variance Equation

	Coefficient	Std. Error	z-Statistic	Prob.
C	6.96E-08	1.54E-08	4.514329	0.0000
RESID(-1)^2	0.070711	0.008645	8.179042	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.100703	0.012684	7.939556	0.0000
GARCH(-1)	0.882743	0.006976	126.5449	0.0000

R-squared	0.003830	Mean dependent var	-7.57E-05
Adjusted R-squared	0.002761	S.D. dependent var	0.002667
S.E. of regression	0.002663	Akaike info criterion	-9.264663
Sum squared resid	0.013210	Schwarz criterion	-9.243913
Log likelihood	8650.931	Hannan-Quinn criter.	-9.257017
Durbin-Watson stat	1.973832		

For a leverage effect, the coefficient is positive and significant.

EGARCH(try this)

## GARCH-M(standard deviation)

Note:

Engle, Lilien and Robins (1987) suggested the ARCH-M specification. A GARCH-M model would be:

$$y_t = \mu + \delta \sigma_{t-1} + u_t, u_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

If  $\delta$  is positive and statistically significant, then increased risk, given by an increase in the conditional variance, leads to a rise in the mean return. Thus  $\delta$  can be interpreted as a risk premium.

Equation: UNTITLED Workfile: GARCH::Garch\				
View	Proc	Object	Print	Name
Freeze	Estimate	Forecast	Stats	Resids
Dependent Variable: RCD Method: ML ARCH - Normal distribution (Marquardt / EViews legacy) Date: 03/12/17 Time: 23:54 Sample (adjusted): 2 1867 Included observations: 1866 after adjustments Convergence achieved after 33 iterations Presample variance: backcast (parameter = 0.7) GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.119462	0.059750	1.999375	0.0456
C	-0.000285	0.000130	-2.193349	0.0283
AR(6)	-0.529798	0.305002	-1.737030	0.0824
MA(6)	0.572767	0.292083	1.960972	0.0499
Variance Equation				
C	9.67E-08	1.79E-08	5.393219	0.0000
RESID(-1)^2	0.134138	0.007509	17.86298	0.0000
GARCH(-1)	0.865985	0.006697	129.3050	0.0000
R-squared	0.005281	Mean dependent var	-7.57E-05	
Adjusted R-squared	0.003678	S.D. dependent var	0.002667	
S.E. of regression	0.002662	Akaike info criterion	-9.250710	
Sum squared resid	0.013191	Schwarz criterion	-9.229959	

## 10. Use your preferred model to produce forecasts.

Estimate a new equation, using in-of-sample to forecast out-of-sample

Equation Estimation

Specification Options

Mean equation

Dependent followed by regressors & ARMA terms OR explicit equation:

rch c ar(6) ma(6)

ARCH-M

None

Variance and distribution specification

Model: GARCH/TARCH

Order:

ARCH: 1 Threshold order: 0

GARCH: 1

Restrictions: None

Variance regressors:

Error distribution: Normal (Gaussian)

Estimation settings

Method: ARCH - Autoregressive Conditional Heteroskedasticity

Sample: 1 1800

Equation: UNTITLED Workfile: GARCH::Garch\

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: RCD

Meth Forecast

Forecast of

Equation: UNTITLED Series: RCD

Series names

Forecast name: rcdf

S.E. (optional):

GARCH(optional):

Method

☒ Dynamic forecast

☐ Static forecast

☐ Structural (ignore ARMA)

☒ Coef uncertainty in S.E. calc

Forecast sample

1801 1867

Output

☒ Forecast graph

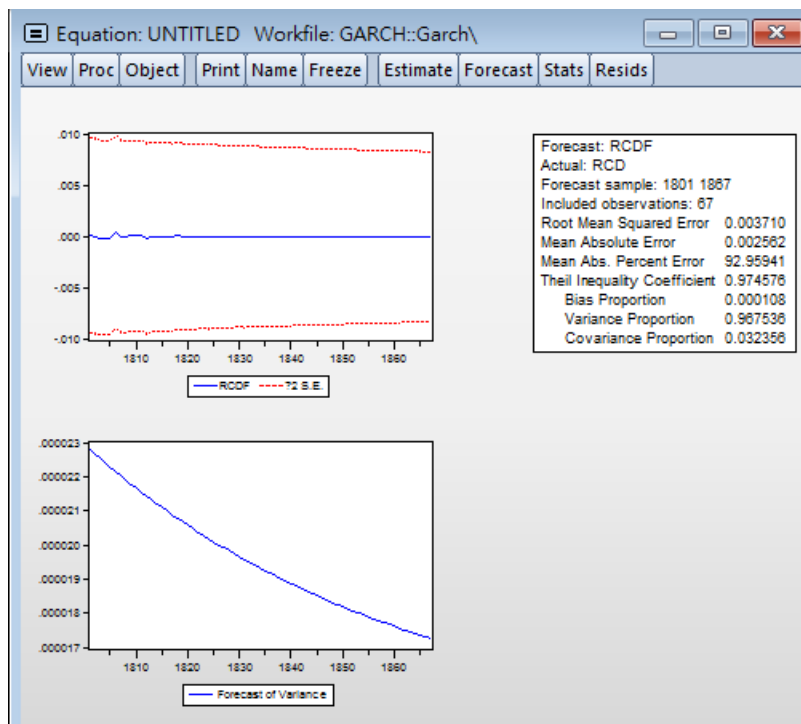
☒ Forecast evaluation

☒ Insert actuals for out-of-sample observations

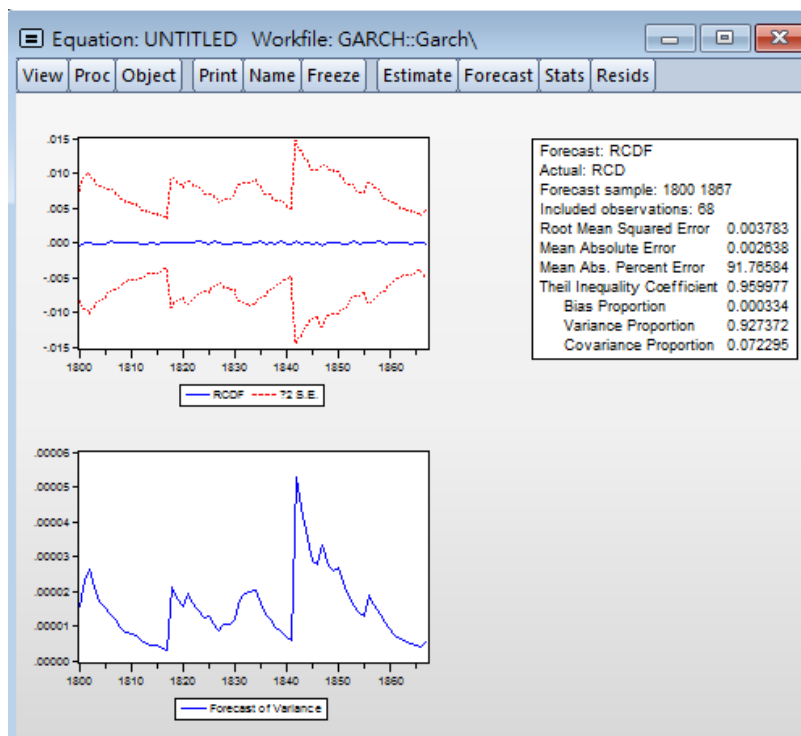
OK Cancel

R-squared	0.001928	S.D. dependent var	0.002918
Adjusted R-squared	0.002617	Akaike info criterion	-9.297666
S.E. of regression	0.012298	Schwarz criterion	-9.279339
Sum squared resid	8369.251	Hannan-Quinn criter.	-9.290901
Log likelihood			

## Dynamic forecast(multiple-steps-ahead)



## Static forecast(single-step-ahead)



One volatility results in more volatility → volatility clustering  
 Static forecast is more unstable.