

Example

Part I

1. Test whether the series spot and future are stationary series.

```
. tsset t
      time variable: t, 1 to 7684
      delta: 1 unit
```

```
. dfuller spot, trend lag(1) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 7682

	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
z(t)	-2.438	-3.960	-3.410	-3.120

Mackinnon approximate p-value for z(t) = 0.3597

D.spot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
spot						
L1.	-.001489	.0006108	-2.44	0.015	-.0026862	-.0002917
LD.	.0440347	.0114011	3.86	0.000	.0216855	.0663839
_trend	.0000171	8.32e-06	2.05	0.040	7.62e-07	.0000334
_cons	.7447753	.302873	2.46	0.014	.1510615	1.338489

```
. dfuller spot, lag(1) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 7682

	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
z(t)	-1.325	-3.430	-2.860	-2.570

Mackinnon approximate p-value for z(t) = 0.6176

D.spot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
spot						
L1.	-.0004809	.0003629	-1.33	0.185	-.0011923	.0002305
LD.	.0435503	.011401	3.82	0.000	.0212012	.0658993
_cons	.2693479	.1950793	1.38	0.167	-.1130608	.6517565

```
. dfuller future, trend lag(1) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 7682

	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
z(t)	-2.563	-3.960	-3.410	-3.120

Mackinnon approximate p-value for z(t) = 0.2971

D.future	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
future						
L1.	-.001768	.0006898	-2.56	0.010	-.0031202	-.0004159
LD.	-.0275938	.0114077	-2.42	0.016	-.0499561	-.0052315

_trend		.0000222	.00001	2.22	0.026	2.62e-06	.0000418
_cons		.86276	.3338726	2.58	0.010	.2082785	1.517241

. dfuller future, lag(1) regress

Augmented Dickey-Fuller test for unit root Number of obs = 7682

	Test Statistic	----- 1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-1.289	-3.430	-2.860	-2.570

Mackinnon approximate p-value for Z(t) = 0.6341

D.future	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
future						
L1.	-.0004968	.0003854	-1.29	0.197	-.0012523	.0002587
LD.	-.0282081	.0114073	-2.47	0.013	-.0505696	-.0058467
_cons	.2758156	.2042151	1.35	0.177	-.1245016	.6761329

- *spot and future are nonstationary.*

- From spot and future, generate spot return (rspot) and future return (rfuture) and test whether they are stationary.

. g rspot=(spot/l.spot)-1
(1 missing value generated)

. g rfuture=(future/l.future)-1
(1 missing value generated)

. dfuller rspot, trend lag(1) regress

Augmented Dickey-Fuller test for unit root Number of obs = 7681

	Test Statistic	----- 1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-63.787	-3.960	-3.410	-3.120

Mackinnon approximate p-value for Z(t) = 0.0000

D.rspot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rspot						
L1.	-1.005168	.0157581	-63.79	0.000	-1.036058	-.9742776
LD.	.0517018	.0113974	4.54	0.000	.0293598	.0740439
_trend	9.56e-10	9.19e-09	0.10	0.917	-1.71e-08	1.90e-08
_cons	.0000199	.0000408	0.49	0.626	-.00006	.0000998

. dfuller rspot, lag(1) regress

Augmented Dickey-Fuller test for unit root Number of obs = 7681

	Test Statistic	----- 1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-63.791	-3.430	-2.860	-2.570

Mackinnon approximate p-value for Z(t) = 0.0000

D.rspot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
---------	-------	-----------	---	------	----------------------	--

rspot						
L1.	-1.005165	.0157571	-63.79	0.000	-1.036053	-.9742771
LD.	.0517007	.0113967	4.54	0.000	.0293601	.0740413
_cons	.0000235	.0000204	1.15	0.248	-.0000164	.0000635

```
. dfuller rfuture, trend lag(1) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 7681

	Test Statistic	----- 1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-65.070	-3.960	-3.410	-3.120

Mackinnon approximate p-value for Z(t) = 0.0000

D.rfuture	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rfuture						
L1.	-1.063572	.0163449	-65.07	0.000	-1.095612	-1.031531
LD.	.03575	.0114053	3.13	0.002	.0133924	.0581076
_trend	1.17e-09	1.06e-08	0.11	0.912	-1.96e-08	2.19e-08
_cons	.0000231	.000047	0.49	0.624	-.0000691	.0001152

```
. dfuller rfuture, lag(1) regress
```

Augmented Dickey-Fuller test for unit root Number of obs = 7681

	Test Statistic	----- 1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-65.074	-3.430	-2.860	-2.570

Mackinnon approximate p-value for Z(t) = 0.0000

D.rfuture	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rfuture						
L1.	-1.063569	.0163439	-65.07	0.000	-1.095608	-1.031531
LD.	.0357488	.0114046	3.13	0.002	.0133927	.0581049
_cons	.0000276	.0000235	1.17	0.241	-.0000185	.0000736

- ***rspot and rfuture are stationary.***

3. Estimate Autoregressive Integrated Moving Average (ARIMA(p,d,q))model for spot return (rspot) and future return (rfuture) – determine the most appropriated order for p, d, and q using SBIC given the maximum lag equals 3.

```
. *Define variable y
. g y = rspot
(1 missing value generated)

. *Specify order p d q
. forvalue d = 0(1)0 {
2. forvalue p = 1(1)3 {
3. forvalue q = 1(1)3 {
4. display "estimate arima`p'`d'`q'"
5. capture: quietly arch y, arima(`p',`d',`q') nolog
6. if _rc~=0 {
7. display "flatlog when pdq =" `p'`d'`q'
8. continue
9. }
10. estimates store arima`p'`d'`q'
11. display "arima`p'`d'`q' already estimated"
```

```

12. }
13. }
14. estimates table arima1`d'1 arima1`d'2 arima1`d'3, star(0.1 0.05 0.01)
stat(aic bic ll)
15. estimates table arima2`d'1 arima2`d'2 arima2`d'3, star(0.1 0.05 0.01)
stat(aic bic ll)
16. estimates table arima3`d'1 arima3`d'2 arima3`d'3, star(0.1 0.05 0.01)
stat(aic bic ll)
17. }
estimate arima101
arima101 already estimated
estimate arima102
arima102 already estimated
estimate arima103
arima103 already estimated
estimate arima201
arima201 already estimated
estimate arima202
arima202 already estimated
estimate arima203
arima203 already estimated
estimate arima301
arima301 already estimated
estimate arima302
arima302 already estimated
estimate arima303
arima303 already estimated

```

Variable		arima101	arima102	arima103
y	_cons	.00002357	.00002356	.00002358
ARMA	ar			
	L1.	-.39238062***	.42864317***	.65166124**
	ma			
	L1.	.44532053***	-.38281172***	-.60615082**
	L2.		-.06806304***	-.07857703***
	L3.			.01545964
SIGMA2	_cons	3.191e-06***	3.186e-06***	3.186e-06***
Statistics	aic	-75418.287	-75428.587	-75426.961
	bic	-75390.5	-75393.854	-75385.281
	ll	37713.144	37719.294	37719.481

legend: * p<.1; ** p<.05; *** p<.01

variable		arima201	arima202	arima203
y	_cons	.00002357	.00002358	.00002357
ARMA	ar			
	L1.	.38006412***	.4428295***	-.2977397
	L2.	-.06526084***	.06441512	.18380533
	ma			
	L1.	-.33454996**	-.39711228***	.34370136
	L2.		-.1329568	-.21915882
	L3.			-.04549931
SIGMA2	_cons	3.186e-06***	3.186e-06***	3.186e-06***
Statistics	aic	-75428.02	-75426.781	-75424.791
	bic	-75393.286	-75385.101	-75376.164
	ll	37719.01	37719.391	37719.396

legend: * p<.1; ** p<.05; *** p<.01

Variable		arima301	arima302	arima303
y	_cons	.00002358	.00002359	.00002358
ARMA				
	ar			
	L1.	.77455424***	.75397066	-.00991889
	L2.	-.08500848***	-.07160519	.14112537
	L3.	.02487315	.02348179	.27346678*
	ma			
	L1.	-.7289429***	-.70834194	.0550623
	L2.		-.01249418	-.19122019
	L3.			-.29971817**
SIGMA2				
	_cons	3.186e-06***	3.186e-06***	3.185e-06***
Statistics				
	aic	-75427.18	-75425.182	-75425.679
	bic	-75385.499	-75376.555	-75370.105
	ll	37719.59	37719.591	37720.84

legend: * p<.1; ** p<.05; *** p<.01

```
. drop y
. *Define Variable y
.   g y = rfuture
(1 missing value generated)

. *Specify order p d q
. forvalue d = 0(1)0 {
2.   forvalue p = 1(1)3 {
3.     forvalue q = 1(1)3 {
4.       display "estimate arima`p'`d'`q'"
5.       capture: quietly arima(`p',`d',`q') nolog
6.       if _rc~=0 {
7.         display "flatlog when pdq =" `p'`d'`q'
8.         continue
9.       }
10.      estimates store arima`p'`d'`q'
11.      display "arima `p'`d'`q' already estimated"
12.    }
13.  }
14.  estimates table arima1`d'1 arima1`d'2 arima1`d'3, star(0.1 0.05 0.01)
stat(aic bic ll)
15.  estimates table arima2`d'1 arima2`d'2 arima2`d'3, star(0.1 0.05 0.01)
stat(aic bic ll)
16.  estimates table arima3`d'1 arima3`d'2 arima3`d'3, star(0.1 0.05 0.01)
stat(aic bic ll)
17. }

estimate arima101
arima101 already estimated
estimate arima102
arima102 already estimated
estimate arima103
arima103 already estimated
estimate arima201
arima201 already estimated
estimate arima202
arima202 already estimated
estimate arima203
arima203 already estimated
estimate arima301
arima301 already estimated
estimate arima302
arima302 already estimated
estimate arima303
arima303 already estimated
```

Variable		arima101	arima102	arima103
----------	--	----------	----------	----------

y	_cons	.00002616	.00002615	.00002616
ARMA				
	ar			
	L1.	.57862596***	.1646139	-.99197318***
	ma			
	L1.	-.61250239***	-.19269514	.96410655***
	L2.		-.03060977**	-.06340363***
	L3.			-.03781342***
sigma	_cons	.00205937***	.00205903***	.00205869***
Statistics				
	aic	-73232.774	-73233.366	-73233.777
	bic	-73204.987	-73198.632	-73192.096
	ll	36620.387	36621.683	36622.888

legend: * p<.1; ** p<.05; *** p<.01

	variable	arima201	arima202	arima203
y	_cons	.00002615	.00002616	.00002616
ARMA				
	ar			
	L1.	.1969293	.15226368	-.89495618***
	L2.	-.02961053**	.01296947	.09640361
	ma			
	L1.	-.22502128	-.18034761	.86721517***
	L2.		-.04390959	-.15687072
	L3.			-.03517174***
sigma	_cons	.00205903***	.00205902***	.00205868***
Statistics				
	aic	-73233.346	-73231.368	-73231.866
	bic	-73198.612	-73189.687	-73183.239
	ll	36621.673	36621.684	36622.933

legend: * p<.1; ** p<.05; *** p<.01

	variable	arima301	arima302	arima303
y	_cons	.00002616	.00002616	.00002616
ARMA				
	ar			
	L1.	.43838803	-.86034043***	-.52724741***
	L2.	-.02297431	.09649443	-.4038636**
	L3.	.0095455	-.03406132***	.5173196***
	ma			
	L1.	-.46647099	.83256382***	.49684324***
	L2.		-.15575814	.36070844**
	L3.			-.55352477***
sigma	_cons	.00205902***	.00205869***	.00205829***
Statistics				
	aic	-73231.387	-73231.797	-73232.791
	bic	-73189.706	-73183.17	-73177.217
	ll	36621.693	36622.898	36624.395

legend: * p<.1; ** p<.05; *** p<.01

- **The most appropriated order for rspot is ARIMA(1,0,2).**
- **The most appropriated order for rfuture is ARIMA(1,0,1).**

Part II

- Estimate VARs models using spot return (rspot) and future return (rfuture) as endogenous variables and determine the most appropriated lags models using SBIC.

```
. varsoc rspot rfuture
```

Selection-order criteria						Number of obs		=	7679
Sample: 6 - 7684									
lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC	
0	76705.7				7.2e-12	-19.9775	-19.9769	-19.9757	
1	76876.4	341.45	4	0.000	6.9e-12	-20.0209	-20.0191	-20.0155	
2	76966.2	179.52	4	0.000	6.8e-12	-20.0433	-20.0402	-20.0342	
3	76999.2	66.06	4	0.000	6.7e-12	-20.0508	-20.0465	-20.0382*	
4	77015.7	32.907*	4	0.000	6.7e-12*	-20.0541*	-20.0485*	-20.0378	
Endogenous: rspot rfuture									
Exogenous: _cons									

- **According to SBIC, the most appropriated lag order is 3.**

- Perform stability test and Granger exogeneity test.

```
. var rspot rfuture, lag(1/3)
```

Vector autoregression

Sample: 5 - 7684	No. of obs	=	7680
Log likelihood = 77010.15	AIC	=	-20.05108
FPE = 6.71e-12	HQIC	=	-20.04674
Det(Sigma_ml) = 6.69e-12	SBIC	=	-20.03842

Equation	Parms	RMSE	R-sq	chi2	P>chi2
rspot	7	.001779	0.0122	95.07421	0.0000
rfuture	7	.002044	0.0181	141.3296	0.0000

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
rspot	rspot						
	L1.	-.0323987	.0159661	-2.03	0.042	-.0636918	-.0011057
	L2.	-.1099664	.0160841	-6.84	0.000	-.1414905	-.0784422
	L3.	-.0418984	.0159205	-2.63	0.008	-.0731019	-.0106949
	rfuture						
	L1.	.0933035	.0138966	6.71	0.000	.0660668	.1205403
	L2.	.0688434	.0141336	4.87	0.000	.0411421	.0965447
	L3.	.0317131	.0139194	2.28	0.023	.0044315	.0589946
	_cons	.0000231	.0000203	1.14	0.256	-.0000167	.0000629
rfuture	rspot						
	L1.	.2004382	.0183405	10.93	0.000	.1644915	.2363849
	L2.	.0600679	.018476	3.25	0.001	.0238557	.0962801
	L3.	.0609707	.018288	3.33	0.001	.0251268	.0968146
	rfuture						
	L1.	-.1528221	.0159632	-9.57	0.000	-.1841093	-.1215349
	L2.	-.0926647	.0162354	-5.71	0.000	-.1244855	-.0608439
	L3.	-.0524571	.0159894	-3.28	0.001	-.0837958	-.0211184

```

_cons | .0000262 .0000233 1.12 0.262 -.0000195 .0000719

```

```
. varstable, graph
```

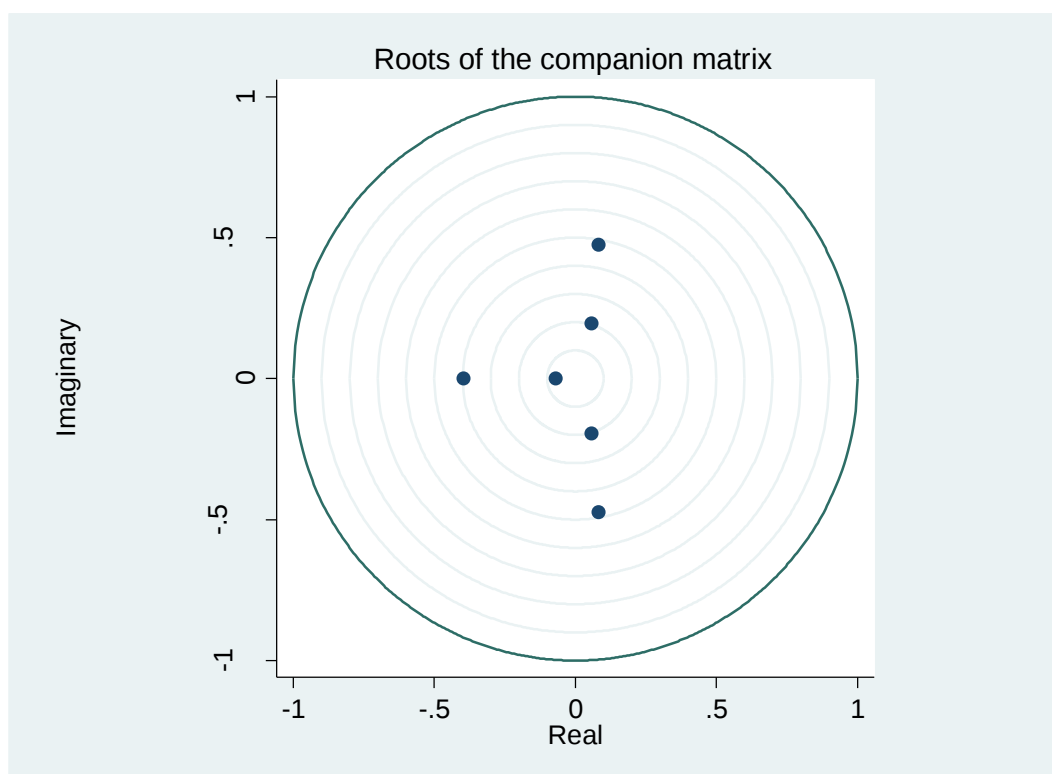
```
Eigenvalue stability condition
```

Eigenvalue		Modulus
.0829301 + .4737693i		.480973
.0829301 - .4737693i		.480973
-.3959128		.395913
.0571976 + .1954789i		.203675
.0571976 - .1954789i		.203675
-.06956342		.069563

```

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

```



```
. vargranger
```

```
Granger causality wald tests
```

Equation	Excluded	chi2	df	Prob > chi2
rspot	rfuture	58.069	3	0.000
rspot	ALL	58.069	3	0.000
rfuture	rspot	125.3	3	0.000
rfuture	ALL	125.3	3	0.000

- According to stability test, the system is stable since all the eigenvalues lie inside the unit circle.
- According to Granger exogeneity, both rspot and rfuture are all endogenous variables since all the tests are significant.

6. Perform Impulse response analysis and determine which variable has more impact.

```
. irf create order1, o(rspot rfuture) step(10) set(irf01)
(file irf01.irf created)
(file irf01.irf now active)
(file irf01.irf updated)
```

```
. irf table oirf, impulse(rspot rfuture) response(rspot rfuture)
```

Results from order1

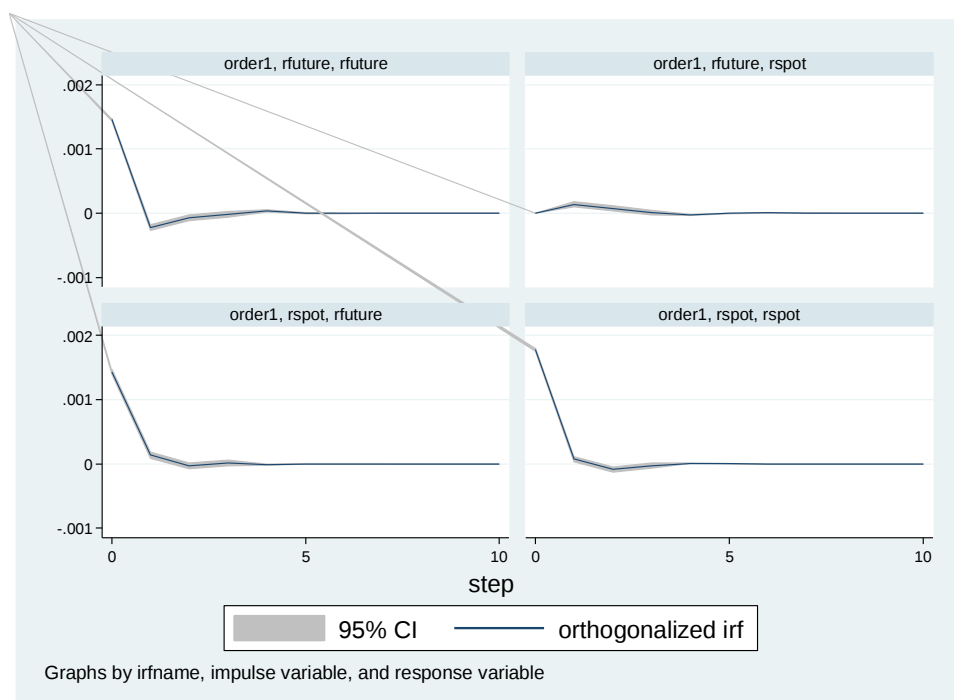
step	(1) oirf	(1) Lower	(1) Upper	(2) oirf	(2) Lower	(2) Upper	(3) oirf	(3) Lower	(3) Upper
0	.001778	.00175	.001806	.001434	.001395	.001474	0	0	0
1	.000076	.000036	.000116	.000137	.000091	.000183	.000136	.000096	.000175
2	-.000086	-.000126	-.000047	-.000032	-.000078	.000014	.000075	.000036	.000114
3	-.000028	-.000068	.000012	.000013	-.000033	.000058	6.6e-06	-.000032	.000045
4	.000011	3.5e-06	.000018	-.000012	-.00002	-4.5e-06	-.000028	-.00004	-.000016
5	5.1e-06	3.5e-07	9.8e-06	-2.5e-06	-7.0e-06	2.1e-06	-3.4e-06	-.00001	3.3e-06
6	-8.3e-07	-2.8e-06	1.1e-06	8.0e-07	-1.0e-06	2.6e-06	4.7e-06	2.1e-06	7.3e-06
7	-1.5e-06	-2.7e-06	-2.5e-07	1.5e-06	1.3e-07	2.9e-06	2.1e-06	-3.3e-07	4.6e-06
8	4.6e-08	-4.1e-07	5.0e-07	-2.1e-07	-5.6e-07	1.3e-07	-9.4e-07	-1.5e-06	-3.4e-07
9	3.1e-07	6.8e-08	5.4e-07	-2.8e-07	-5.2e-07	-3.8e-08	-5.7e-07	-1.1e-06	-4.2e-08
10	5.4e-08	-1.0e-07	2.1e-07	-4.3e-08	-1.9e-07	1.0e-07	9.1e-08	-1.3e-07	3.1e-07

step	(4) oirf	(4) Lower	(4) Upper
0	.001454	.001431	.001477
1	-.000222	-.000268	-.000177
2	-.000074	-.000119	-.000028
3	-.000021	-.000066	.000024
4	.000036	.00002	.000052
5	-3.4e-07	-6.6e-06	5.9e-06
6	-4.1e-06	-6.9e-06	-1.4e-06
7	-2.2e-06	-4.9e-06	5.1e-07
8	1.2e-06	5.8e-07	1.9e-06
9	4.6e-07	-5.3e-08	9.7e-07
10	-1.1e-07	-3.1e-07	8.6e-08

95% lower and upper bounds reported

- (1) irfname = order1, impulse = rspot, and response = rspot
- (2) irfname = order1, impulse = rspot, and response = rfuture
- (3) irfname = order1, impulse = rfuture, and response = rspot
- (4) irfname = order1, impulse = rfuture, and response = rfuture

```
. irf graph oirf, impulse(rspot rfuture) response(rspot rfuture)
```



```
. irf table coirf, impulse(rspot rfuture) response(rspot rfuture)
```

Results from order1

step	(1) coirf	(1) Lower	(1) Upper	(2) coirf	(2) Lower	(2) Upper	(3) coirf	(3) Lower	(3) Upper
0	.001778	.00175	.001806	.001434	.001395	.001474	0	0	0
1	.001855	.001805	.001904	.001572	.001513	.00163	.000136	.000096	.000175
2	.001768	.001704	.001832	.00154	.001467	.001613	.000211	.000154	.000268
3	.00174	.001665	.001815	.001552	.001468	.001637	.000217	.00015	.000285
4	.00175	.001676	.001825	.00154	.001457	.001623	.000189	.000132	.000247
5	.001756	.001684	.001827	.001538	.001457	.001618	.000186	.000132	.00024
6	.001755	.001683	.001826	.001538	.001458	.001619	.00019	.000135	.000245
7	.001753	.001681	.001825	.00154	.001459	.001621	.000192	.000136	.000249
8	.001753	.001681	.001825	.00154	.001459	.001621	.000192	.000135	.000248
9	.001754	.001682	.001826	.001539	.001459	.00162	.000191	.000135	.000247
10	.001754	.001682	.001826	.001539	.001459	.00162	.000191	.000135	.000247

step	(4) coirf	(4) Lower	(4) Upper
0	.001454	.001431	.001477
1	.001232	.001183	.001282
2	.001159	.001093	.001224
3	.001137	.001061	.001214
4	.001173	.001109	.001238
5	.001173	.001111	.001235
6	.001169	.001105	.001232
7	.001166	.001102	.001231
8	.001168	.001104	.001232
9	.001168	.001104	.001232
10	.001168	.001104	.001232

95% lower and upper bounds reported

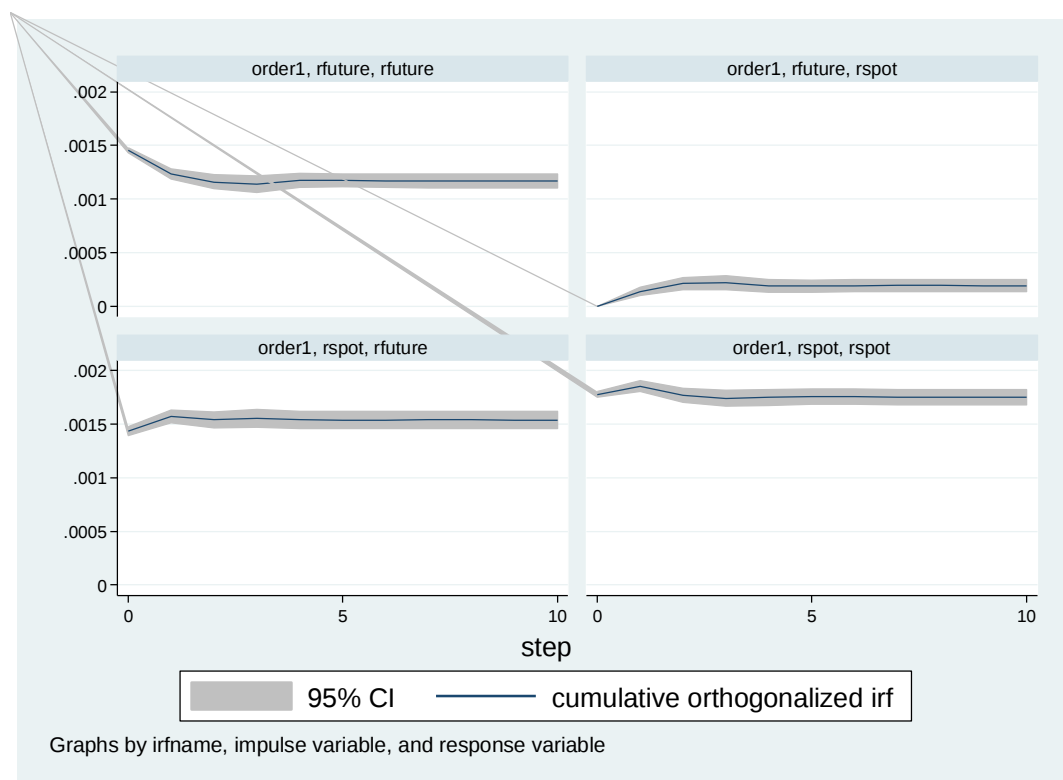
(1) irfname = order1, impulse = rspot, and response = rspot

(2) irfname = order1, impulse = rspot, and response = rfuture

(3) irfname = order1, impulse = rfuture, and response = rspot

(4) irfname = order1, impulse = rfuture, and response = rfuture

```
. irf graph coirf, impulse(rspot rfuture) response(rspot rfuture)
```



- According to IRF analysis, rspot has more impact on rfuture.

7. Perform Forecast error variance decomposition and determine variable that has more impact on each endogenous variable.

```
. irf table fevd, impulse(rspot rfuture) response(rspot rfuture)
```

Results from order1

step	(1) fevd	(1) Lower	(1) Upper	(2) fevd	(2) Lower	(2) Upper	(3) fevd	(3) Lower	(3) Upper
0	0	0	0	0	0	0	0	0	0
1	1	1	1	.493053	.47713	.508975	0	0	0
2	.994221	.990856	.997585	.48956	.473586	.505534	.005779	.002415	.009144
3	.992487	.988616	.996357	.489057	.473061	.505053	.007513	.003643	.011384
4	.992475	.988611	.996339	.489024	.47303	.505018	.007525	.003661	.011389
5	.992228	.988242	.996214	.488895	.472897	.504893	.007772	.003786	.011758
6	.992224	.988237	.996212	.488895	.472897	.504893	.007776	.003788	.011763
7	.992218	.988226	.996209	.488894	.472895	.504892	.007782	.003791	.011774
8	.992216	.988224	.996208	.488893	.472895	.504891	.007784	.003792	.011776
9	.992216	.988224	.996208	.488893	.472895	.504891	.007784	.003792	.011776
10	.992216	.988223	.996208	.488893	.472895	.504891	.007784	.003792	.011777

step	(4) fevd	(4) Lower	(4) Upper
0	0	0	0
1	.506947	.491025	.52287
2	.51044	.494466	.526414
3	.510943	.494947	.526939
4	.510976	.494982	.52697
5	.511105	.495107	.527103
6	.511105	.495107	.527103
7	.511106	.495108	.527105
8	.511107	.495109	.527105
9	.511107	.495109	.527105
10	.511107	.495109	.527105

95% lower and upper bounds reported

- (1) irfname = order1, impulse = rspot, and response = rspot
 (2) irfname = order1, impulse = rspot, and response = rfuture
 (3) irfname = order1, impulse = rfuture, and response = rspot
 (4) irfname = order1, impulse = rfuture, and response = rfuture

- **According to Forecast error variance decomposition, rspot has more impact on rfuture.**

Part III

8. Estimate GARCH(p,q) for spot return (rspot) using future return (rfuture) as explanatory variable for mean equation – determine the most appropriated order p and q for variance equation using SBIC given the maximum lag equals to 2.

```
. reg rspot rfuture
```

Source	SS	df	MS	Number of obs =	7683
Model	.011539538	1	.011539538	F(1, 7681) =	6787.70
Residual	.013058198	7681	1.7001e-06	Prob > F =	0.0000
Total	.024597736	7682	3.2020e-06	R-squared =	0.4691
				Adj R-squared =	0.4691
				Root MSE =	.0013

rspot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
rfuture	.594594	.007217	82.39	0.000	.5804466 .6087413
_cons	8.01e-06	.0000149	0.54	0.590	-.0000212 .0000372

```
. estat archlm
```

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	4.919	1	0.0266

H0: no ARCH effects vs. H1: ARCH(p) disturbance

- **According to ARCH-effect test, there exists significant ARCH effect.**

```
. arch rspot rfuture, arch(1/1) nolog
```

ARCH family regression

Sample: 2 - 7684
Distribution: Gaussian
Log likelihood = 40210.38

Number of obs = 7683
wald chi2(1) = 199294.69
Prob > chi2 = 0.0000

rspot	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]
rspot					
rfuture	.6210687	.0013912	446.42	0.000	.618342 .6237954
_cons	9.98e-06	.0000141	0.71	0.479	-.0000177 .0000376
ARCH					
arch					
L1.	.1165902	.0073183	15.93	0.000	.1022466 .1309338
_cons	1.52e-06	7.38e-09	206.28	0.000	1.51e-06 1.54e-06

```
. estat ic
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7683	.	40210.38	4	-80412.77	-80384.98

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

```
. arch rspot rfuture, arch(1/2) nolog
```

ARCH family regression

Sample: 2 - 7684
Distribution: Gaussian
Log likelihood = 40497.51

Number of obs = 7683
wald chi2(1) = 129656.55
Prob > chi2 = 0.0000

	rspot	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rspot							
	rfuture	.6005692	.0016679	360.08	0.000	.5973002	.6038382
	_cons	-7.86e-07	9.42e-06	-0.08	0.934	-.0000192	.0000177
ARCH							
	arch						
	L1.	.1095312	.0080469	13.61	0.000	.0937597	.1253028
	L2.	.338373	.006708	50.44	0.000	.3252255	.3515205
	_cons	1.09e-06	1.08e-08	100.43	0.000	1.07e-06	1.11e-06

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7683	.	40497.51	5	-80985.01	-80950.28

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

. arch rspot rfuture, arch(1/1) garch(1/1) nolog

ARCH family regression

Sample: 2 - 7684	Number of obs	=	7683
Distribution: Gaussian	wald chi2(1)	=	126853.27
Log likelihood = 40518.76	Prob > chi2	=	0.0000

	rspot	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rspot							
	rfuture	.6471703	.0018171	356.16	0.000	.6436089	.6507317
	_cons	6.44e-07	.0000111	0.06	0.954	-.0000212	.0000225
ARCH							
	arch						
	L1.	.1834017	.0074922	24.48	0.000	.1687171	.1980862
	garch						
	L1.	.6065876	.0136353	44.49	0.000	.5798629	.6333124
	_cons	3.86e-07	1.45e-08	26.62	0.000	3.57e-07	4.14e-07

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7683	.	40518.76	5	-81027.53	-80992.8

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

. arch rspot rfuture, arch(1/1) garch(1/2) nolog

ARCH family regression

Sample: 2 - 7684	Number of obs	=	7683
Distribution: Gaussian	wald chi2(1)	=	131273.11
Log likelihood = 40536.75	Prob > chi2	=	0.0000

	rspot	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rspot							
	rfuture	.6400212	.0017665	362.32	0.000	.636559	.6434835
	_cons	-2.53e-06	.0000106	-0.24	0.811	-.0000233	.0000182
ARCH							

arch						
L1.	.1704453	.0078813	21.63	0.000	.1549983	.1858922
garch						
L1.	.8490056	.0319153	26.60	0.000	.7864527	.9115585
L2.	-.2069829	.0208903	-9.91	0.000	-.247927	-.1660387
_cons	3.50e-07	1.26e-08	27.84	0.000	3.26e-07	3.75e-07

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7683	.	40536.75	6	-81061.51	-81019.83

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

. arch rspot rfuture, arch(1/2) garch(1/1) nolog

ARCH family regression

Sample: 2 - 7684
 Distribution: Gaussian
 Log likelihood = 40581.4

Number of obs = 7683
 Wald chi2(1) = 127297.62
 Prob > chi2 = 0.0000

rspot	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rspot						
rfuture	.6259104	.0017543	356.79	0.000	.6224721	.6293488
_cons	-8.75e-06	9.74e-06	-0.90	0.369	-.0000278	.0000103
ARCH						
arch						
L1.	.1039058	.0084471	12.30	0.000	.0873498	.1204617
L2.	.2378366	.0060369	39.40	0.000	.2260044	.2496688
garch						
L1.	.340368	.0079195	42.98	0.000	.3248461	.3558899
_cons	6.23e-07	1.10e-08	56.63	0.000	6.01e-07	6.44e-07

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7683	.	40581.4	6	-81150.8	-81109.12

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

. arch rspot rfuture, arch(1/2) garch(1/2) nolog

ARCH family regression

Sample: 2 - 7684
 Distribution: Gaussian
 Log likelihood = 40603.26

Number of obs = 7683
 Wald chi2(1) = 120951.20
 Prob > chi2 = 0.0000

rspot	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rspot						
rfuture	.6237113	.0017934	347.78	0.000	.6201963	.6272263
_cons	-.0000106	9.47e-06	-1.12	0.262	-.0000292	7.93e-06
ARCH						
arch						
L1.	.1014148	.0082533	12.29	0.000	.0852386	.1175909
L2.	.2988765	.0063886	46.78	0.000	.286355	.3113979
garch						

L1.	.0765894	.0154151	4.97	0.000	.0463764	.1068024
L2.	.1771544	.0174298	10.16	0.000	.1429927	.2113161
_cons	6.86e-07	1.36e-08	50.58	0.000	6.60e-07	7.13e-07

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7683	.	40603.26	7	-81192.53	-81143.9

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

- **According BIC, the most appropriated lags order in this case is GARCH(2,2)**

9. From (8), predict the variance of spot return (rspot).

```
. predict sigmahat, v
. line sigmahat t
```

