

Example Time Series

ARIMA: From the data set example.dta:

Requirements:

1. Test whether the series spot and future are stationary series.
2. Determine order of integration of the series spot and future.
3. Generate series of the return of spot (*rspot*) and return of future (*rfuture*) and test whether they are stationary.
4. 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 5.

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 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

- **spot and future are nonstationary.**

2. Determine order of integration of the series spot and future.

```
. dfuller d.spot, 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)	-63.765	-3.960	-3.410	-3.120
Mackinnon approximate p-value for Z(t) = 0.0000				

D2.spot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
D.spot						
L1.	-1.005364	.0157667	-63.77	0.000	-1.036271	-.974457
LD.	.0508571	.011398	4.46	0.000	.0285139	.0732003
_trend	7.82e-07	4.94e-06	0.16	0.874	-8.90e-06	.0000105
_cons	.0088178	.0219189	0.40	0.687	-.0341492	.0517848

```
. dfuller d.future , 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)	-65.269	-3.960	-3.410	-3.120
Mackinnon approximate p-value for Z(t) = 0.0000				

D2.future	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
D.future						
L1.	-1.067592	.0163567	-65.27	0.000	-1.099655	-1.035528
LD.	.038008	.0114045	3.33	0.001	.0156522	.0603639
_trend	1.01e-06	5.59e-06	0.18	0.856	-9.94e-06	.000012
_cons	.0096235	.0247823	0.39	0.698	-.0389566	.0582036

- **spot and future are Integrated series of order 1 or I(1).**

3. Generate series of the return of spot (*rspot*) and return of future (*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	-.000006	.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.*

4. 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 5.

```
. *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)5 {
3.   forvalue q = 1(1)5 {
4.       display "estimate arima`p'`d'`q'"
5.       capture: quietly arima 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 arima1`d'4 arima1`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
15. estimates table arima2`d'1 arima2`d'2 arima2`d'3 arima2`d'4 arima2`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
16. estimates table arima3`d'1 arima3`d'2 arima3`d'3 arima3`d'4 arima3`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
17. estimates table arima4`d'1 arima4`d'2 arima4`d'3 arima4`d'4 arima4`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
18. estimates table arima5`d'1 arima5`d'2 arima5`d'3 arima5`d'4 arima5`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
19. }
estimate arima101
arima101 already estimated
estimate arima102
arima102 already estimated
estimate arima103
arima103 already estimated
estimate arima104
arima104 already estimated
estimate arima105
arima105 already estimated
estimate arima201
arima201 already estimated
estimate arima202
arima202 already estimated
estimate arima203
arima203 already estimated
estimate arima204
arima204 already estimated
estimate arima205
arima205 already estimated
estimate arima301
arima301 already estimated
estimate arima302
arima302 already estimated
estimate arima303
arima303 already estimated
estimate arima304
arima304 already estimated
estimate arima305
arima305 already estimated
estimate arima401
arima401 already estimated
estimate arima402
arima402 already estimated
estimate arima403
arima403 already estimated
estimate arima404
arima404 already estimated
estimate arima405
arima405 already estimated
estimate arima501
arima501 already estimated
estimate arima502
```

arima502 already estimated
 estimate arima503
 arima503 already estimated
 estimate arima504
 arima504 already estimated
 estimate arima505
 arima505 already estimated

Variable	arima101	arima102	arima103	arima104	arima105
y					
_cons	.00002358	.00002358	.00002358	.00002357	.0000236
ARMA					
ar					
L1.	-.39222121***	.42866768***	.65121793**	-.4418708	.19422255
ma					
L1.	.44515732***	-.38284317***	-.60570251**	.48778125	-.14853288
L2.		-.06805288***	-.0785457***	-.02952616	-.0578027**
L3.			.01541405	-.04117543	-.00879285
L4.				-.00216733	.00427518
L5.					-.02212732*
sigma					
_cons	.00178634***	.00178491***	.00178487***	.00178491***	.00178452***
Statistics					
aic	-75418.284	-75428.583	-75426.956	-75424.609	-75425.916
bic	-75390.497	-75393.85	-75385.276	-75375.982	-75370.342
ll	37713.142	37719.292	37719.478	37719.305	37720.958

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

Variable	arima201	arima202	arima203	arima204	arima205
y					
_cons	.00002357	.00002358	.00002357	.00002358	.00002357
ARMA					
ar					
L1.	.38018903***	.4428634***	-.29668626	.20849565	.63263472***
L2.	-.06525664***	.06485063	.18525538	.37776554	-.91731069***
ma					
L1.	-.33467542**	-.39715673***	.3426502	-.16260084	-.58710754***
L2.		-.13338401	-.22062902	-.43688009	.83965418***
L3.			-.0455461	-.02892354	.05476885***
L4.				.02145155	-.03409321***
L5.					-.03012065***
sigma					
_cons	.00178498***	.00178489***	.00178489***	.00178475***	.00178388***
Statistics					
aic	-75428.017	-75426.777	-75424.788	-75423.974	-75429.446
bic	-75393.283	-75385.096	-75376.161	-75368.4	-75366.925
ll	37719.008	37719.388	37719.394	37719.987	37723.723

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

Variable	arima301	arima302	arima303	arima304	arima305
y					
_cons	.00002358	.00002358	.00002358	.00002358	.00002358
ARMA					
ar					
L1.	.77437319***	.75391093	-.00931271	.11659349	.17008802
L2.	-.08500113***	-.07142142	.14076076	-.77533292***	-.75369599***
L3.	.02486609	.02349348	.27348399*	.50690923***	.56028712*
ma					
L1.	-.72875825***	-.70829213	.05444554	-.07071828	-.12430409

	L2.		-.0126675	-.19087608	.72187978***	.69757843***
	L3.			-.29968133**	-.48363964***	-.53414149*
	L4.				-.06737484***	-.06847599***
	L5.					.00392386
sigma	_cons		.00178484***	.00178484***	.00178455***	.00178409***
Statistics	aic		-75427.175	-75425.178	-75425.675	-75427.585
	bic		-75385.495	-75376.55	-75370.101	-75365.064
	ll		37719.588	37719.589	37720.837	37722.792
legend: * p<.1; ** p<.05; *** p<.01						
	variable		arima401	arima402	arima403	arima404
y	_cons		.00002358	.00002358	.00002358	.00002358
ARMA	ar					
	L1.		.7666053*	.19158964	.11479526	.11582617
	L2.		-.0847024***	.40155116	-.84422456***	-.75582354***
	L3.		.02504525	-.03039789	.47666348***	.51458285***
	L4.		-.00097078	.02217215	-.06669164***	.01927272
	ma					
	L1.		-.72097599*	-.14607877	-.06913672	-.07000046
	L2.			-.45952184	.79177357***	.70233001***
	L3.				-.45297968***	-.49146562***
	L4.					-.08652975
	L5.					
sigma	_cons		.00178484***	.0017848***	.00178412***	.00178409***
Statistics	aic		-75425.181	-75423.574	-75427.294	-75425.598
	bic		-75376.553	-75368	-75364.773	-75356.13
	ll		37719.59	37719.787	37722.647	37722.799
legend: * p<.1; ** p<.05; *** p<.01						
	variable		arima501	arima502	arima503	arima504
y	_cons		.00002358	.00002357	.00002357	.00002358
ARMA	ar					
	L1.		.16545423	.27864543	.40337768	.45212007
	L2.		-.05696613**	-.38380203	-.81291959**	-.79726544***
	L3.		-.00729372	.0132755	-.23210031	.79847234
	L4.		.00131373	-.01409715	-.01694377	-.14234401
	L5.		-.02387488**	-.027723**	-.03800524	.02403092
	ma					
	L1.		-.11967988	-.23291974	-.35773961	-.40627736
	L2.			.32183897	.74635725**	.72752725***
	L3.				.27245433	-.75638633
	L4.					.06670883
	L5.					
sigma	_cons		.0017845***	.00178443***	.00178393***	.00178407***
Statistics	aic		-75426.156	-75424.789	-75426.981	-75423.79
	bic		-75370.582	-75362.269	-75357.513	-75347.376
	ll		37721.078	37721.395	37723.49	37722.895
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 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 arima1`d'4 arima1`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
15.  estimates table arima2`d'1 arima2`d'2 arima2`d'3 arima2`d'4 arima2`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
16.  estimates table arima3`d'1 arima3`d'2 arima3`d'3 arima3`d'4 arima3`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
17.  estimates table arima4`d'1 arima4`d'2 arima4`d'3 arima4`d'4 arima4`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
18.  estimates table arima5`d'1 arima5`d'2 arima5`d'3 arima5`d'4 arima5`d'5, star(0.1 0.05
0.01) stat(aic bic ll)
19. }
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	arima104	arima105
y	_cons	.00002616	.00002615	.00002616	.00002357	.0000236
ARMA	ar					
	L1.	.57862596***	.1646139	-.99197304***	-.4418708	.19422255
	ma					
	L1.	-.61250239***	-.19269514	.96410702***	.48778125	-.14853288
	L2.		-.03060977**	-.06339899***	-.02952616	-.0578027**
	L3.			-.03780979***	-.04117543	-.00879285
	L4.				-.00216733	.00427518
	L5.					-.02212732*
sigma	_cons	.00205937***	.00205903***	.00205869***	.00178491***	.00178452***
Statistics	aic	-73232.774	-73233.366	-73233.777	-75424.609	-75425.916
	bic	-73204.987	-73198.632	-73192.096	-75375.982	-75370.342
	ll	36620.387	36621.683	36622.888	37719.305	37720.958

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

variable	arima201	arima202	arima203	arima204	arima205
y					
_cons	.00002615	.00002616	.00002616	.00002358	.00002357
ARMA					
ar					
L1.	.1969293	.15226369	-.89430512***	.20849565	.63263472***
L2.	-.02961053**	.01296948	.09704817	.37776554	-.91731069***
ma					
L1.	-.22502128	-.18034762	.8665611***	-.16260084	-.58710754***
L2.		-.0439096	-.15750986	-.43688009	.83965418***
L3.			-.03516485***	-.02892354	.05476885***
L4.				.02145155	-.03409321***
L5.					-.03012065***
sigma					
_cons	.00205903***	.00205902***	.00205869***	.00178475***	.00178388***
Statistics					
aic	-73233.346	-73231.368	-73231.866	-75423.974	-75429.446
bic	-73198.612	-73189.687	-73183.239	-75368.4	-75366.925
ll	36621.673	36621.684	36622.933	37719.987	37723.723

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

variable	arima301	arima302	arima303	arima304	arima305
y					
_cons	.00002616	.00002616	.00002618	.00002358	.00002358
ARMA					
ar					
L1.	.43745093	-.8588441***	-.52730643***	.11659349	.17008802
L2.	-.02300296	.09802834	-.40394239**	-.77533292***	-.75369599***
L3.	.00950901	-.03401356**	.5172721***	.50690923***	.56028712*
ma					
L1.	-.46553637	.83106571***	.49689489***	-.07071828	-.12430409
L2.		-.15724365	.3607837**	.72187978***	.69757843***
L3.			-.55348204***	-.48363964***	-.53414149*
L4.				-.06737484***	-.06847599***
L5.					.00392386
sigma					
_cons	.00205902***	.00205869***	.0020583***	.00178409***	.00178409***
Statistics					
aic	-73231.387	-73231.797	-73232.791	-75427.585	-75425.609
bic	-73189.706	-73183.17	-73177.217	-75365.064	-75356.141
ll	36621.693	36622.898	36624.395	37722.792	37722.804

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

variable	arima401	arima402	arima403	arima404	arima405
y					
_cons	.00002358	.00002358	.00002358	.00002358	.00002358
ARMA					
ar					
L1.	.7666053*	.19158964	.11479526	.11582617	-.55025558
L2.	-.0847024***	.40155116	-.84422456***	-.75582354***	-.78564519***
L3.	.02504525	-.03039789	.47666348***	.51458285***	-.04871012
L4.	-.00097078	.02217215	-.06669164***	.01927272	.25153939
ma					
L1.	-.72097599*	-.14607877	-.06913672	-.07000046	.59631735
L2.		-.45952184	.79177357***	.70233001***	.76311658***
L3.			-.45297968***	-.49146562***	.03723265
L4.				-.08652975	-.30357175
L5.					-.04488519
sigma					

		_cons	.00178484***	.0017848***	.00178412***	.00178409***	.00178406***
Statistics							
	aic		-75425.181	-75423.574	-75427.294	-75425.598	-75423.821
	bic		-75376.553	-75368	-75364.773	-75356.13	-75347.407
	ll		37719.59	37719.787	37722.647	37722.799	37722.91
Legend: * p<.1; ** p<.05; *** p<.01							
Variable			arima501	arima502	arima503	arima504	arima505
y	_cons		.00002358	.00002357	.00002357	.00002358	.00002357
ARMA							
	ar						
	L1.		.16545423	.27864543	.40337768	.45212007	.65262081
	L2.		-.05696613**	-.38380203	-.81291959**	-.79726544***	-.84750045
	L3.		-.00729372	.0132755	-.23210031	.79847234	.13436587
	L4.		.00131373	-.01409715	-.01694377	-.14234401	-.03733553
	L5.		-.02387488**	-.027723**	-.03800524	.02403092	.21196901
	ma						
	L1.		-.11967988	-.23291974	-.35773961	-.40627736	-.6073824
	L2.			.32183897	.74635725**	.72752725***	.76923758
	L3.				.27245433	-.75638633	-.08161162
	L4.					.06670883	.00421319
	L5.						-.24353795
sigma	_cons		.0017845***	.00178443***	.00178393***	.00178407***	.00178371***
Statistics							
	aic		-75426.156	-75424.789	-75426.981	-75423.79	-75424.907
	bic		-75370.582	-75362.269	-75357.513	-75347.376	-75341.546
	ll		37721.078	37721.395	37723.49	37722.895	37724.453
Legend: * p<.1; ** p<.05; *** p<.01							

end of do-file

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

GARCH:

The following GARCH model:

Mean Equation: $rfuture_t = \alpha + \beta rspot_t + \varepsilon_t$ (1)

Variance Equation: $\sigma_t^2 = \alpha_0 + \sum_{j=1}^p \delta_j \sigma_{t-j}^2 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2$ (2)

From the data set example.dta:

Requirements:

1. Test whether there exists significant ARCH effects.
2. 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.
3. From (2), predict the variance of future return (*rfuture*).

1. Test whether there exists significant ARCH effects.

```
. reg rfuture rspot
```

Source	SS	df	MS	Number of obs	=	7,683
Model	.01531231	1	.01531231	F(1, 7681)	=	6787.70
Residual	.017327485	7,681	2.2559e-06	Prob > F	=	0.0000
Total	.032639795	7,682	4.2489e-06	R-squared	=	0.4691
				Adj R-squared	=	0.4691
				Root MSE	=	.0015

rfuture	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rspot	.7889924	.0095766	82.39	0.000	.7702196	.8077651
_cons	7.58e-06	.0000171	0.44	0.658	-.000026	.0000412

```
. estat archlm
```

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	6.951	1	0.0084

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

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

2. 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.

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

ARCH family regression

Sample: 2 - 7684

Distribution: Gaussian

Log likelihood = 39218.14

Number of obs = 7,683

wald chi2(1) = 110866.60

Prob > chi2 = 0.0000

rfuture	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
---------	-------	------------------	---	------	----------------------	--

rfuture						
	rspot	.8122738	.0024395	332.97	0.000	.8074924
	_cons	-1.78e-06	.0000129	-0.14	0.890	-.000027
ARCH						
	arch L1.	.2336873	.0081368	28.72	0.000	.2177393
	_cons	1.84e-06	8.36e-09	219.94	0.000	1.82e-06

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7,683	.	39218.14	4	-78428.29	-78400.5

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

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

ARCH family regression

Sample: 2 - 7684
Distribution: Gaussian
Log likelihood = 39351.85

Number of obs = 7,683
wald chi2(1) = 108336.82
Prob > chi2 = 0.0000

rfuture		Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rfuture							
	rspot	.8356596	.0025389	329.15	0.000	.8306835	.8406357
	_cons	-.0000147	9.46e-06	-1.55	0.121	-.0000332	3.89e-06
ARCH							
	arch L1.	.2467993	.0079396	31.08	0.000	.2312379	.2623607
	L2.	.1915003	.0060913	31.44	0.000	.1795616	.203439
	_cons	1.50e-06	1.03e-08	145.53	0.000	1.48e-06	1.52e-06

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7,683	.	39351.85	5	-78693.69	-78658.96

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

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

ARCH family regression

Sample: 2 - 7684
Distribution: Gaussian
Log likelihood = 39695.02

Number of obs = 7,683
wald chi2(1) = 144307.98
Prob > chi2 = 0.0000

rfuture		Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rfuture							
	rspot	.8163588	.002149	379.88	0.000	.8121468	.8205708
	_cons	9.03e-06	.0000117	0.77	0.441	-.000014	.000032
ARCH							
	arch L1.	.1583928	.0035413	44.73	0.000	.1514519	.1653336

garch						
L1.	.7734065	.0038485	200.96	0.000	.7658637	.7809494
_cons	1.95e-07	5.80e-09	33.59	0.000	1.84e-07	2.06e-07

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7,683	.	39695.02	5	-79380.04	-79345.3

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

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

ARCH family regression

Sample: 2 - 7684
 Distribution: Gaussian
 Log likelihood = 39697.75

Number of obs = 7,683
 Wald chi2(1) = 118871.71
 Prob > chi2 = 0.0000

rfuture	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]
rfuture					
rspot	.8153033	.0023647	344.78	0.000	.8106685 .819938
_cons	8.43e-06	.0000118	0.71	0.476	-.0000148 .0000316
ARCH					
arch					
L1.	.1729364	.0061173	28.27	0.000	.1609467 .1849261
garch					
L1.	.6135491	.0310685	19.75	0.000	.5526559 .6744422
L2.	.1402425	.0250312	5.60	0.000	.0911823 .1893027
_cons	2.09e-07	8.64e-09	24.17	0.000	1.92e-07 2.26e-07

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7,683	.	39697.75	6	-79383.5	-79341.82

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

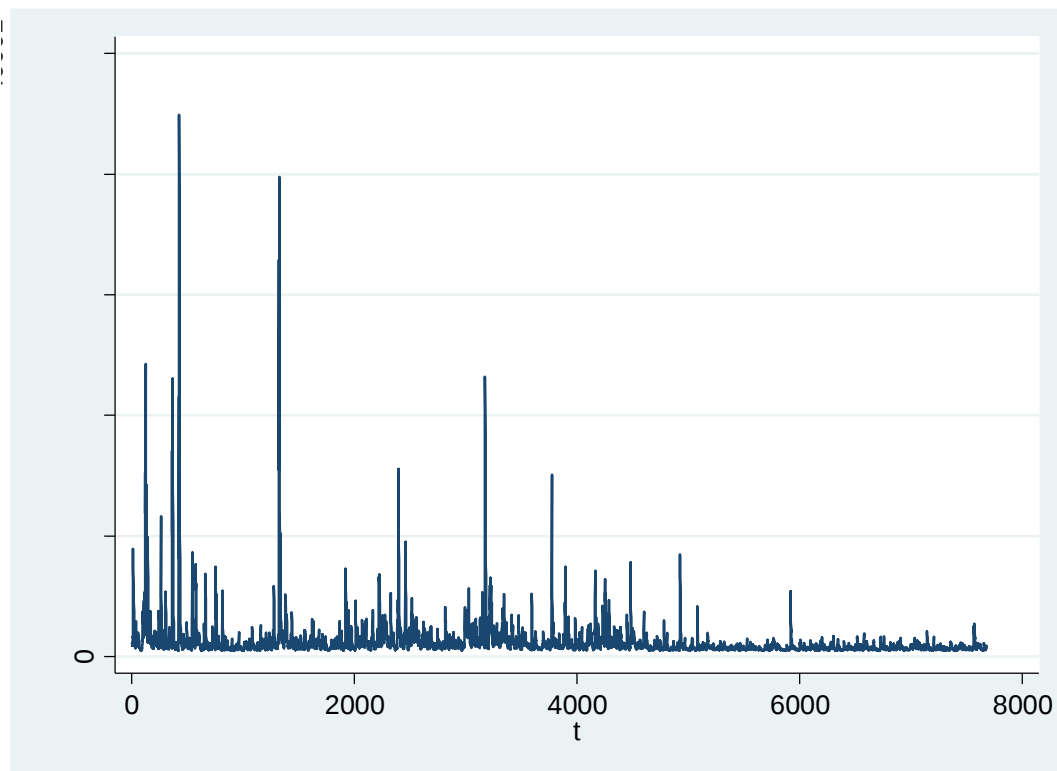
. arch rfuture rspot, arch(1/2) garch(1/1) nolog
 flat log likelihood encountered, cannot find uphill direction
 r(430);

. arch rfuture rspot, arch(1/2) garch(1/2) nolog
 flat log likelihood encountered, cannot find uphill direction
 r(430);

- **According BIC, the most appropriated lags order in this case is GARCH(1,1)**

3. From (2), predict the variance of future return (r_{future}).

```
. predict sigma_hat, v  
. line sigma_hat t
```



VAR:

The following VARs models:

$$Y_t = A_0 + A_1 Y_{t-1} + \epsilon_t$$

where: $Y_t = \begin{pmatrix} rspot_t \\ rfuture_t \end{pmatrix}$, $A_0 = \begin{pmatrix} a_{10} \\ a_{20} \end{pmatrix}$, $A_1 = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, $\epsilon_t = \begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix}$

From the data set example.dta:

Requirements:

1. Estimate VARs models using spot return (*rspot*) and future return (*rfuture*) as endogenous variables and determine the most appropriated lags models using SBIC.
2. Perform stability test and Granger exogeneity test.
3. Perform Impulse response analysis and determine which variable has more impact.
4. Perform Forecast error variance decomposition and determine variable that has more impact on each endogenous variable.

1. 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								
Sample: 6 - 7684					Number of obs		=	7679
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.

2. 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					

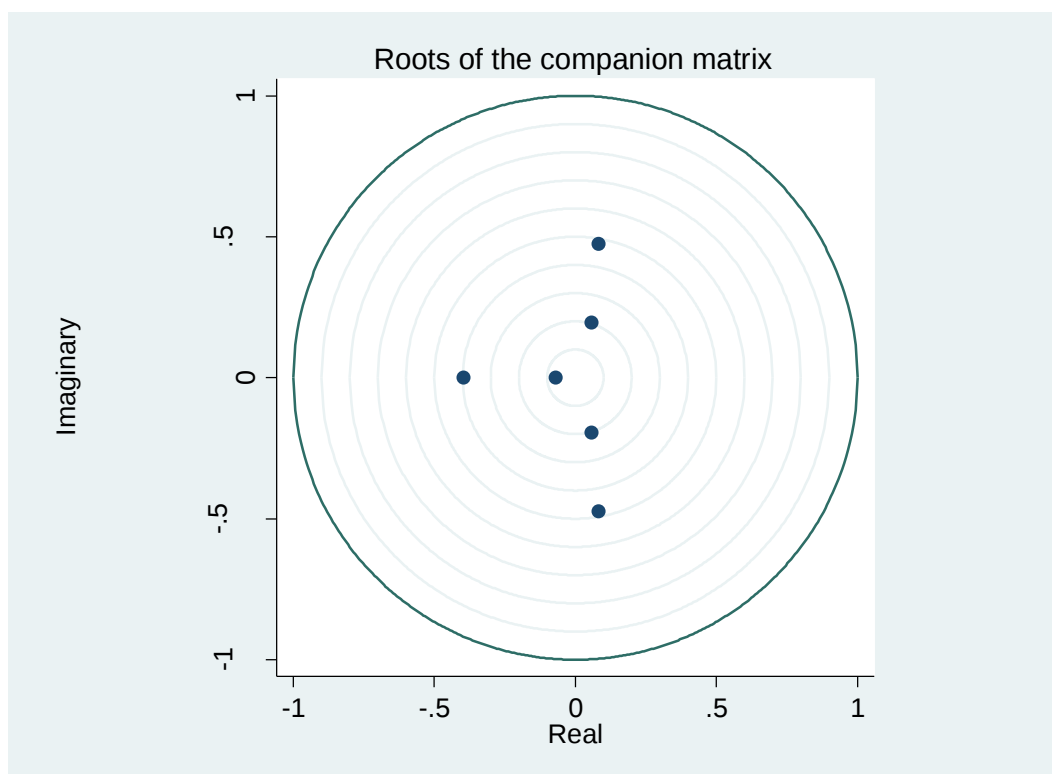
rspot						
L1.	-.0323987	.0159661	-2.03	0.042	-.0636918	-.0011057
L2.	-.1099664	.0160841	-6.84	0.000	-.1414905	-.0784422
L3.	-.0418984	.0159205	-2.63	0.008	-.0731019	-.0106949
rfuture						
L1.	.0933035	.0138966	6.71	0.000	.0660668	.1205403
L2.	.0688434	.0141336	4.87	0.000	.0411421	.0965447
L3.	.0317131	.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.

3. 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

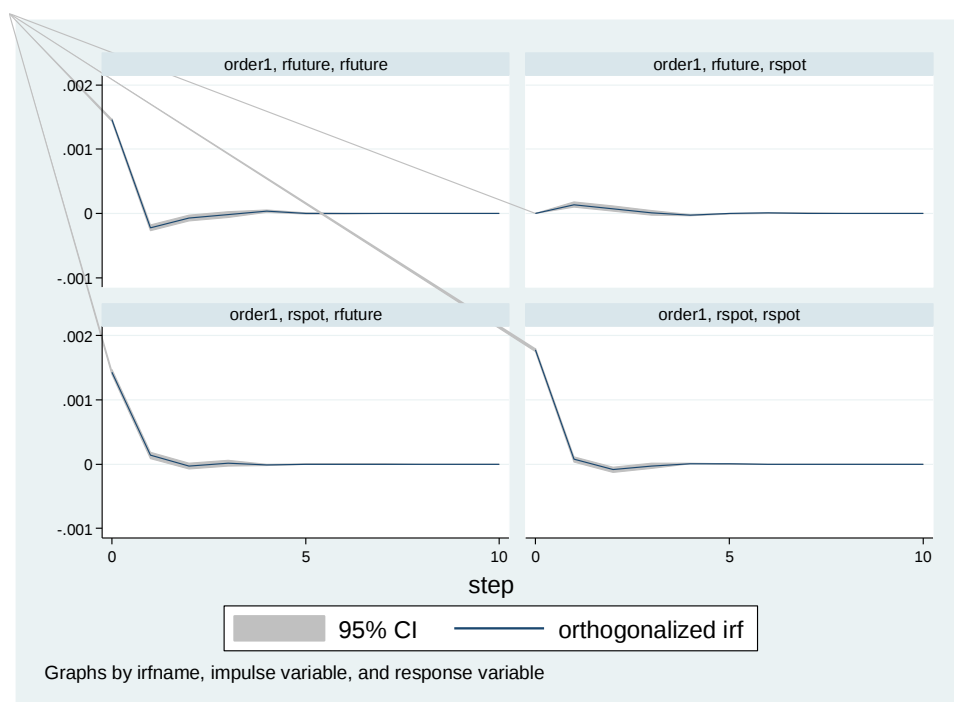
step	(1) oirf	(1) Lower	(1) Upper	(2) oirf	(2) Lower	(2) Upper	(3) oirf	(3) Lower	(3) Upper
0	.001778	.00175	.001806	.001434	.001395	.001474	0	0	0
1	.000076	.000036	.000116	.000137	.000091	.000183	.000136	.000096	.000175
2	-.000086	-.000126	-.000047	-.000032	-.000078	.000014	.000075	.000036	.000114
3	-.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

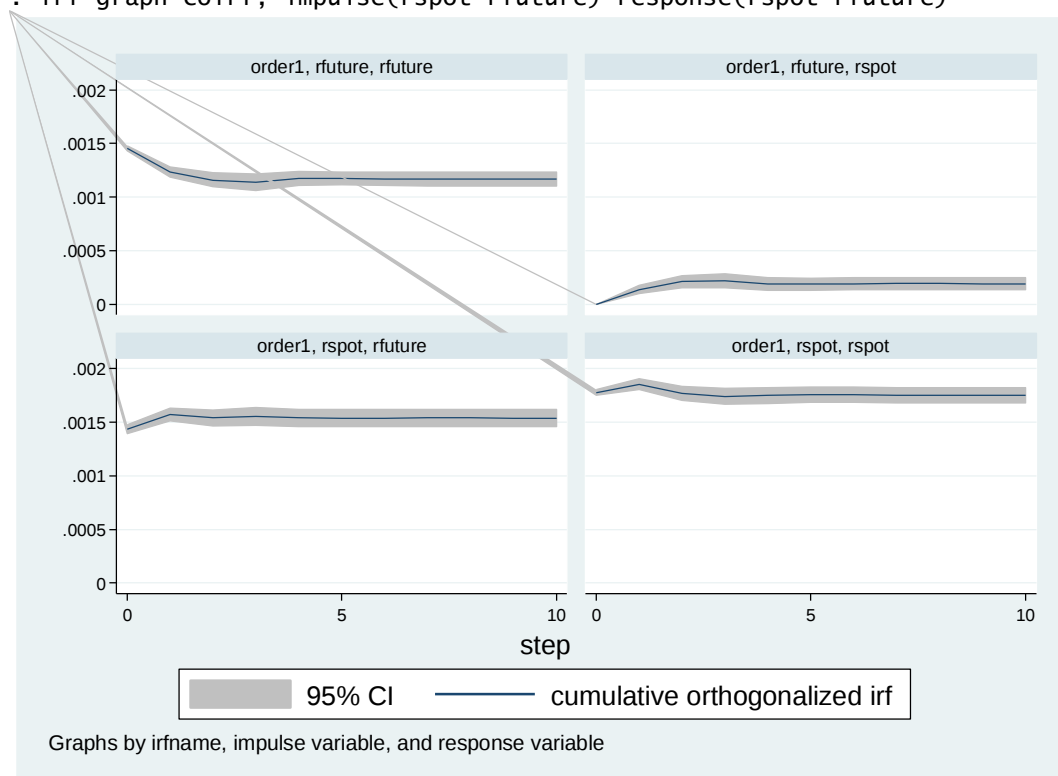
step	(1) coirf	(1) Lower	(1) Upper	(2) coirf	(2) Lower	(2) Upper	(3) coirf	(3) Lower	(3) Upper
0	.001778	.00175	.001806	.001434	.001395	.001474	0	0	0
1	.001855	.001805	.001904	.001572	.001513	.00163	.000136	.000096	.000175
2	.001768	.001704	.001832	.00154	.001467	.001613	.000211	.000154	.000268
3	.00174	.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.

4. 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.*