

1.

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

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

```
. 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
				R-squared	=	0.4691
				Adj R-squared	=	0.4691
Total	.032639795	7,682	4.2489e-06	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 the estimated results, the p-value of the ARCH effect test is less than level of significance ($0.0084 < 0.05$). Therefore, the null hypothesis is rejected, and there exists a significant ARCH effect in this model.

2.

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

ARCH family regression

Sample: 2 - 7684
Distribution: Gaussian
Log likelihood = 39218.14

Number of obs = 7,683
Wald chi2(1) = 110869.06
Prob > chi2 = 0.0000

rfuture	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
rfuture						
rspot	.8122742	.0024395	332.97	0.000	.8074929	.8170555
_cons	-1.78e-06	.0000129	-0.14	0.890	-.000027	.0000234
ARCH						
arch						
L1.	.2336904	.0081368	28.72	0.000	.2177425	.2496383
_cons	1.84e-06	8.36e-09	219.94	0.000	1.82e-06	1.86e-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	Number of obs	=	7,683
Distribution: Gaussian	Wald chi2(1)	=	108339.74
Log likelihood = 39351.85	Prob > chi2	=	0.0000

		OPG				
rfuture		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
rfuture						
rspot		.8356571	.0025388	329.15	0.000	.8306811 .8406332
_cons		-.0000147	9.46e-06	-1.55	0.122	-.0000332 3.90e-06
ARCH						
arch						
L1.		.2468027	.0079396	31.09	0.000	.2312414 .262364
L2.		.1914993	.0060912	31.44	0.000	.1795608 .2034378
_cons		1.50e-06	1.03e-08	145.53	0.000	1.48e-06 1.52e-06

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. 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) garch(1) nolog
```

ARCH family regression

Sample: 2 - 7684	Number of obs	=	7,683
Distribution: Gaussian	Wald chi2(1)	=	144308.34
Log likelihood = 39695.02	Prob > chi2	=	0.0000

		OPG					
rfuture		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
rfuture							
rspot		.8163529	.002149	379.88	0.000	.8121409	.8205648
_cons		9.03e-06	.0000117	0.77	0.442	-.000014	.000032
ARCH							
arch							
L1.		.1583902	.0035413	44.73	0.000	.1514495	.165331
garch							
L1.		.7734087	.0038485	200.97	0.000	.7658659	.7809516
_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) garch(1/2) nolog

ARCH family regression

Sample: 2 - 7684 Number of obs = 7,683
Distribution: Gaussian Wald chi2(1) = 118873.81
Log likelihood = 39697.75 Prob > chi2 = 0.0000

rfuture	OPG		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
rfuture						
rspot	.8153013	.0023647	344.78	0.000	.8106665	.819936
_cons	8.43e-06	.0000118	0.71	0.476	-.0000148	.0000316
ARCH						
arch						
L1.	.172934	.0061174	28.27	0.000	.1609441	.1849239
garch						
L1.	.6135791	.0310701	19.75	0.000	.5526828	.6744754
L2.	.1402146	.0250325	5.60	0.000	.0911518	.1892774
_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) nolog

flat log likelihood encountered, cannot find uphill direction
r(430);

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

ARCH family regression

Sample: 2 - 7684 Number of obs = 7,683
Distribution: Gaussian Wald chi2(1) = 110222.84
Log likelihood = 39717.26 Prob > chi2 = 0.0000

rfuture	OPG		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
rfuture						
rspot	.8240949	.0024822	332.00	0.000	.8192298	.82896
_cons	9.85e-06	.0000119	0.83	0.409	-.0000135	.0000332
ARCH						
arch						
L1.	.1329643	.0033009	40.28	0.000	.1264947	.1394339
L2.	.1345768	.0032471	41.45	0.000	.1282126	.140941
garch						
L1.	-.1805627	.00401	-45.03	0.000	-.1884221	-.1727033
L2.	.8101002	.0034601	234.12	0.000	.8033184	.8168819
_cons	2.94e-07	1.07e-08	27.39	0.000	2.73e-07	3.15e-07

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. estat ic
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Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	7,683	.	39717.26	7	-79420.51	-79371.89

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

To identify the order of GARCH(p,q), we do it by estimating GARCH models in several orders and choose the model with the lowest BIC or as known as SIC. From the result, the model arch(1/2) garch(1/2) or GARCH22 has the lowest SIC with the value of -79371.89, thus, the order of GARCH(p,q) should be p = 2 and q = 2 or GARCH(2,2).

3.

```
. predict sigmahat, v
```

```
. line sigmahat t
```

