

**Example 1:** We will analyse monthly UK house price series for the period from January 1991 to May 2013, already prepared in Stata data file `ukhp.dta`. The programming code is given in Stata Do file `ukhp-commands.do`.

First, we will inspect, test and ensure stationarity of our monthly UK house price series.

- a) Inspect the UK house price (time series *HP*) visually. Does it look stationary? Perform the Augmented Dickey-Fuller (ADF) test on the time series. How many lags should you use? Should you include a trend into the DF regression? What do you find?
- b) Also perform the Dickey-Fuller GLS test (DFGLS), which has in general more statistical power than the ADF test. What do you find? You can use information on the number of lags from the DFGLS test in the ADF test. Has the conclusion changed?
- c) How can you make a time series stationary? Apply first differences on the time series *HP* and inspect the new time series visually. Does it look stationary? Repeat the ADF test on the new time series. What do you find?
- d) Another way of making a time series stationary, often used in finance, is to generate continuously compounded percentage returns (percentage changes). Do this and inspect the new time series visually. Repeat the ADF test on this time series. What do you find?

Now, we will build an ARMA model for the house price changes. Recall that there are three stages involved: identification, estimation and diagnostic checking.

- e) Identification is carried out by looking at the autocorrelation and partial autocorrelation coefficients to identify any structure in the data. Generate a table of autocorrelations, partial correlations and related test statistics. Draw the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Does the time series appear to be an autoregressive (AR) process, a moving average (MA) process or a mixed ARMA process?
- f) Use information criteria to decide on model orders  $p$  and  $q$ . Consider at least the first four lags. Which information criterion will you focus on? What do you find?
- g) Estimate the model, proposed by the information criteria analysis, by employing the maximum likelihood estimator. Interpret the Stata output, but keep in mind that because the construction of these models is not based on economic or financial theory, it is often best not to interpret the individual parameter estimates, but rather to examine the plausibility of the model as a whole, and to determine whether it describes the data well and produces accurate forecasts. Also obtain the impulse responses (IRs).
- h) Check for stability of the chosen model by examining inverse AR and MA roots of the characteristic equation. What do you find?
- i) Now, suppose that the chosen time series model was estimated using observations from the period February 1991 – December 2010, leaving 29 remaining observations for constructing forecasts (for the period January 2011 – May 2013). Generate static and dynamic forecasts and present them graphically, together with the actual data, which are in fact available for the forecasting period. What do you find?

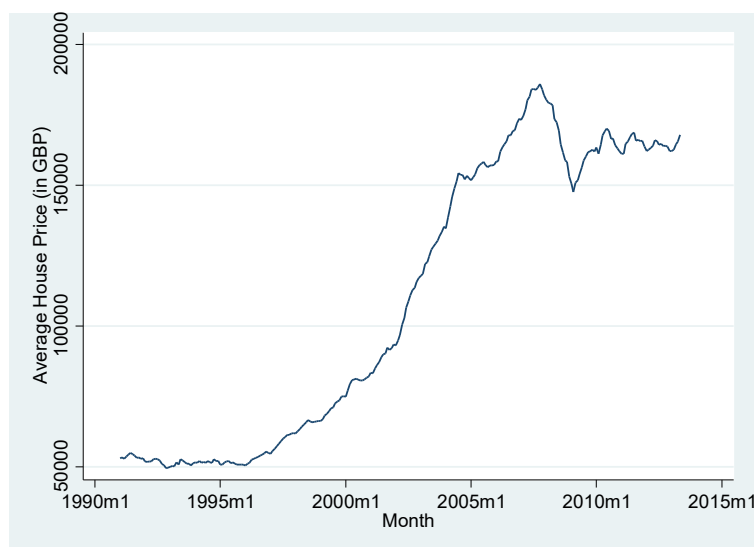
Static forecasts imply a sequence of one-step-ahead forecasts, rolling the sample forwards one observation after each forecast. Dynamic forecast calculates multi-step forecasts starting from the first period in the forecast sample. The dynamic forecasts quickly converge upon the long-term unconditional mean value as the horizon increases. This does not occur with the series of one-step-ahead forecasts, which seem to more closely resemble the actual series.

## Computer printout of the results in Stata:

Data exploration

```
. tsset Month
      time variable:  Month, 1991m1 to 2013m5
                delta:  1 month
```

```
. twoway line HP Month
```



Performing the Dickey-Fuller tests

```
. dfuller HP, lags(12)
```

Augmented Dickey-Fuller test for unit root                      Number of obs    =            256

----- Interpolated Dickey-Fuller -----			
Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-0.960	-3.460	-2.880
			-2.570

MacKinnon approximate p-value for Z(t) = 0.7676

```
. dfuller HP, regress lags(12)
```

Augmented Dickey-Fuller test for unit root                      Number of obs    =            256

----- Interpolated Dickey-Fuller -----			
Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-0.960	-3.460	-2.880
			-2.570

MacKinnon approximate p-value for Z(t) = 0.7676

D.HP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
HP					
L1.	-.0014392	.0014994	-0.96	0.338	-.0043926 .0015143
LD.	.2859919	.0633351	4.52	0.000	.1612334 .4107504

L2D.		.3226638	.0656779	4.91	0.000	.1932906	.4520371
L3D.		.0217977	.0687253	0.32	0.751	-.1135784	.1571738
L4D.		.0249136	.0685106	0.36	0.716	-.1100396	.1598668
L5D.		-.0288369	.0684909	-0.42	0.674	-.1637514	.1060775
L6D.		.0128432	.0683735	0.19	0.851	-.1218399	.1475263
L7D.		-.1132738	.0683326	-1.66	0.099	-.2478763	.0213288
L8D.		.0238635	.0687485	0.35	0.729	-.1115583	.1592852
L9D.		.0884816	.0686746	1.29	0.199	-.0467948	.223758
L10D.		-.1151423	.0689386	-1.67	0.096	-.2509386	.020654
L11D.		.0911545	.0662825	1.38	0.170	-.0394098	.2217187
L12D.		.1653165	.0640052	2.58	0.010	.039238	.2913949
_cons		271.1407	183.6549	1.48	0.141	-90.62553	632.9069

Augmented Dickey-Fuller test for unit root                      Number of obs       =            256

MacKinnon approximate p-value for  $Z(t) = 0.3987$

Augmented Dickey-Fuller test for unit root      Number of obs      =      256

MacKinnon approximate p-value for  $Z(t) = 0.3987$

**. dfgls HP, maxlag(12)**

DF-GLS for HP

Number of obs = 256

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
12	-2.019	-3.480	-2.836	-2.554
11	-1.706	-3.480	-2.844	-2.561
10	-1.478	-3.480	-2.851	-2.568
9	-1.510	-3.480	-2.859	-2.575
8	-1.317	-3.480	-2.866	-2.582
7	-1.223	-3.480	-2.873	-2.589
6	-1.296	-3.480	-2.880	-2.595
5	-1.269	-3.480	-2.887	-2.601
4	-1.344	-3.480	-2.893	-2.606
3	-1.349	-3.480	-2.899	-2.612
2	-1.310	-3.480	-2.905	-2.617
1	-0.897	-3.480	-2.910	-2.622

Opt Lag (Ng-Perron seq t) = 12 with RMSE 1139.738

Min SC = 14.22714 at lag 2 with RMSE 1189.249

Min MAIC = 14.19142 at lag 2 with RMSE 1189.249

**. dfuller HP, trend lags(2)**

Augmented Dickey-Fuller test for unit root

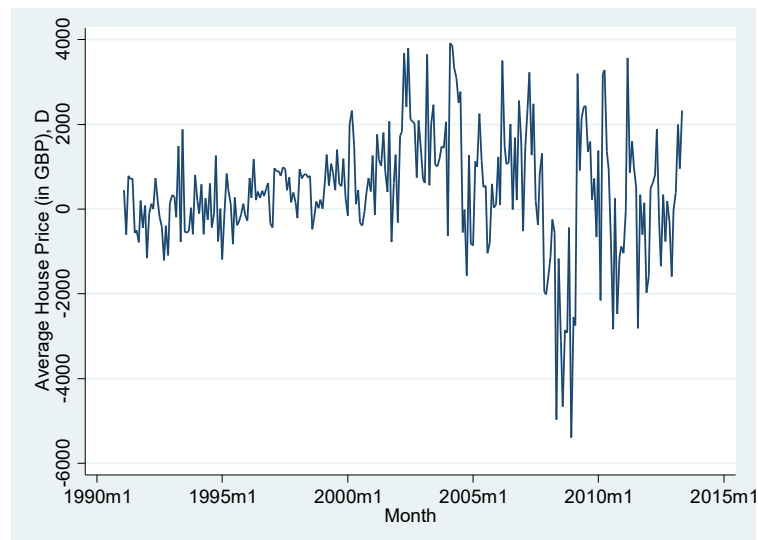
Number of obs = 266

	Test Statistic	----- 1% Critical Value	----- 5% Critical Value	----- 10% Critical Value
Interpolated Dickey-Fuller				
Z(t)	-1.674	-3.989	-3.429	-3.130

MacKinnon approximate p-value for Z(t) = 0.7623

*Applying first differences and repeating the ADF test*

**. twoway line d.HP Month**



```
. dfuller d.HP, lags(2)
```

Augmented Dickey-Fuller test for unit root                      Number of obs    =            265

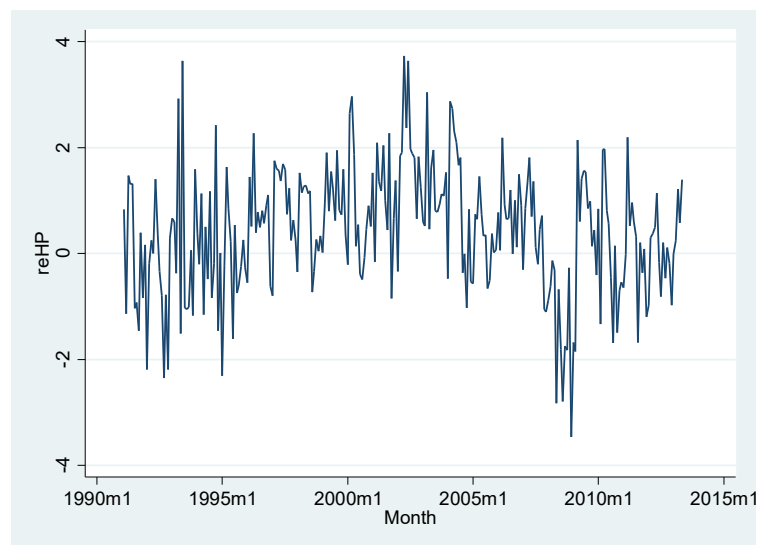
	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.344	-3.459	-2.879	-2.570

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

*Generating continuously compounded percentage returns (percentage changes) and repeating the ADF test*

```
. generate reHP=100*(ln(HP/L.HP))
(1 missing value generated)
```

```
. twoway line reHP Month
```



```
. dfuller reHP, lags(2)
```

Augmented Dickey-Fuller test for unit root                      Number of obs    =            265

	Test Statistic	----- Interpolated Dickey-Fuller -----		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.771	-3.459	-2.879	-2.570

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

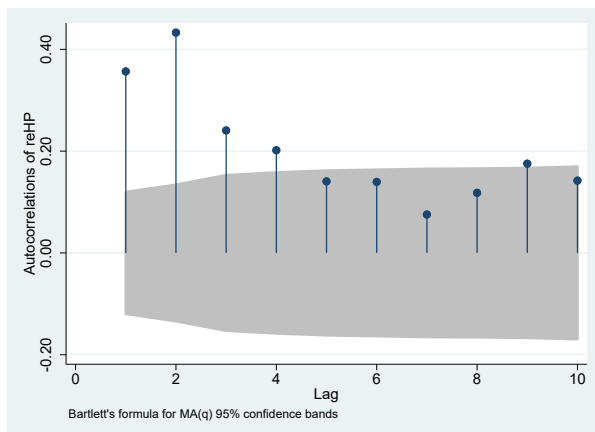
*Constructing an ARMA model*

```
. corrgram reHP, lags(10)
```

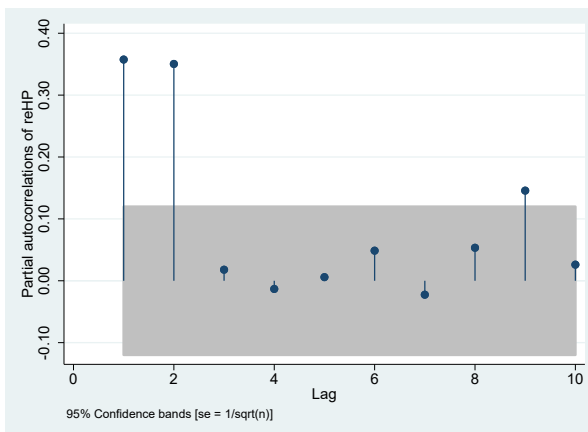
LAG	AC	PAC	Q	Prob>Q	-1	0	1	-1	0	1
					[Autocorrelation]			[Partial Autocor]		
1	0.3566	0.3575	34.468	0.0000		--			--	
2	0.4329	0.3504	85.444	0.0000		---			---	
3	0.2407	0.0179	101.27	0.0000		-				

4	0.2018	-0.0132	112.43	0.0000	-	
5	0.1406	0.0058	117.86	0.0000	-	
6	0.1396	0.0486	123.24	0.0000	-	
7	0.0755	-0.0225	124.82	0.0000		
8	0.1182	0.0533	128.71	0.0000		
9	0.1754	0.1457	137.31	0.0000	-	-
10	0.1421	0.0260	142.97	0.0000	-	

`. ac reHP, lags(10)`



`. pac reHP, lags(10)`



`. arima reHP, arima(0,0,0)`

```
(setting optimization to BHHH)
Iteration 0:  log likelihood = -427.80328
Iteration 1:  log likelihood = -427.80328
```

ARIMA regression

Sample: 1991m2 - 2013m5	Number of obs	=	268
	Wald chi2(.)	=	.
Log likelihood = -427.8033	Prob > chi2	=	.

	reHP	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]
reHP						
	_cons	.4299142	.0732932	5.87	0.000	.2862623 .5735662
	/sigma	1.19404	.0484286	24.66	0.000	1.099122 1.288958

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

`. estat ic`

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	268	.	-427.8033	2	859.6066	866.7885

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

```
// We continue to estimate all possible ARMA models manually. //
// Alternatively, we can use the following program: //
```

```

. generate variable=reHP
(1 missing value generated)

. scalar pset=4
. scalar qset=4

. forvalues p=0/\`pset' {
  2. forvalues q=0/\`qset' {
  3. qui arima variable, arima(`p',0,`q')
  4. scalar aic_`p'__`q'=-2*e(ll)+2*e(rank)
  5. scalar bic_`p'__`q'=-2*e(ll)+e(rank)*ln(e(N))
  6. }
  7. }

. forvalues p=0/\`pset' {
  2. forvalues q=0/\`qset' {
  3. display "AIC(`p',`q') = "aic_`p'__`q'
  4. }
  5. }

```

```

AIC(0,0) = 859.60656
AIC(0,1) = 840.82476
AIC(0,2) = 804.35416
AIC(0,3) = 801.8014
AIC(0,4) = 800.01893
AIC(1,0) = 825.17453
AIC(1,1) = 802.16762
AIC(1,2) = 795.50644
AIC(1,3) = 794.0435
AIC(1,4) = 795.2866
AIC(2,0) = 792.09006
AIC(2,1) = 794.01043
AIC(2,2) = 795.95615
AIC(2,3) = 794.75456
AIC(2,4) = 796.10834
AIC(3,0) = 794.00444
AIC(3,1) = 793.38271
AIC(3,2) = 797.94062
AIC(3,3) = 796.4548
AIC(3,4) = 795.86876
AIC(4,0) = 795.95778
AIC(4,1) = 795.26527
AIC(4,2) = 791.60913
AIC(4,3) = 791.43349
AIC(4,4) = 795.39434

```

```

. forvalues p=0/\`pset' {
  2. forvalues q=0/\`qset' {
  3. display "SBIC(`p',`q') = "bic_`p'__`q'
  4. }
  5. }

```

```

SBIC(0,0) = 866.78854
SBIC(0,1) = 851.59773
SBIC(0,2) = 818.71811
SBIC(0,3) = 819.75633
SBIC(0,4) = 821.56485
SBIC(1,0) = 835.94749
SBIC(1,1) = 816.53157
SBIC(1,2) = 813.46137
SBIC(1,3) = 815.58942
SBIC(1,4) = 820.42351
SBIC(2,0) = 806.45401
SBIC(2,1) = 811.96537
SBIC(2,2) = 817.50207

```

```

SBIC(2,3) = 819.89146
SBIC(2,4) = 824.83624
SBIC(3,0) = 811.95937
SBIC(3,1) = 814.92863
SBIC(3,2) = 823.07753
SBIC(3,3) = 825.1827
SBIC(3,4) = 828.18765
SBIC(4,0) = 817.5037
SBIC(4,1) = 820.40218
SBIC(4,2) = 816.74604
SBIC(4,3) = 823.75237
SBIC(4,4) = 831.30421

```

// SBIC is consistent, but requires a large sample, which we seem to have (T = 268) //

**. arima reHP, ar(1/2)**

(setting optimization to BHHH)

```

Iteration 0: log likelihood = -392.04832
Iteration 1: log likelihood = -392.04526
Iteration 2: log likelihood = -392.04505
Iteration 3: log likelihood = -392.04503

```

ARIMA regression

```

Sample: 1991m2 - 2013m5      Number of obs   =      268
                             Wald chi2(2)       =      79.64
Log likelihood = -392.045    Prob > chi2      =      0.0000

```

	reHP	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
reHP							
	_cons	.4324219	.1542394	2.80	0.005	.1301183	.7347255
ARMA							
	ar						
	L1.	.2299696	.0508839	4.52	0.000	.130239	.3297002
	L2.	.3508321	.0488959	7.18	0.000	.2549978	.4466663
	/sigma	1.044089	.0415722	25.12	0.000	.9626087	1.125569

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

**. arima reHP, arima(2,0,0)**

(setting optimization to BHHH)

```

Iteration 0: log likelihood = -392.04832
Iteration 1: log likelihood = -392.04526
Iteration 2: log likelihood = -392.04505
Iteration 3: log likelihood = -392.04503

```

ARIMA regression

```

Sample: 1991m2 - 2013m5      Number of obs   =      268
                             Wald chi2(2)       =      79.64
Log likelihood = -392.045    Prob > chi2      =      0.0000

```



	reHP	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
reHP							
	_cons	.4324219	.1542394	2.80	0.005	.1301183	.7347255
ARMA							
	ar						
	L1.	.2299696	.0508839	4.52	0.000	.130239	.3297002
	L2.	.3508321	.0488959	7.18	0.000	.2549978	.4466663
	/sigma	1.044089	.0415722	25.12	0.000	.9626087	1.125569

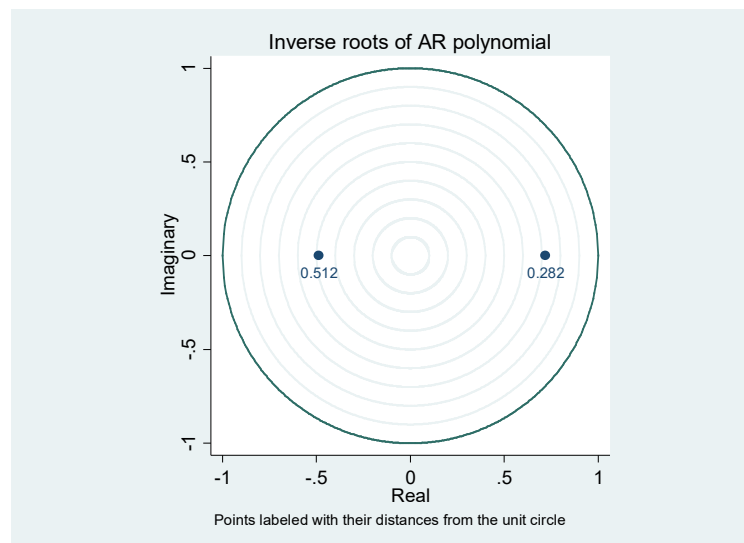
Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

#### . estat aroots, dlabel

Eigenvalue stability condition

Eigenvalue	Modulus
.7183533	.718353
-.4883837	.488384

All the eigenvalues lie inside the unit circle.  
AR parameters satisfy stability condition.



#### . irf create AR2, set(myirf, replace) step(12)

(file myirf.irf created)  
(file myirf.irf now active)  
(file myirf.irf updated)

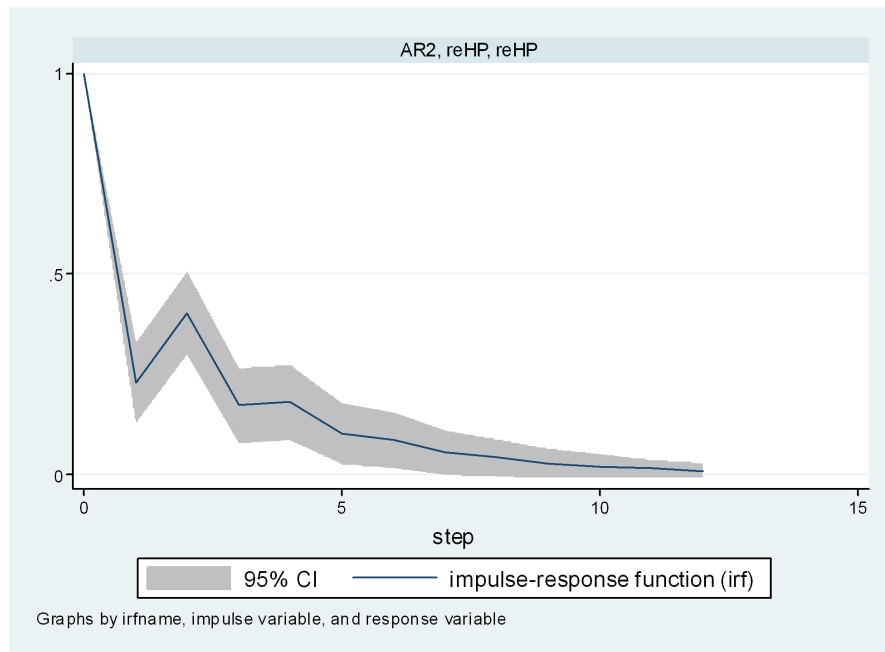
#### . irf describe

Contains irf results from myirf.irf

irfname	model	endogenous variables and order (*)
AR2	arima	reHP

(\*) order is relevant only when model is var

```
. irf graph irf
```



```
. irf table irf
```

Results from AR2

step	(1) irf	(1) Lower	(1) Upper
0	1	1	1
1	.22997	.130239	.3297
2	.403718	.301934	.505502
3	.173524	.081296	.265751
4	.181542	.088293	.274792
5	.102627	.027752	.177502
6	.087292	.018908	.155676
7	.056079	.002009	.11015
8	.043521	-.002335	.089378
9	.029683	-.006318	.065684
10	.022095	-.007103	.051293
11	.015495	-.007249	.038239
12	.011315	-.00664	.02927

95% lower and upper bounds reported

(1) irfname = AR2, impulse = reHP, and response = reHP

Forecasting using an ARMA model

```
. arima reHP if Month<=tm(2010m12), arima(2,0,0)
```

(setting optimization to BHHH)

```
Iteration 0: log likelihood = -355.03462
Iteration 1: log likelihood = -355.02874
Iteration 2: log likelihood = -355.02815
Iteration 3: log likelihood = -355.02809
Iteration 4: log likelihood = -355.02808
```

# ARIMA regression

Sample: 1991m2 - 2010m12

Number of obs = 239

Wald chi2(2) = 73.84

Log likelihood = -355.0281

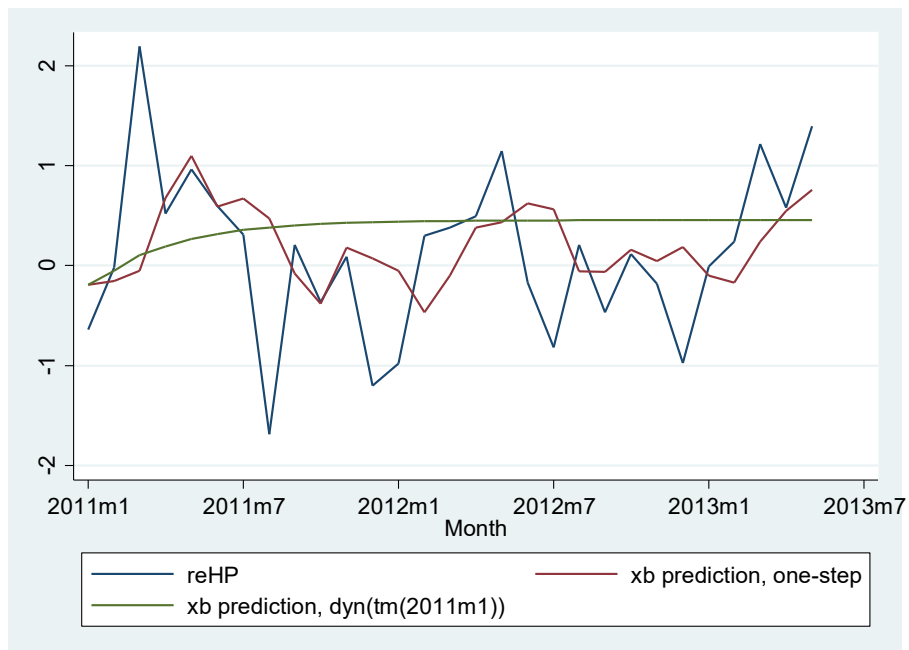
Prob > chi2 = 0.0000

		Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
reHP							
	_cons	.4540309	.1702274	2.67	0.008	.1203913	.7876704
ARMA							
	ar						
	L1.	.2255672	.0535307	4.21	0.000	.120649	.3304854
	L2.	.3631374	.0516035	7.04	0.000	.2619963	.4642784
	/sigma	1.06785	.0460784	23.17	0.000	.9775385	1.158163

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

```
. predict reHP_fstatic, xb
. predict reHP_fdynamic, xb dynamic(tm(2011m1))

. twoway (tsline reHP) (tsline reHP_fstatic) (tsline reHP_fdynamic) if
Month>tm(2010m12)
```



**Example 2:** We will examine whether there are lead-lag relationships between the returns to three exchange rates against the US dollar: the euro, the British pound and the Japanese yen. The data are daily and run from 7 July 2002 to 6 June 2013, giving a total of 3,988 observations. The data are contained in Stata data file `currencies.dta`. The programming code is given in Stata Do file `currencies-commands-118.do`.

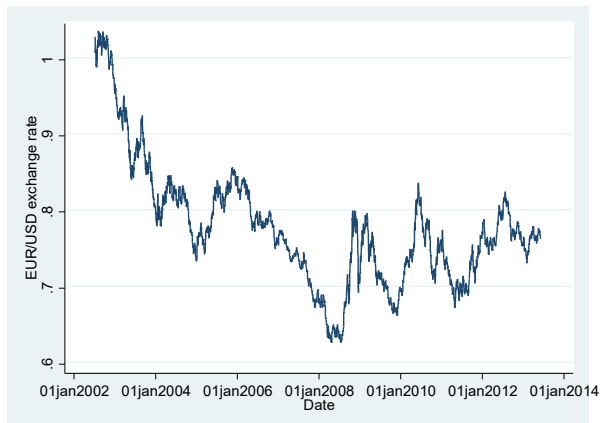
- a) Inspect the three time series visually. Do they look stationary? Perform the Dickey-Fuller GLS test (DFGLS) on each of the three time series. What do you find?
- b) Construct a set of continuously compounded percentage returns (percentage changes). Check for stationarity of the newly generated time series. What do you find?
- c) Now, we will focus on a vector autoregressive (VAR) model based on the returns to three exchange rates. Choose the optimal lag length based on multivariate information criteria and estimate the suggested VAR model. Interpret the Stata output, but keep in mind that because the construction of these models is usually not based on economic or financial theory, it is often best not to interpret the individual parameter estimates, but rather to examine the plausibility of the model as a whole, and to determine whether it describes the data well and produces accurate forecasts.
- d) After fitting a VAR model, one hypothesis of interest is that all the variables at a given lag are jointly zero. In order to test this hypothesis, perform the Wald lag-exclusion tests for different lag orders. What do you find?
- e) Check for stability of the chosen model by examining roots of the companion matrix (whether the eigenvalues lie inside the unit circle). What do you find?
- f) Check for residual autocorrelation of at least the first two lag orders with an appropriate Lagrange-multiplier (LM) test. What do you find?
- g) Run Granger causality Wald tests and figure out whether the “excluded” variable Granger-causes the “equation” variable. Do you find evidence of lead-lag interactions between the series? Which exchange rate reacts the fastest to market information?
- h) Obtain the impulse responses (IRs), orthogonalised impulse responses (OIRs) and forecast-error variance decompositions (FEVDs) for the estimated model. Interpret the results. Could these results have been expected based on previous results?
- i) Remember that the ordering of variables has an effect on the impulse responses and variance decompositions, and when, as in this case, theory does not suggest an obvious ordering of the series, sensitivity analysis should be undertaken. Reverse the ordering of variables and compare the new results with the initial ones. What do you find?
- j) Finally, employ the estimated VAR model in order to compute dynamic forecasts of the returns to three exchange rates for the following 20 days. Present the forecasts graphically, together with 95% confidence intervals.

### ***Computer printout of the results in Stata:***

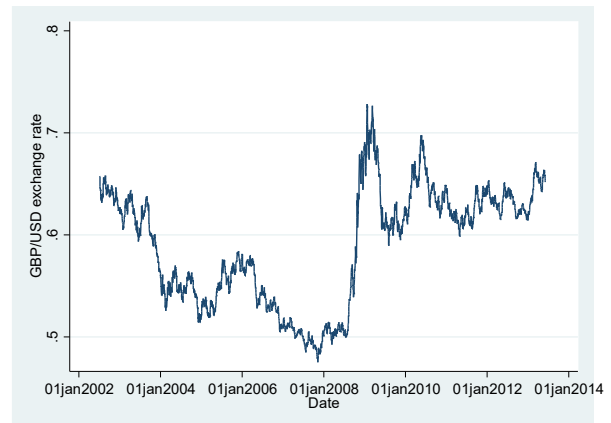
*Data exploration*

```
. tsset Date
      time variable:  Date, 07jul2002 to 06jun2013
              delta:  1 day
```

. twoway line EUR Date



. twoway line GBP Date



. twoway line JPY Date



Performing the Dickey-Fuller GLS test

. dfqls EUR, maxlag(5)

DF-GLS for EUR

Number of obs = 3982

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
5	-0.985	-3.480	-2.841	-2.554
4	-0.960	-3.480	-2.842	-2.554
3	-1.000	-3.480	-2.842	-2.554
2	-1.016	-3.480	-2.842	-2.554
1	-1.026	-3.480	-2.843	-2.555

Opt Lag (Ng-Perron seq t) = 1 with RMSE .0037332  
 Min SC = -11.17684 at lag 1 with RMSE .0037332  
 Min MAIC = -11.17997 at lag 1 with RMSE .0037332

. dfqls GBP, maxlag(5)

DF-GLS for GBP

Number of obs = 3982

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
5	-1.185	-3.480	-2.841	-2.554
4	-1.204	-3.480	-2.842	-2.554

3	-1.237	-3.480	-2.842	-2.554
2	-1.223	-3.480	-2.842	-2.554
1	-1.306	-3.480	-2.843	-2.555

Opt Lag (Ng-Perron seq t) = 2 with RMSE .002617  
 Min SC = -11.88519 at lag 2 with RMSE .002617  
 Min MAIC = -11.88968 at lag 2 with RMSE .002617

**. dfqls JPY, maxlag(5)**

DF-GLS for JPY

Number of obs = 3982

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
5	-1.625	-3.480	-2.841	-2.554
4	-1.644	-3.480	-2.842	-2.554
3	-1.771	-3.480	-2.842	-2.554
2	-1.788	-3.480	-2.842	-2.554
1	-1.764	-3.480	-2.843	-2.555

Opt Lag (Ng-Perron seq t) = 4 with RMSE .4787147  
 Min SC = -1.46636 at lag 1 with RMSE .47938  
 Min MAIC = -1.469925 at lag 4 with RMSE .4787147

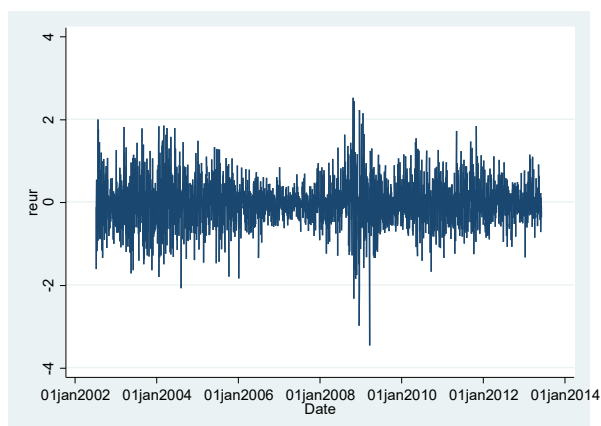
*Generating continuously compounded percentage returns (percentage changes) and repeating the Dickey-Fuller GLS test*

**. generate reur=100\*(ln(EUR/L.EUR))**  
 (1 missing value generated)

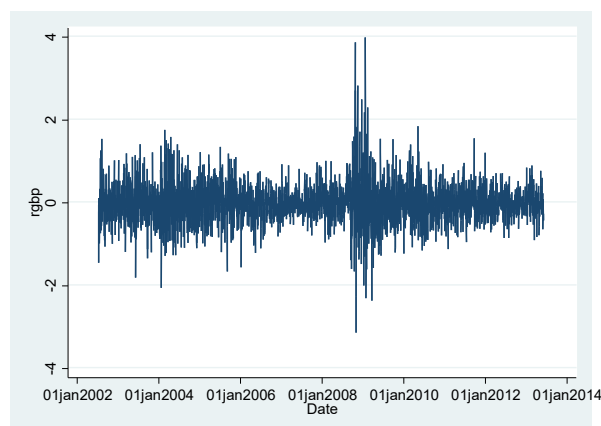
**. generate rGBP=100\*(ln(GBP/L.GBP))**  
 (1 missing value generated)

**. generate rjpy=100\*(ln(JPY/L.JPY))**  
 (1 missing value generated)

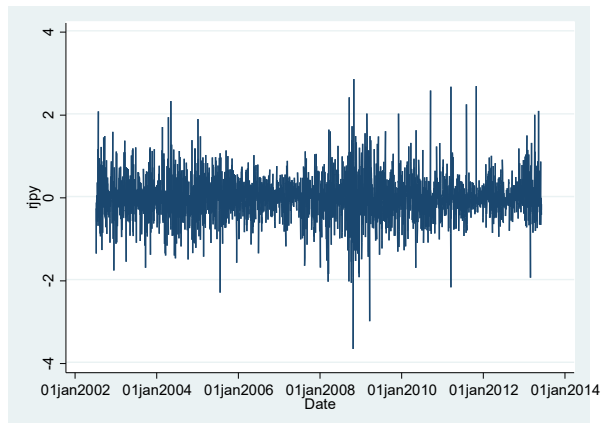
**. twoway line reur Date**



**. twoway line rGBP Date**



. twoway line rjpy Date



. dfgls reur, maxlag(5)

DF-GLS for reur

Number of obs = 3981

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
5	-24.487	-3.480	-2.841	-2.554
4	-26.944	-3.480	-2.842	-2.554
3	-30.815	-3.480	-2.842	-2.554
2	-34.634	-3.480	-2.842	-2.554
1	-41.158	-3.480	-2.843	-2.555

Opt Lag (Ng-Perron seq t) = 4 with RMSE .4722431  
 Min SC = -1.495368 at lag 1 with RMSE .4724769  
 Min MAIC = -.0863627 at lag 5 with RMSE .4722112

. dfgls rgbp, maxlag(5)

DF-GLS for rgbp

Number of obs = 3981

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
5	-25.393	-3.480	-2.841	-2.554
4	-27.246	-3.480	-2.842	-2.554
3	-30.256	-3.480	-2.842	-2.554
2	-33.928	-3.480	-2.842	-2.554
1	-40.914	-3.480	-2.843	-2.555

Opt Lag (Ng-Perron seq t) = 1 with RMSE .4333588  
 Min SC = -1.668214 at lag 1 with RMSE .4333588  
 Min MAIC = -.3197095 at lag 2 with RMSE .4333307

. dfgls rjpy, maxlag(5)

DF-GLS for rjpy

Number of obs = 3981

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
5	-24.263	-3.480	-2.841	-2.554
4	-27.220	-3.480	-2.842	-2.554
3	-30.605	-3.480	-2.842	-2.554
2	-33.610	-3.480	-2.842	-2.554
1	-40.031	-3.480	-2.843	-2.555

Opt Lag (Ng-Perron seq t) = 5 with RMSE .4701428  
Min SC = -1.503243 at lag 1 with RMSE .4706203  
Min MAIC = -.1675009 at lag 5 with RMSE .4701428

Estimating a VAR model

. varsoc reur rgbp rjpy, maxlag(10)

```

Selection-order criteria
Sample: 18jul2002 - 06jun2013          Number of obs   =       3977
+-----+-----+-----+-----+-----+-----+-----+-----+
|lag|   LL   LR   df   p   FPE   AIC   HQIC   SBIC   |
+-----+-----+-----+-----+-----+-----+-----+-----+
| 0 | -6324.33          .004836   3.18196   3.18364   3.18671 |
| 1 | -6060.26  528.13   9  0.000   .004254   3.05369   3.06042   3.07266* |
| 2 | -6034.87  50.784   9  0.000   .004219*  3.04545*  3.05722*  3.07865 |
| 3 | -6030.96  7.8286   9  0.552   .00423   3.048   3.06482   3.09544 |
| 4 | -6022.94  16.04   9  0.066   .004232   3.0485   3.07036   3.11016 |
| 5 | -6015.11  15.655   9  0.074   .004234   3.04909   3.076   3.12498 |
| 6 | -6009.17  11.881   9  0.220   .004241   3.05063   3.08258   3.14075 |
| 7 | -6000.17  17.998*  9  0.035   .004241   3.05063   3.08763   3.15498 |
| 8 | -5992.97  14.408   9  0.109   .004245   3.05153   3.09358   3.17012 |
| 9 | -5988.13  9.6673   9  0.378   .004254   3.05362   3.10072   3.18644 |
|10 | -5984.25  7.7658   9  0.558   .004264   3.0562   3.10834   3.20325 |
+-----+-----+-----+-----+-----+-----+-----+-----+
Endogenous:  reur rgbp rjpy
Exogenous:   _cons

```

. var reur rgbp rjpy, lags(1/2)

Vector autoregression

```

Sample: 10jul2002 - 06jun2013          Number of obs   =       3,985
Log likelihood = -6043.54              AIC               =       3.043684
FPE           = .0042115              HQIC              =       3.055437
Det(Sigma_ml) = .0041673              SBIC              =       3.076832

```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
reur	7	.470301	0.0255	104.1884	0.0000
rgbp	7	.430566	0.0522	219.6704	0.0000
rjpy	7	.466151	0.0243	99.23658	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
reur					
reur					
L1.	.2001552	.0226876	8.82	0.000	.1556883 .2446221
L2.	-.0334134	.0225992	-1.48	0.139	-.077707 .0108802
rgbp					
L1.	-.0615658	.0240862	-2.56	0.011	-.1087738 -.0143578
L2.	.024656	.0240581	1.02	0.305	-.0224971 .0718091
rjpy					
L1.	-.0201509	.0166431	-1.21	0.226	-.0527707 .0124689
L2.	.002628	.0166676	0.16	0.875	-.0300398 .0352958
_cons	-.0058355	.0074464	-0.78	0.433	-.0204301 .0087591



rgbp							
	reur						
	L1.	-.0427769	.0207708	-2.06	0.039	-.0834868	-.0020669
	L2.	.0567707	.0206898	2.74	0.006	.0162194	.097322
	rgbp						
	L1.	.2616429	.0220512	11.87	0.000	.2184234	.3048623
	L2.	-.0920986	.0220255	-4.18	0.000	-.1352678	-.0489294
	rjpy						
	L1.	-.0566386	.0152369	-3.72	0.000	-.0865024	-.0267747
	L2.	.0029643	.0152593	0.19	0.846	-.0269435	.0328721
	_cons	.0000454	.0068172	0.01	0.995	-.0133161	.0134069
-----							
rjpy							
	reur						
	L1.	.0241862	.0224874	1.08	0.282	-.0198883	.0682607
	L2.	-.0313338	.0223997	-1.40	0.162	-.0752365	.0125689
	rgbp						
	L1.	-.0679786	.0238736	-2.85	0.004	-.1147701	-.0211872
	L2.	.0324034	.0238458	1.36	0.174	-.0143336	.0791404
	rjpy						
	L1.	.1508446	.0164962	9.14	0.000	.1185127	.1831766
	L2.	.0007184	.0165205	0.04	0.965	-.0316611	.0330979
	_cons	-.0036822	.0073807	-0.50	0.618	-.0181481	.0107836
-----							

VAR model diagnostics

. varwle

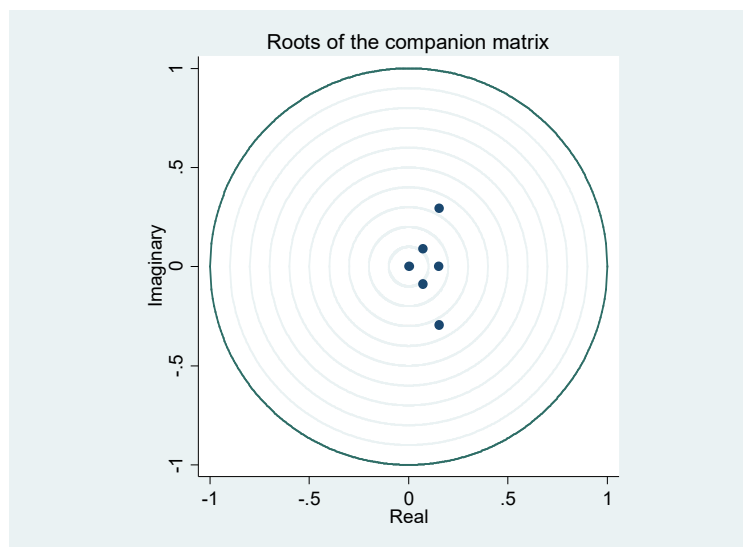
Equation: reur				
+-----+				
lag	chi2	df	Prob > chi2	
+-----+				
1	104.0216	3	0.000	
2	2.222079	3	0.528	
+-----+				
Equation: rgbp				
+-----+				
lag	chi2	df	Prob > chi2	
+-----+				
1	214.893	3	0.000	
2	17.60756	3	0.001	
+-----+				
Equation: rjpy				
+-----+				
lag	chi2	df	Prob > chi2	
+-----+				
1	95.98737	3	0.000	
2	2.298777	3	0.513	
+-----+				
Equation: All				
+-----+				
lag	chi2	df	Prob > chi2	
+-----+				
1	592.6466	9	0.000	

2	51.14752	9	0.000
---	----------	---	-------

**. varstable, graph**

```
Eigenvalue stability condition
+-----+
| Eigenvalue | Modulus |
+-----+
| .1556644 + .2942196i | .332861 |
| .1556644 - .2942196i | .332861 |
| .1531685 | .153168 |
| .07266967 + .08855483i | .114555 |
| .07266967 - .08855483i | .114555 |
| .00280605 | .002806 |
+-----+

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



**. varlmar**

```
Lagrange-multiplier test
+-----+
| lag | chi2 | df | Prob > chi2 |
+-----+
| 1 | 6.8459 | 9 | 0.65316 |
| 2 | 9.7778 | 9 | 0.36877 |
+-----+

H0: no autocorrelation at lag order
```

*Performing Granger causality tests*

**. vargranger**

```
Granger causality Wald tests
+-----+
| Equation | Excluded | chi2 | df | Prob > chi2 |
+-----+
| reur | rgbp | 6.6529 | 2 | 0.036 |
| reur | rjpy | 1.4668 | 2 | 0.480 |
| reur | ALL | 7.9253 | 4 | 0.094 |
+-----+
| rgbp | reur | 9.8352 | 2 | 0.007 |
+-----+
```

	rgbp	rjpy	13.963	2	0.001
	rgbp	ALL	28.095	4	0.000
-----					
	rjpy	reur	2.5974	2	0.273
	rjpy	rgbp	8.4808	2	0.014
	rjpy	ALL	10.905	4	0.028
-----					

Impulse responses and variance decompositions for 20 time periods (days)

```
. varbasic reur rgbp rjpy, lags(1/2) step(20) irf
// Impulse response functions, IRFs //
```

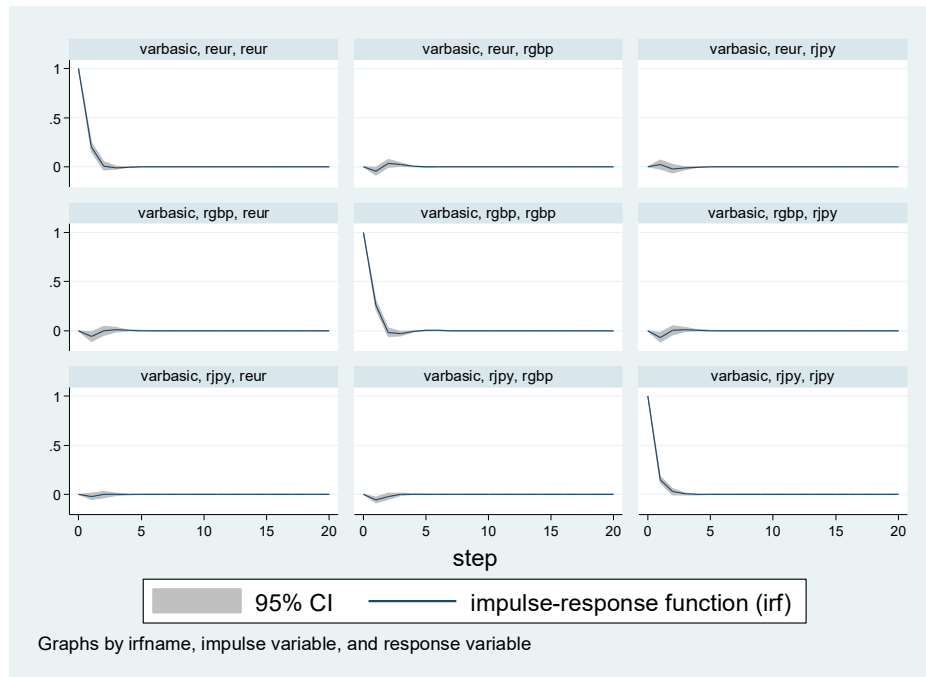
Vector autoregression

```
Sample: 10jul2002 - 06jun2013      Number of obs   =      3,985
Log likelihood = -6043.54           AIC              =      3.043684
FPE            = .0042115           HQIC             =      3.055437
Det(Sigma_ml)  = .0041673           SBIC            =      3.076832
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
-----	-----	-----	-----	-----	-----
reur	7	.470301	0.0255	104.1884	0.0000
rgbp	7	.430566	0.0522	219.6704	0.0000
rjpy	7	.466151	0.0243	99.23658	0.0000
-----	-----	-----	-----	-----	-----

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----							
reur							
	reur						
	L1.	.2001552	.0226876	8.82	0.000	.1556883	.2446221
	L2.	-.0334134	.0225992	-1.48	0.139	-.077707	.0108802
	rgbp						
	L1.	-.0615658	.0240862	-2.56	0.011	-.1087738	-.0143578
	L2.	.024656	.0240581	1.02	0.305	-.0224971	.0718091
	rjpy						
	L1.	-.0201509	.0166431	-1.21	0.226	-.0527707	.0124689
	L2.	.002628	.0166676	0.16	0.875	-.0300398	.0352958
	_cons	-.0058355	.0074464	-0.78	0.433	-.0204301	.0087591
-----							
rgbp							
	reur						
	L1.	-.0427769	.0207708	-2.06	0.039	-.0834868	-.0020669
	L2.	.0567707	.0206898	2.74	0.006	.0162194	.097322
	rgbp						
	L1.	.2616429	.0220512	11.87	0.000	.2184234	.3048623
	L2.	-.0920986	.0220255	-4.18	0.000	-.1352678	-.0489294
	rjpy						
	L1.	-.0566386	.0152369	-3.72	0.000	-.0865024	-.0267747
	L2.	.0029643	.0152593	0.19	0.846	-.0269435	.0328721
	_cons	.0000454	.0068172	0.01	0.995	-.0133161	.0134069
-----							
rjpy							
	reur						
	L1.	.0241862	.0224874	1.08	0.282	-.0198883	.0682607
	L2.	-.0313338	.0223997	-1.40	0.162	-.0752365	.0125689

rgbp						
L1.	-.0679786	.0238736	-2.85	0.004	-.1147701	-.0211872
L2.	.0324034	.0238458	1.36	0.174	-.0143336	.0791404
rjpy						
L1.	.1508446	.0164962	9.14	0.000	.1185127	.1831766
L2.	.0007184	.0165205	0.04	0.965	-.0316611	.0330979
_cons	-.0036822	.0073807	-0.50	0.618	-.0181481	.0107836



```
. varbasic reur rgbp rjpy, lags(1/2) step(20)
// Orthogonalised impulse response functions, OIRFs //
```

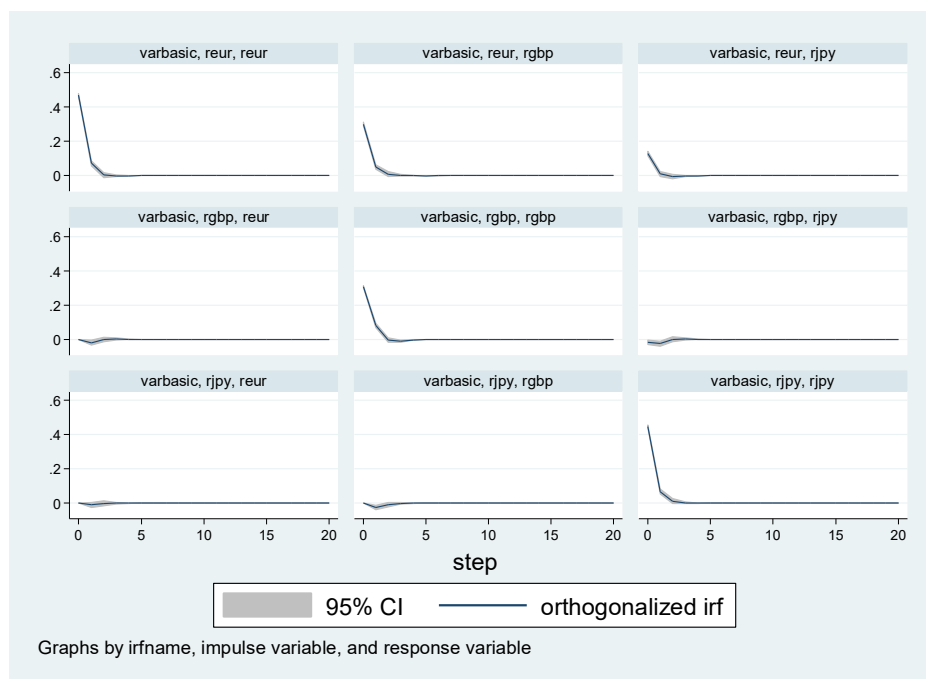
Vector autoregression

```
Sample: 10jul2002 - 06jun2013
Log likelihood = -6043.54
FPE = .0042115
Det(Sigma_ml) = .0041673
Number of obs = 3,985
AIC = 3.043684
HQIC = 3.055437
SBIC = 3.076832
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
-----	-----	-----	-----	-----	-----
reur	7	.470301	0.0255	104.1884	0.0000
rgbp	7	.430566	0.0522	219.6704	0.0000
rjpy	7	.466151	0.0243	99.23658	0.0000
-----	-----	-----	-----	-----	-----

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----	-----	-----	-----	-----	-----	-----
reur						
	reur					
	L1.	.2001552	.0226876	8.82	0.000	.1556883 .2446221
	L2.	-.0334134	.0225992	-1.48	0.139	-.077707 .0108802
	rgbp					
	L1.	-.0615658	.0240862	-2.56	0.011	-.1087738 -.0143578
	L2.	.024656	.0240581	1.02	0.305	-.0224971 .0718091

	rjpy						
	L1.	-.0201509	.0166431	-1.21	0.226	-.0527707	.0124689
	L2.	.002628	.0166676	0.16	0.875	-.0300398	.0352958
	_cons	-.0058355	.0074464	-0.78	0.433	-.0204301	.0087591
-----							
rgbp	reur						
	L1.	-.0427769	.0207708	-2.06	0.039	-.0834868	-.0020669
	L2.	.0567707	.0206898	2.74	0.006	.0162194	.097322
	rgbp						
	L1.	.2616429	.0220512	11.87	0.000	.2184234	.3048623
	L2.	-.0920986	.0220255	-4.18	0.000	-.1352678	-.0489294
	rjpy						
	L1.	-.0566386	.0152369	-3.72	0.000	-.0865024	-.0267747
	L2.	.0029643	.0152593	0.19	0.846	-.0269435	.0328721
	_cons	.0000454	.0068172	0.01	0.995	-.0133161	.0134069
-----							
rjpy	reur						
	L1.	.0241862	.0224874	1.08	0.282	-.0198883	.0682607
	L2.	-.0313338	.0223997	-1.40	0.162	-.0752365	.0125689
	rgbp						
	L1.	-.0679786	.0238736	-2.85	0.004	-.1147701	-.0211872
	L2.	.0324034	.0238458	1.36	0.174	-.0143336	.0791404
	rjpy						
	L1.	.1508446	.0164962	9.14	0.000	.1185127	.1831766
	L2.	.0007184	.0165205	0.04	0.965	-.0316611	.0330979
	_cons	-.0036822	.0073807	-0.50	0.618	-.0181481	.0107836
-----							



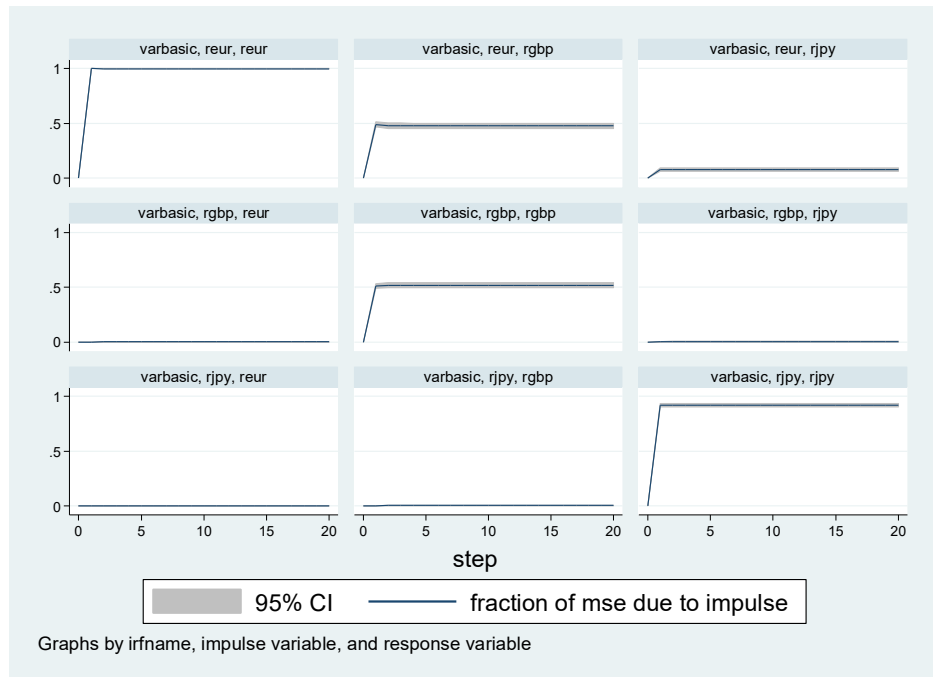
```
. varbasic reur rgbp rjpy, lags(1/2) step(20) fevd
// Forecast-error variance decompositions, FEVDs //
```

Vector autoregression

```
Sample: 10jul2002 - 06jun2013      Number of obs   =      3,985
Log likelihood = -6043.54           AIC              =      3.043684
FPE            = .0042115           HQIC            =      3.055437
Det(Sigma_ml)  = .0041673           SBIC            =      3.076832
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
reur	7	.470301	0.0255	104.1884	0.0000
rgbp	7	.430566	0.0522	219.6704	0.0000
rjpy	7	.466151	0.0243	99.23658	0.0000

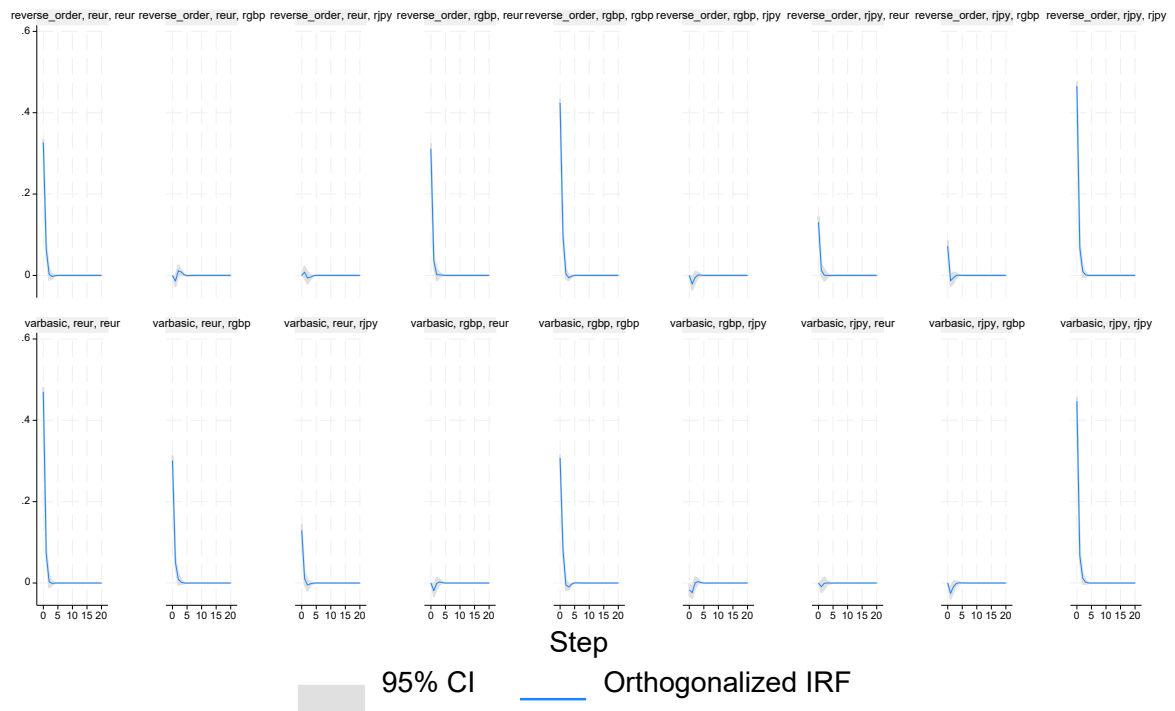
		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
reur	reur					
	L1.	.2001552	.0226876	8.82	0.000	.1556883 .2446221
	L2.	-.0334134	.0225992	-1.48	0.139	-.077707 .0108802
	rgbp					
	L1.	-.0615658	.0240862	-2.56	0.011	-.1087738 -.0143578
	L2.	.024656	.0240581	1.02	0.305	-.0224971 .0718091
	rjpy					
	L1.	-.0201509	.0166431	-1.21	0.226	-.0527707 .0124689
	L2.	.002628	.0166676	0.16	0.875	-.0300398 .0352958
	_cons	-.0058355	.0074464	-0.78	0.433	-.0204301 .0087591
rgbp	reur					
	L1.	-.0427769	.0207708	-2.06	0.039	-.0834868 -.0020669
	L2.	.0567707	.0206898	2.74	0.006	.0162194 .097322
	rgbp					
	L1.	.2616429	.0220512	11.87	0.000	.2184234 .3048623
	L2.	-.0920986	.0220255	-4.18	0.000	-.1352678 -.0489294
	rjpy					
	L1.	-.0566386	.0152369	-3.72	0.000	-.0865024 -.0267747
	L2.	.0029643	.0152593	0.19	0.846	-.0269435 .0328721
	_cons	.0000454	.0068172	0.01	0.995	-.0133161 .0134069
rjpy	reur					
	L1.	.0241862	.0224874	1.08	0.282	-.0198883 .0682607
	L2.	-.0313338	.0223997	-1.40	0.162	-.0752365 .0125689
	rgbp					
	L1.	-.0679786	.0238736	-2.85	0.004	-.1147701 -.0211872
	L2.	.0324034	.0238458	1.36	0.174	-.0143336 .0791404
	rjpy					
	L1.	.1508446	.0164962	9.14	0.000	.1185127 .1831766
	L2.	.0007184	.0165205	0.04	0.965	-.0316611 .0330979
	_cons	-.0036822	.0073807	-0.50	0.618	-.0181481 .0107836



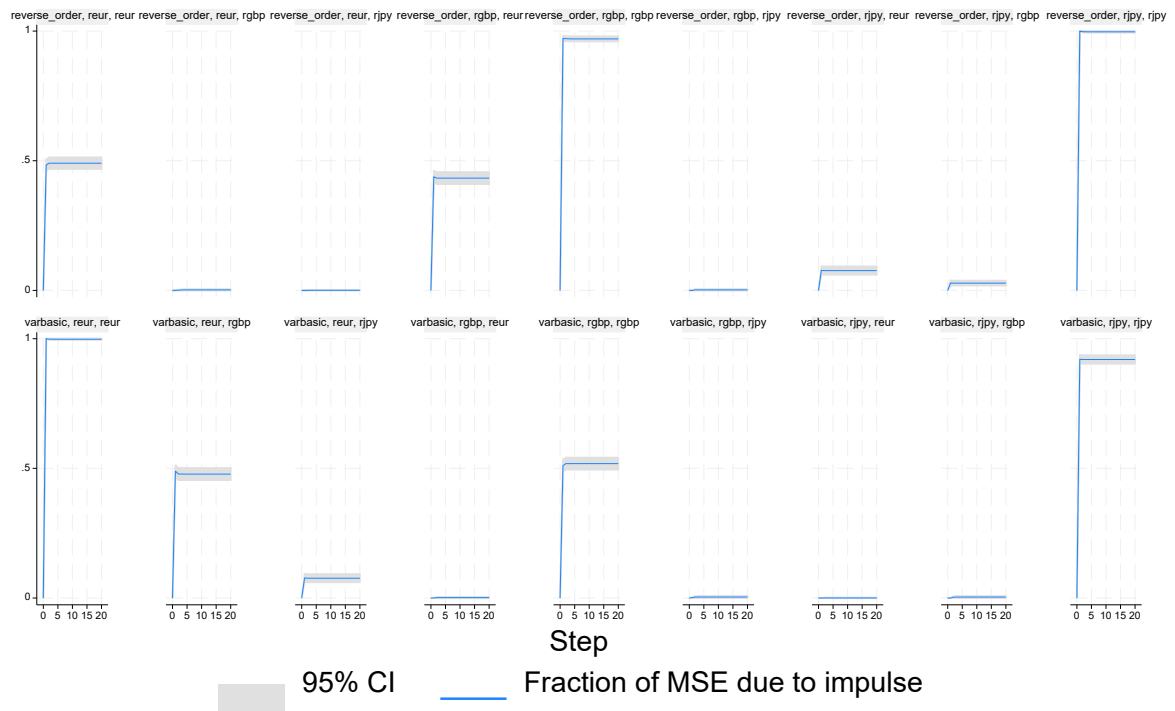
*Changing the ordering of variables*

```
. irf create reverse_order, replace step(20) order(rjpy rgbp reur)
irfname reverse_order not found in _varbasic.irf
(file _varbasic.irf updated)

. irf graph oirf, byopts(c(9))
```



```
. irf graph fevd, byopts(c(9))
```



Graphs by irfname, impulse variable, and response variable

Forecasting based on VAR(2) for the following 20 time periods (days)

```
. qui var reur rGBP rJPY, lags(1/2)
. fcast compute fc_, step(20)
  // generates level, lower bound, upper bound, and std error //
. fcast graph fc_reur fc_rGBP fc_rJPY
```

