<u>Matlab: R2015a</u> IRIS: 20150527

# Compare Second Moment Properties in Model and Data

compare\_model\_and\_data.m

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#### Summary

Compute and compare several second-moment properties of the estimated model and the data. Describe the data using an estimated VAR; this also allows to evaluate sampling uncertainty of the empirical estimates using bootstrap methods.

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#### 1 Clear Workspace

Clear workspace, close all graphics figures, clear command window, and check the IRIS version.

```
14 clear;
15 close all;
16 clc;
17 irisrequired 20140315;
```

#### 2 Load Estimated Model Object, and Historical Database

Load the model object estimated in estimate\_params, and the historical database created in read\_data. Run estimate\_params and filter\_hist\_data at least once before running this m-file.

```
load estimate_params.mat mest;
load read_data.mat d startHist endHist;
```

#### 3 Estimate VAR and BVAR

Estimate an unrestricted 2nd-order VAR, and a 2nd-order Bayesian VAR with Litterman-type priors. First, create an empty VAR object 2 specifying the names of the endogenous variables. The names are identical to the names of measurement variables in the DSGE model 1. Second, call the function estimate with an input database. For bayesian VARs, create prior dummy observations before running estimate 3.

```
ylist = get(mest,'yList'); 1
38
39
40
    p = 2;
41
    v = VAR(ylist) %#ok<NOPTS> 2
42
    [v,vdata] = estimate(v,d,startHist:endHist,'order=',p);
43
44
    v %#ok<NOPTS>
45
46
   X = BVAR.litterman(0, sqrt(30), 0) %#ok<NOPTS> 3
47
    bv = VAR(ylist) %#ok<NOPTS>
48
    [bv,bvdata] = estimate(bv,d,startHist:endHist,'order=',p, ...
49
50
        'BVAR=',X,'stdize=',true);
    bv %#ok<NOPTS>
```

```
v =
       empty VAR object
       variables: [4] 'Short' 'Infl' 'Growth' 'Wage'
       exogenous: [0]
        instruments: [0]
       groups: implicit
       comment: ''
       user data: empty
       export files: [0]
v =
       VAR(2) object: [1] parameterisation(s)
       variables: [4] 'Short' 'Infl' 'Growth' 'Wage'
       exogenous: [0]
        instruments: [0]
       groups: implicit
       comment: ''
       user data: empty
       export files: [0]
X =
 bvarobj with properties:
   name: 'litterman'
     y0: @litterman/y0
      y1: @litterman/y1
     k0: @litterman/k0
      g1: @litterman/g1
bv =
       empty VAR object
       variables: [4] 'Short' 'Infl' 'Growth' 'Wage'
       exogenous: [0]
       instruments: [0]
       groups: implicit
       comment: ''
       user data: empty
       export files: [0]
bv =
       VAR(2) object: [1] parameterisation(s)
       variables: [4] 'Short' 'Infl' 'Growth' 'Wage'
       exogenous: [0]
       instruments: [0]
       groups: implicit
       comment: ''
```

```
user data: empty
export files: [0]
```

#### 4 Compare Transition Matrices

Get and print the transition matrices from the plain VAR and the BVAR objects. The transition matrices are Ny-by-Ny-by-P matrices, where Ny is the number of variables, and P is the order of the VAR.

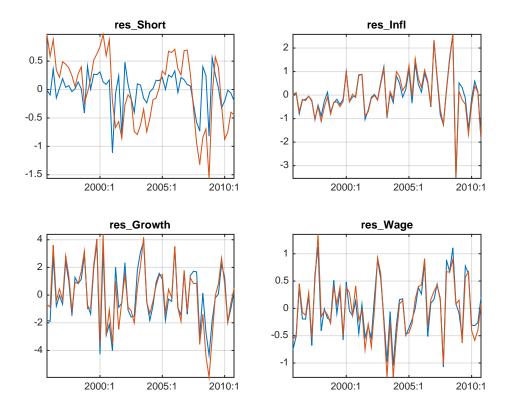
```
59 A = get(v,'A*');
60 BA = get(bv,'A*');
61
62 disp('Unrestricted VAR transition matrix');
63 A(:,:,1)
64 A(:,:,2)
65 disp('BVAR transition matrix');
66 BA(:,:,1)
67 BA(:,:,2)
```

```
Unrestricted VAR transition matrix
ans =
  1.5407 -0.0653 0.0334
                            0.0759
  -0.0501 0.3143 0.0641 -0.1158
   1.6851 -0.3895 0.0969 -1.0528
   0.2922 -0.0748 -0.0505
                          0.3510
ans =
  -0.5799 0.0513 -0.0048
                          -0.1275
   0.0950 0.2476 0.0344 -0.1642
  -0.8984 -0.3549 0.1728 -0.8460
          0.1175 0.0473
                          -0.0704
  -0.0739
BVAR transition matrix
ans =
   0.3343 0.0721 0.1029
                          0.2844
   0.0191
          0.2178 0.0421
                          -0.0576
   0.2147
         -0.1388 0.1927
                          -0.4495
   0.0882 0.0086 -0.0114
                          0.2253
ans =
   0.2589
          0.0683
                   0.0710
                           0.1545
   0.0089
         0.1812 0.0341 -0.1151
   0.1136 -0.2504 0.1935 -0.4159
   0.0778
          0.0724
                   0.0336
                            0.0733
```

## 5 Compare Residuals

Plot and compare the estimated residuals from the plain VAR and the BVAR. Use the output data, vdata and bvdata returned from estimate. These databases containing both the endogenous variables and estimated residuals. By default, the residuals are named res\_XXX where XXX is the name of the respective variable,

```
77
    elist = get(v,'eList');
78
79
   figure();
80
    for i = 1 : 4
81
        name = elist{i};
82
        subplot(2,2,i);
83
        plot(vdata.(name));
84
        hold all;
85
        plot(bvdata.(name));
86
        title(name, 'interpreter', 'none');
87
        grid on;
88
        axis tight;
89
    end
    grfun.bottomlegend('Unrestricted VAR(2)', 'BVAR(2)');
90
```



## 6 Resample From Estimated VAR

Use a wild bootstrap to generate N=500 of VARs; a wild bootstrap is robust to potential heteroscedasticity of residuals. Note that some of the resampled VAR parameterisations may be explosive, and remove them from the VAR object.

```
N = 1000;
 99
100
     Y = resample(v,vdata,Inf,N,'wild=',true,'progress=',true);
101
     size(Y)
102
103
     Nv = VAR(ylist);
     Nv = estimate(Nv,Y,Inf,'order=',p);
104
105
     inx = isstationary(Nv);
106
107
     sum(inx)
108
     Nv = Nv(inx);
```

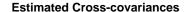
#### 7 Compare ACF From Model and Data

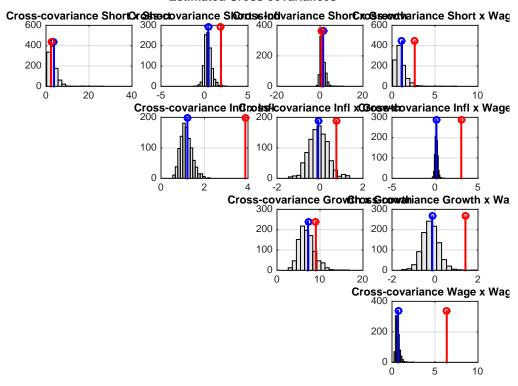
Compute and plot the autocovariance/autocorrelation functions (ACF) for the estimated VAR, the resampled VARs, and the model.

Comments on the code below:

4 helper\_plot\_acf is a helper function (for plotting ACFs) created just for this exercise (it is not part of the IRIS toolbox).

```
[Cv,Rv] = acf(v,'order=',1);
121
     [CNv,RNv] = acf(Nv,'order=',1);
122
     [Cm,Rm] = acf(mest,'order=',1,'select=',ylist);
123
124
125
     figure();
126
     for i = 1 : length(ylist)
         for j = i : length(ylist)
127
128
             subplot(4,4,(i-1)*4+j);
             helper_plot_acf(CNv(i,j,1,:),Cv(i,j,1),Cm(i,j,1)); 4
129
130
             title(sprintf('Cross-covariance %s x %s',ylist{i},ylist{j}));
131
132
     end
133
134
     grfun.bottomlegend( ...
         'VAR: Bootstrap','VAR: Point Estimate','Model: Asymptotic');
135
     grfun.ftitle('Estimated Cross-covariances');
136
```





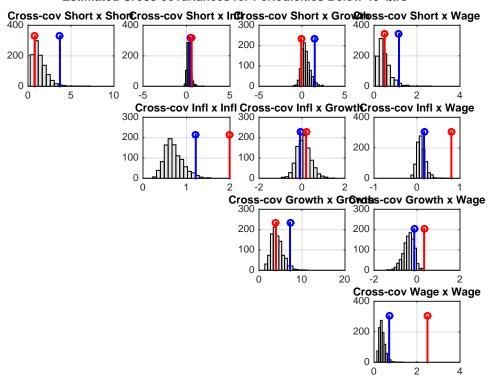
#### 8 Compare Frequency Selective ACF

Use the 'filter=' option to compute the ACF (both from the strucural model and the VAR) that corresponds to cyclical fluctuations with periodicity between 4 and 40 quarters (1 to 10 years).

```
[Cv1,Rv1] = acf(v,'order=',1,'filter=','per <= 40 \& per > 4');
144
     [Cv2,Rv2] = acf(v,'order=',1,'filter=','per > 40');
145
     [Cv3,Rv3] = acf(v,'order=',1,'filter=','per <= 4');</pre>
146
147
     maxabs(Cv1+Cv2+Cv3 - Cv)
148
149
150
     [CNv1,RNv1] = acf(Nv,'filter=','per <= 40 & per > 4','progress=',true);
151
     [Cm1,Rm1] = acf(mest,'filter=','per <= 40 & per > 4','select=',ylist);
152
153
154
     figure();
155
     for i = 1 : length(ylist)
         for j = i : length(ylist)
156
```

```
subplot(4,4,(i-1)*4+j);
157
158
                \label{eq:helper_plot_acf(CNv1(i,j,1,:),Cv(i,j,1),Cm1(i,j,1));} \\ \text{helper_plot_acf(CNv1(i,j,1,:),Cv(i,j,1),Cm1(i,j,1));} \\
                 title(sprintf('Cross-cov %s x %s',ylist{i},ylist{j}));
159
160
           end
161
      end
162
163
      grfun.bottomlegend( ...
164
           'VAR: Bootstrap','VAR: Point Estimate','Model: Asymptotic');
165
      grfun.ftitle( ...
           'Estimated Cross-covariances for Periodicities Below 40 Qtrs');
166
```

#### **Estimated Cross-covariances for Periodicities Below 40 Qtrs**



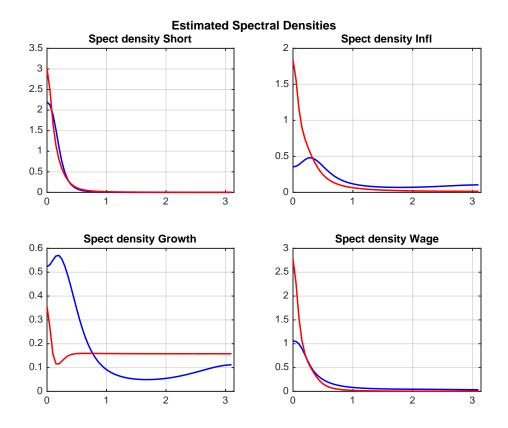
## 9 Compare VAR and Model Spectra

Compute and plot the power spectra and spectral densities for the estimated VAR and for the model.

Comments on the code below:

belper\_plot\_xsf is a helper function (for plotting the spectral densities) created just for this exercise in this directory (it is not part of the IRIS toolbox); it can be opened and viewed in the Matlab editor.

```
freq = 0 : 0.05 : pi;
     [Pv,Sv] = xsf(v,freq);
181
     [Pm,Sm] = xsf(mest,freq,'select=',ylist);
182
183
184
     figure();
185
186
     for i = 1 : length(ylist)
187
         subplot(2,2,i);
         helper_plot_xsf(freq,Sv(i,i,:),Sm(i,i,:)); 5
188
189
         title(sprintf('Spect density %s',ylist{i}));
190
     end
191
192
     grfun.bottomlegend('VAR: Point Estimate', 'Model: Asymptotic');
193
    grfun.ftitle('Estimated Spectral Densities');
```



## 10 Help on IRIS Functions Used in This Files

Use either help to display help in the command window, or idoc to display help in an HTML browser window.

help VAR

help VAR/estimate

help VAR/get

help VAR/isstationary

help VAR/resample

help VAR/subsasgn

help VAR/acf

help VAR/xsf

help model/acf

help model/xsf

help grfun/bottomlegend

help grfun/ftitle