VECM_demo.mlx

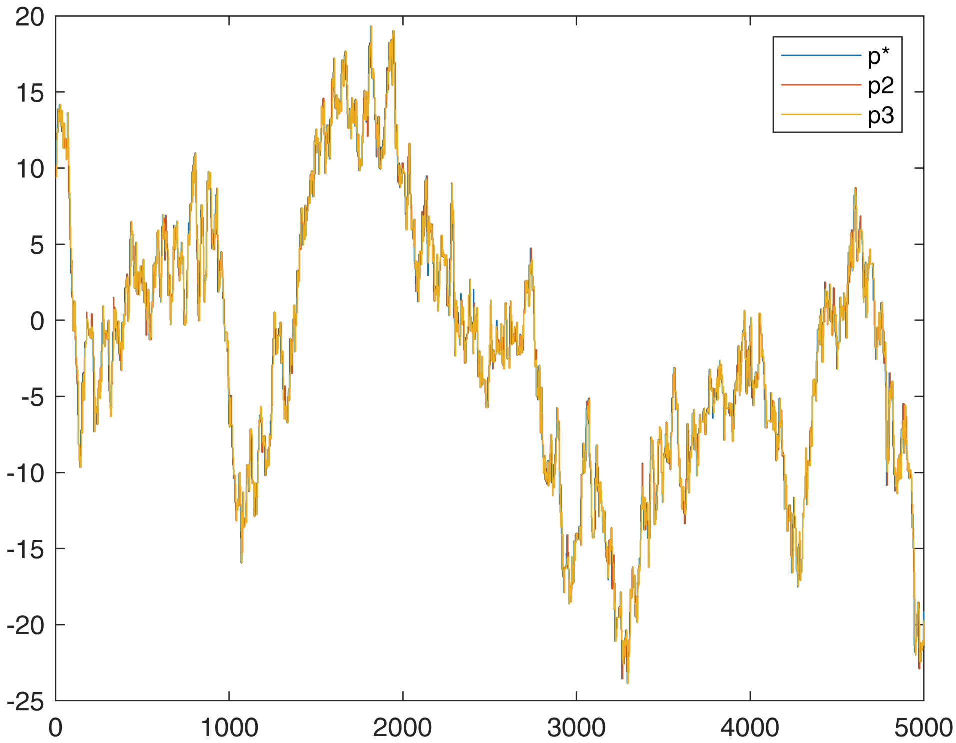
Joel Hasbrouck

November 7, 2018

- Simulate a small number of cointegrated prices
- Estimate a VECM of order P using Matlab's Econometrics Toolbox vecm routines.
- Construct a random-walk decomposition from the Matlab vecm estimates.
- Estimate the same VECM using the sparse routines in an MVARi object.
- Construct a random-walk decomposition from the MVARi estimates.

Initializations and simulations

```
clc; clear all; close all
format compact
addpath('./mClasses','./mFiles')
rng('default')
mv = MVARi;
T=5000;
spd.setgetMax(T);
nPrices = 3;
density = .6;
mv.sim(density,nPrices,0,5) % The first price is the leader; other obs are randomly lag
mv.pricePlot
```



Estimation

Estimate with matlab VECM routines

```
P1 = 3; % order of AR
first = 100-P1; last=4900;  % defines window over which data will be analyzed.
xs = [];
for i=1:mv.nPrices
    xs=[xs mv.prices(i).toCol];
end
xs = xs(first:last,:);
xs = xs - repmat(mean(xs),size(xs,1),1);    % demean the data.
n = size(xs,2);
%   set up model
mdl = vecm(n,mv.nPrices-1,P1);
B = [ones(n-1,1) -eye(n-1)];
mdl.Cointegration = B';
mdl.Constant = zeros(n,1);
mdl.Trend = zeros(n,1);
mdl.SeriesNames = mv.priceNames;
[est,se] = estimate(mdl,xs,'Display','full','Model','H2','MaxIterations',1);
```

```
3-Dimensional Rank = 2 VEC(3) Model

 Johansen Model: H2
 Effective Sample Size: 4800
 Number of Estimated Parameters: 33
 LogLikelihood: -12144.5
 AIC: 24355
 BIC: 24568.8
```

	Value	StandardError	TStatistic	PValue
Adjustment(1,1)	-0.00065459	0.02114	-0.030964	0.9753
Adjustment(2,1)	0.58275	0.016206	35.959	3.5983e-283
Adjustment(3,1)	-0.03999	0.016313	-2.4513	0.014232
Adjustment(1,2)	0.010767	0.021329	0.50479	0.61371
Adjustment(2,2)	-0.0033231	0.016351	-0.20324	0.83895
Adjustment(3,2)	0.55577	0.016459	33.766	6.1849e-250
Impact(1,1)	0.010112	0.021818	0.46346	0.64303
Impact(2,1)	0.57943	0.016726	34.643	5.7733e-263
Impact(3,1)	0.51578	0.016837	30.634	4.3481e-206
Impact(1,2)	0.00065459	0.02114	0.030964	0.9753
Impact(2,2)	-0.58275	0.016206	-35.959	3.5983e-283
Impact(3,2)	0.03999	0.016313	2.4513	0.014232
Impact(1,3)	-0.010767	0.021329	-0.50479	0.61371
Impact(2,3)	0.0033231	0.016351	0.20324	0.83895
Impact(3,3)	-0.55577	0.016459	-33.766	6.1849e-250
ShortRun{1}(1,1)	0.002774	0.025236	0.10993	0.91247
ShortRun{1}(2,1)	-0.36499	0.019345	-18.867	2.1222e-79
ShortRun{1}(3,1)	-0.31139	0.019474	-15.99	1.5024e-57
ShortRun{1}(1,2)	0.0083637	0.020191	0.41423	0.67871
ShortRun{1}(2,2)	0.089463	0.015478	5.7799	7.4751e-09
ShortRun{1}(3,2)	0.021042	0.015581	1.3505	0.17687
ShortRun{1}(1,3)	-0.01136	0.020353	-0.55814	0.57675
ShortRun{1}(2,3)	0.018846	0.015603	1.2079	0.22709
ShortRun{1}(3,3)	0.041033	0.015706	2.6125	0.0089874

```
    ShortRun{2}(1,1)      -0.015025      0.022872        -0.65695        0.51121
    ShortRun{2}(2,1)       -0.22871      0.017533         -13.044     6.8404e-39
    ShortRun{2}(3,1)       -0.14784       0.01765         -8.3765     5.4524e-17
    ShortRun{2}(1,2)      0.0060835      0.018085         0.33639        0.73658
    ShortRun{2}(2,2)    -0.00082216      0.013864       -0.059303        0.95271
    ShortRun{2}(3,2)       0.029379      0.013956          2.1052       0.035276
    ShortRun{2}(1,3)       0.013494      0.018173         0.74254        0.45776
    ShortRun{2}(2,3)        0.02327      0.013931          1.6703        0.09485
    ShortRun{2}(3,3)       0.018888      0.014024          1.3468        0.17803
    ShortRun{3}(1,1)      0.0027408      0.019996         0.13707        0.89098
    ShortRun{3}(2,1)      -0.083649      0.015329         -5.4569     4.8444e-08
    ShortRun{3}(3,1)    -0.00076454      0.015431       -0.049547        0.96048
    ShortRun{3}(1,2)      0.0058065      0.016509         0.35172        0.72505
    ShortRun{3}(2,2)      0.0048028      0.012656          0.3795        0.70432
    ShortRun{3}(3,2)    -0.00073185       0.01274       -0.057446        0.95419
    ShortRun{3}(1,3)       0.013767      0.016367         0.84119        0.40024
    ShortRun{3}(2,3)      0.0092081      0.012547         0.73391          0.463
    ShortRun{3}(3,3)     -0.0075509       0.01263        -0.59786        0.54993

   Cointegration Matrix (User-Specified):
     1     1
    -1     0
     0    -1

   Innovations Covariance Matrix:
    0.4520    0.0329    0.0384
    0.0329    0.2656    0.0049
    0.0384    0.0049    0.2692

   Innovations Correlation Matrix:
    1.0000    0.0951    0.1100
    0.0951    1.0000    0.0183
    0.1100    0.0183    1.0000
```

```
% [est,se] = estimate(mdl,xs,'Display','full','MaxIterations',1);
```

Now perform the same estimation using the sparse routines.

The sparse routines are set up using polynomial distributed lag specifications. Here, we want the usual AR terms. This is done by setting the polynomials to that the the design matrix is the identity matrix of order P1.

```
pdls = polynom.empty();
for k=1:P1
    pdls = horzcat(pdls,polynom(0,1,['pdl' int2str(k)],k-1));
end
```

The design matrix works out to the identity matrix:

```
pdls.designMatrix
```

```
ans = 3×3
     1     0     0
     0     1     0
     0     0     1
```

Now finish the estimates.

```
mv.polys = pdls.copy();
mv.intercept = false;
```

```
mv.ecm = true;
mv.setup(true);
```

```
setup.
Computing eVecs
```

```
mv.setNamesPDL(true);
```

```
zNames:
const            dp*              dp*pdl1d0        dp*pdl2d0        dp*pdl3d0        dp2
dp2pdl1d0        dp2pdl2d0        dp2pdl3d0        dp3              dp3pdl1d0        dp3pdl2d0
dp3pdl3d0        p*-p2            p*-p3
yNames:
dp*              dp2              dp3
xNames:
dp*pdl1d0        dp*pdl2d0        dp*pdl3d0        dp2pdl1d0        dp2pdl2d0        dp2pdl3d0
dp3pdl1d0        dp3pdl2d0        dp3pdl3d0        p*-p2            p*-p3
```

```
mv.zpzLayoutPDL();
mv.firstValid = first; mv.lastValid = last;
mv.eVecDemean(true);
```

```
eVecMeans: -0.013494  -0.0010435
```

```
zpzDisplay = 1;
mv.buildzpzSparsePDLpar(zpzDisplay,0);
```

```
buildzpzSparsePDLpar (nCPU=0)
Across the full for/parfor loop, the start to finish elapsed time is 6.65 sec.
```

```
mv.estimateSparse();
mv.dispEstimates
```

```
VAR/VECM estimates
                     dp*         t        dp2         t         dp3          t
dp*pdl1d0       0.002285   0.09054    -0.3635    -18.78     -0.3111     -15.98
dp*pdl2d0       -0.01561   -0.6824    -0.2285    -13.04     -0.1462     -8.286
dp*pdl3d0       0.002222    0.1111   -0.08386    -5.468  -0.0004644   -0.03009
dp2pdl1d0       0.008581    0.4249    0.08927     5.767     0.02143      1.376
dp2pdl2d0       0.007757    0.4289  -0.001066  -0.07685     0.02893      2.074
dp2pdl3d0       0.006293    0.3811   0.005879    0.4644   -0.000984   -0.07725
dp3pdl1d0       -0.01164   -0.5717    0.01901     1.217     0.04103      2.612
dp3pdl2d0        0.01447    0.7957    0.02326     1.669     0.01911      1.363
dp3pdl3d0        0.01333    0.8144    0.01017      0.81   -0.007665    -0.6069
p*-p2         -0.0004345  -0.02055     0.5824     35.92    -0.04111     -2.521
p*-p3            0.01101    0.5161   -0.00276   -0.1687      0.5562      33.79
eCov
          dp*       dp2       dp3
dp*    0.4526   0.03289   0.03833
dp2   0.03289     0.266  0.004848
dp3   0.03833  0.004848    0.2693
eCorr
          dp*       dp2      dp3
dp*         1   0.09478   0.1098
dp2   0.09478         1  0.01811
dp3    0.1098   0.01811        1
```

The two sets of estimates are quite close, but not identical to numerical precision. I have not determined the source of the discrepancies.

Random-walk decompositions

The random-walk decomposition for the Toolbox vecm:

```
r = randomWalkDecomp;
r.initm(est);
r.isBoundsGrouped({{'p*'},{'p2','p3'}});
r.rDisplay('rwd from the toolbox vecm');
```

```
rwd from the toolbox vecm
Sum of vma coefficients:
     p*          p2        p3
  1.056  -0.0002178  -0.02046
per period var_w:    0.502749 sd_w:    0.709048
info share bounds:
        Min      Max
p*  0.98227  0.99978
p2  0.00000  0.00899
p3  0.00022  0.00907
Grouped info share bounds
           Min      Max
p*     0.98227  0.99978
p2 p3  0.00022  0.01773
```

The random-walk decomposition for the sparse (MVARi) vecm

```
r=randomWalkDecomp;
r.init(mv);
r.isBoundsGrouped({{'p*'},{'p2','p3'}});
r.rDisplay('rwd from the sparse vecm');
```

```
rwd from the sparse vecm
Sum of vma coefficients:
     p*          p2        p3
  1.059  -0.0006903  -0.02097
per period var_w:    0.505747 sd_w:    0.711159
info share bounds:
        Min      Max
p*  0.98249  0.99977
p2  0.00000  0.00887
p3  0.00023  0.00896
Grouped info share bounds
           Min      Max
p*     0.98249  0.99977
p2 p3  0.00023  0.01751
```

IRF Computation (MVARi only)

```
nAhead = 20;
mv.irfPDLpacked(nAhead, 1, 0);
```

irfPDLpacked (nCPU=0)

```
irf=squeeze(mv.irfPacked(3,:,1));
irft=mv.irft;
plot(irft,irf)
title('p3 after a one-unit shock to p*')
```