PcGive 10:0 Multiple equation Dynamic Modelling

Index:

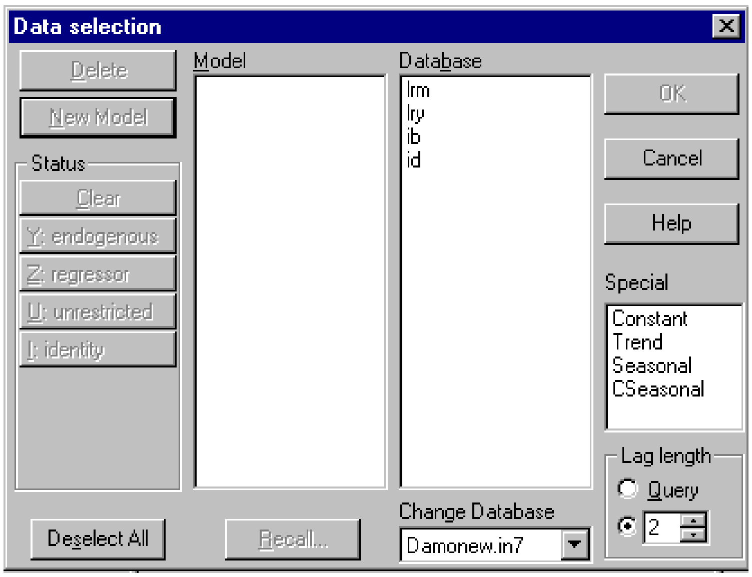
Introduction

The document Givewin 2 and PcGive10 gave students a basic introduction to the features of Givewin 2 and PcGive 10, demonstrating how to read in data, undertake data transformations, graph the data and undertake some single equation regressions. This document discusses the option Multiple equation Dynamic Modelling within Econometric Modelling (PcGive). This option is very similar to the old PcFIML program.

1.1 Formulating a model

Clicking on Model in PcGive and selecting Multiple equation Dynamic Modelling you get Figure 1:

Figure 1: Model formulation box



This box is identical to the one seen with Single-equation Dynamic Modelling (see section 2.2 page 15 of the document Givwin 2 and PcGive 10). However, you are now dealing with the estimation of a system of equations, in which it is assumed you have more than one dependent variable. In fact the package is designed assuming that you wish to estimate a VAR model or a VECM model. Define the vector Y with k=4 variables: lrm=log real money, lry=log real income, ib=interest rates on bonds, id=interest rates on deposits.

$Y = \begin{bmatrix} lrm \\ lry \\ ib \\ id \end{bmatrix}$ and the VAR with lag length=p as

$$Y_t = \mu + A_1 Y_{t-1} + \ldots A_p Y_{t-p} + u_t, \quad u_t \sim N(0, \Omega)$$

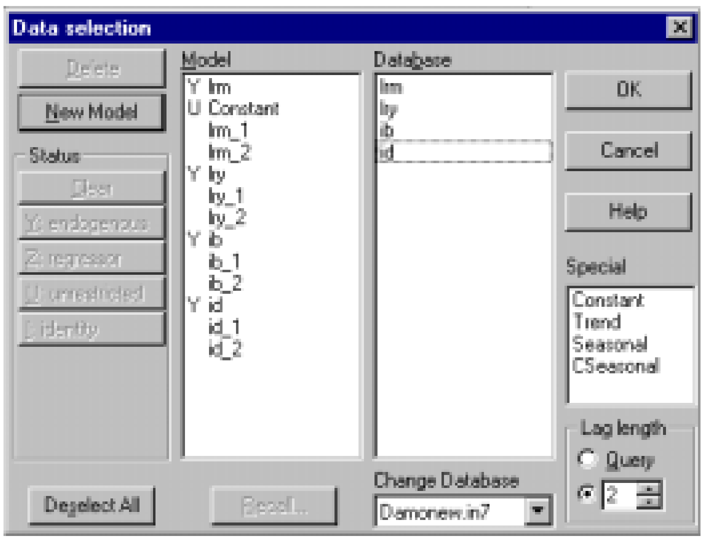
Rearranging the model we can write this model as

$$\Delta Y_t = \mu + \Gamma_1 Y_{t-1} + \ldots \Gamma_{p-1} Y_{t-p+1} + \Pi Y_{t-p} + u_t$$

If the $\text{rank}(\Pi) = r$, where $1 < r < k$, then Π can be decomposed as $\Pi = \alpha\beta'$, where the rank of both α and β is r.

To estimate a VAR model with a lag length of p=2, you must first set the Lag length (in the bottom right hand corner), then double clicking on the each of the variables in turn produces a model as in Figure 2. Alternatively, highlighting a variable in the Database box and clicking <<Add (which replaces OK) moves the variable (and its lags) to the Model box. A model with different variable length on the lagged endogenous variables is not a VAR model.

Figure 2: Model formulation box for a VAR(2) for 4 variables



In this model there are 4 endogenous variables each marked as Y in the Model box. The Constant is marked with a U indicating that this variable will be entered into the VAR as unrestricted. Unrestricted variables are in the ECM, but not in the Cointegrating equation. If we highlight the constant in the model box and press Clear then the intercept will appear restrictedly in the Cointegrating equation, as

$$\Delta Y_t = \Gamma_1 Y_{t-1} + \ldots \Gamma_{p-1} Y_{t-p+1} + \alpha(\beta_0 + \beta' Y_{t-p}) + u_t$$

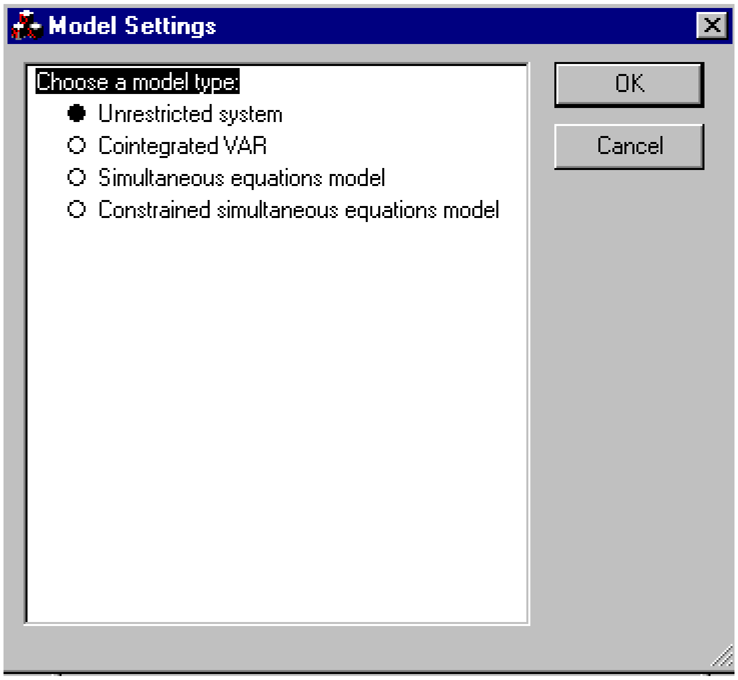
Additional variables which could be included in the model would be a Trend and Seasonal dummy variables. Seasonal dummy variables are often included as CSeasonal (centred seasonal dummy variables – these have a zero mean). When including exogenous variables on the RHS of the VAR, PcGive will automatically assume these variables are endogenous (Y) variables – you will need to change the Status of these variables.

You can delete variables from the Model box, by simple highlighting the variable(s) in the Model box and clicking the Delete button. When the Model box is correct, clicking OK produces Figure 3.

Clicking OK in Figure 2 produces Figure 3.

1.2 Model Settings: Unrestricted VAR

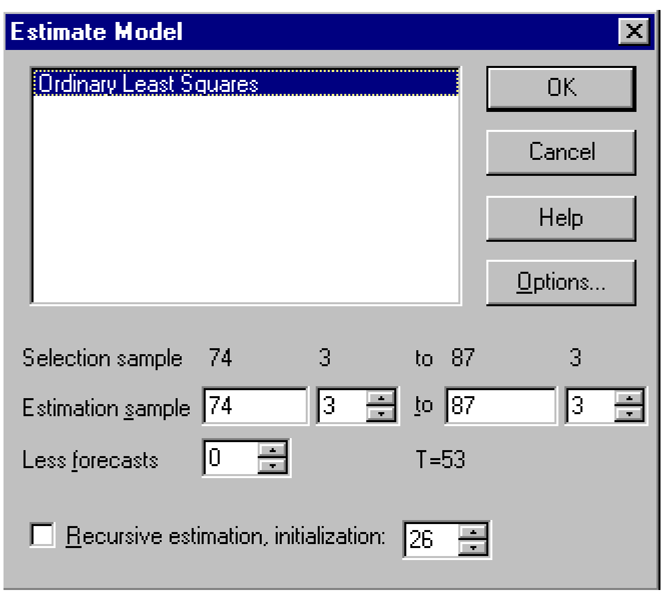
Figure 3: Model setting box



In this box you must select the estimation method. We are interested in estimating an unrestricted VAR model (Unrestricted system). Clicking OK yields figure 4.

1.3 Model Estimation

Figure 4: Estimation box



In this box you select the sample period over which you wish to estimate the model. The estimation sample defaults to the largest sample available. To undertake forecasting you may wish to hold back some data from the estimation sample. For recursive estimation you must place an x in the appropriate box and tell the computer how many observations can be used as initial data points for estimation. Clicking OK produces the output below:

1.4 Model Output

SYS(1) Estimating the system by OLS (using Damonew.in7)
The estimation sample is: 74 (3) to 87 (3)

URF equation for: lrm

	Coefficient	Std.Error	t-value	t-prob
lrm_1	0.463715	0.1742	2.66	0.011
lrm_2	0.273738	0.1555	1.76	0.085
lry_1	0.273004	0.1984	1.38	0.176
lry_2	-0.0975622	0.1930	-0.506	0.616
ib_1	-1.47287	0.4592	-3.21	0.002
ib_2	0.0187760	0.5343	0.0351	0.972
id_1	-0.300111	0.7337	-0.409	0.684
id_2	1.03434	0.6753	1.53	0.133
Constant U	2.21234	0.6749	3.28	0.002

sigma = 0.0278575   RSS = 0.03414587868

URF equation for: lry

	Coefficient	Std.Error	t-value	t-prob
lrm_1	0.301669	0.1446	2.09	0.043
lrm_2	-0.174273	0.1291	-1.35	0.184
lry_1	0.808026	0.1648	4.90	0.000
lry_2	-0.0640660	0.1603	-0.400	0.691
ib_1	0.00390730	0.3814	0.0102	0.992
ib_2	0.324112	0.4438	0.730	0.469
id_1	-0.934781	0.6093	-1.53	0.132
id_2	0.431547	0.5609	0.769	0.446
Constant U	0.0221981	0.5605	0.0396	0.969

sigma = 0.0231363   RSS = 0.0235526598

URF equation for: ib

	Coefficient	Std.Error	t-value	t-prob
lrm_1	0.000441971	0.05517	0.00801	0.994
lrm_2	0.00172445	0.04925	0.0350	0.972
lry_1	0.135618	0.06286	2.16	0.036
lry_2	-0.139286	0.06112	-2.28	0.028
ib_1	1.33362	0.1454	9.17	0.000
ib_2	-0.328030	0.1692	-1.94	0.059
id_1	-0.00632976	0.2324	-0.0272	0.978
id_2	-0.106306	0.2139	-0.497	0.622
Constant U	0.00444966	0.2138	0.0208	0.983

sigma = 0.008824   RSS = 0.003425969322

URF equation for: id

	Coefficient	Std.Error	t-value	t-prob
lrm_1	0.0230131	0.03402	0.676	0.502
lrm_2	-0.0331484	0.03038	-1.09	0.281
lry_1	0.0177281	0.03877	0.457	0.650
lry_2	0.00774650	0.03770	0.206	0.838
ib_1	0.349351	0.08970	3.89	0.000
ib_2	-0.238804	0.1044	-2.29	0.027
id_1	0.911208	0.1433	6.36	0.000
id_2	-0.216872	0.1319	-1.64	0.107
Constant U	-0.0225364	0.1318	-0.171	0.865

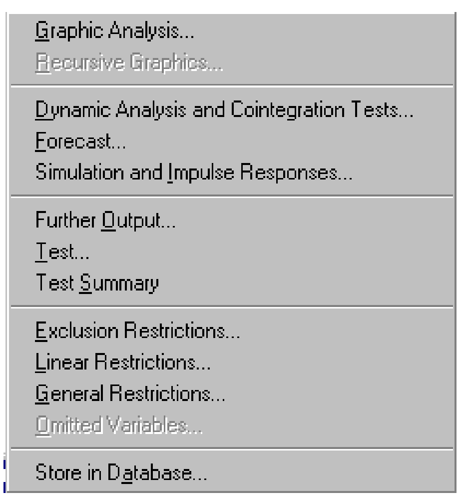
```
sigma = 0.00544226   RSS = 0.001303201639
log-likelihood     653.389041  -T/2log|Omega|      954.20401
|Omega|       2.30173459e-016  log|Y'Y/T|        -28.4697994
R^2(LR)               0.999467  R^2(LM)             0.758573
no. of observations        53  no. of parameters          36

F-test on regressors except unrestricted: F(32,152) = 32.0939 [0.0000]
**
F-tests on retained regressors, F(4,41) =
       lrm_1       2.09591 [0.099]        lrm_2       3.85759 [0.009]**
       lry_1       7.12637 [0.000]**      lry_2       1.94034 [0.122]
        ib_1       20.6101 [0.000]**       ib_2       2.12395 [0.095]
        id_1       9.98790 [0.000]**       id_2       1.19499 [0.328]
    Constant U     4.65713 [0.003]**

correlation of URF residuals (standard deviations on diagonal)
                lrm          lry           ib           id
lrm        0.027858      0.56873     -0.37615    -0.060012
lry         0.56873     0.023136    -0.030841     -0.13537
ib         -0.37615    -0.030841    0.0088240      0.21003
id        -0.060012     -0.13537      0.21003    0.0054423
correlation between actual and fitted
          lrm          lry           ib           id
        0.98585      0.95654      0.96565      0.93744
```

Reported are the OLS estimates for each of the k=4 variables in the system. Additionally, there are reported some system information statistics. F-tests on retained regressors, these are F-tests on the joint significance for each lag (p=2) for each variable (k=4) in the system as a whole. In addition, the correlation matrix of the residuals is reported.

To evaluate the model clicking on Test in PcGive yield Figure 5.

1.6 Model Testing

Figure 5: Test options



These options are very similar to those available for Single-equation Dynamic Modelling, and most of these will be discussed in turn.

1.6.1 Graphical analysis

Figure 6: Graphical analysis

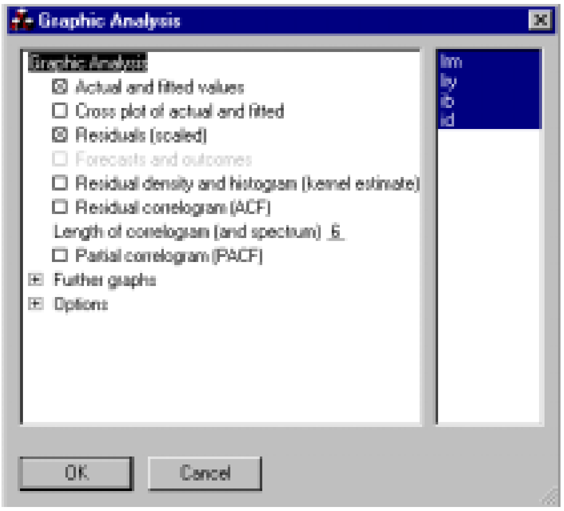
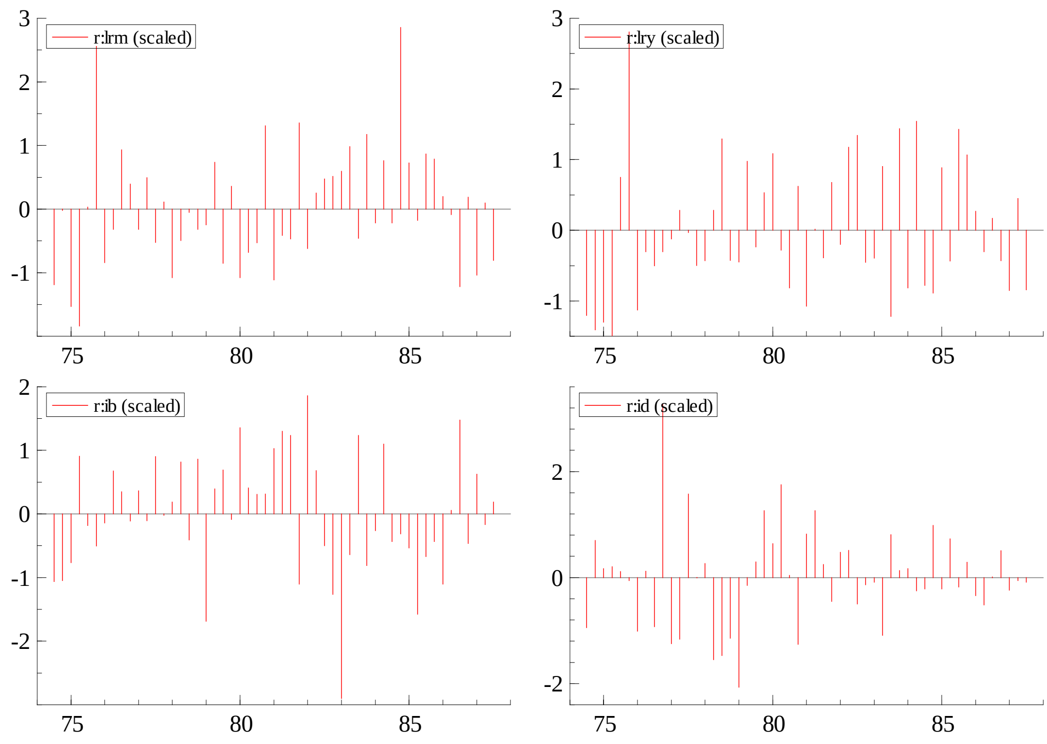


Figure 7: plot of the scaled residuals for each equation

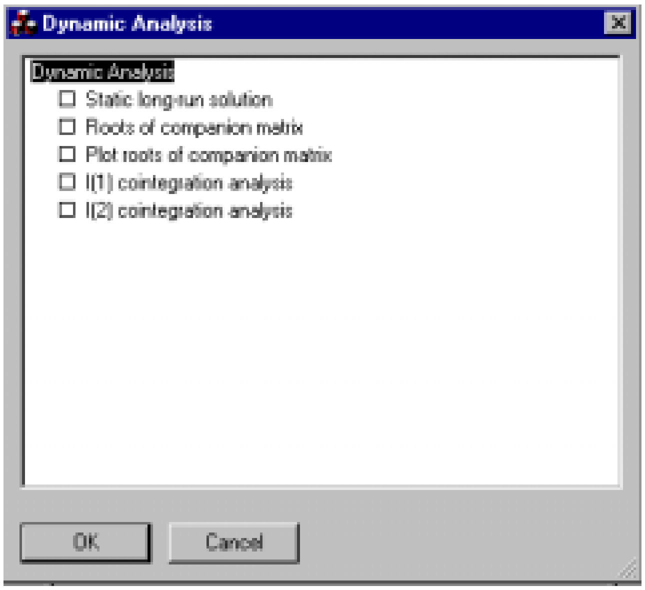


1.6.1 Recursive graphics

Having chosen recursive estimation in Figure ?, this enable you to investigate the stability of your model.

1.6.2 Dynamic analysis

Figure 8: Dynamic analysis



Placing a cross in I(1) Cointegration analysis, gives the Johansen Trace test of the number of Cointegrating relations and this is seen below:

```
I(1) cointegration analysis, 74 (3) to 87 (3)
  eigenvalue     loglik for rank
                  628.9908   0
     0.44813      644.7435   1
     0.17421      649.8161   2
     0.11692      653.1112   3
    0.010431      653.3890   4

  H0:rank<=  Trace test  pvalue
      0          48.796 [0.039] *
      1          17.291 [0.627]
      2          7.1459 [0.567]
      3         0.55577 [0.456]

Asymptotic p-values based on: Unrestricted constant
Unrestricted variables:
[0] = Constant
Number of lags used in the analysis: 2

beta (scaled on diagonal)
lrm          1.0000     -0.72667      0.71377      -2.0075
lry        -0.97586       1.0000      -1.6527      0.71320
ib           5.4079      0.20550       1.0000      -2.8829
id          -4.1611      -6.4472      -2.6333       1.0000
```

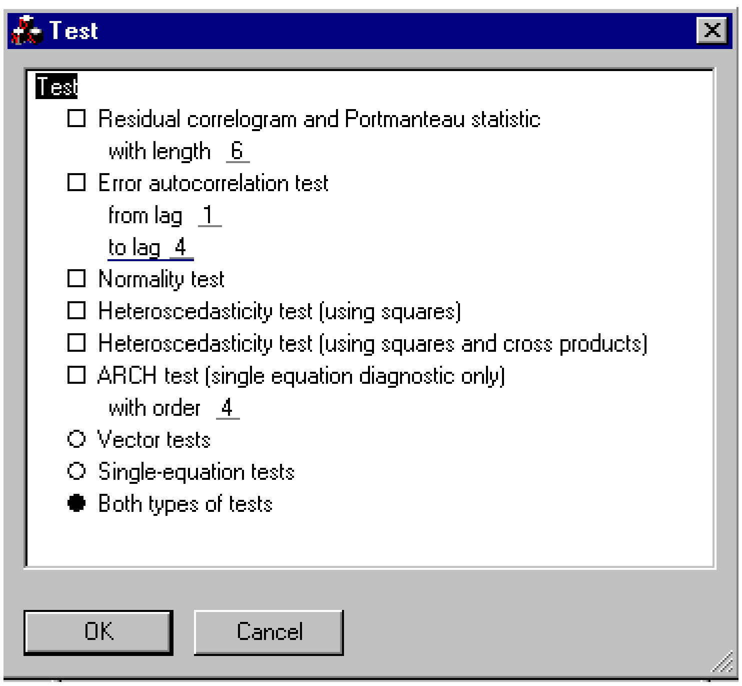
```
alpha
lrm        -0.28151     0.034560     0.084463    0.0080761
lry        0.037477  -0.00034758      0.13385    0.0029232
ib       -0.0038990     0.014617     0.011551   -0.0042051
id         0.019957     0.036596   -0.0050823 -6.4056e-005

long-run matrix, rank 4
                lrm          lry           ib           id
lrm        -0.26255      0.17544      -1.4541      0.73423
lry         0.12740     -0.25604      0.32802     -0.50323
ib        0.0021664   -0.0036683    0.0055928     -0.11264
id        -0.010135     0.025475      0.11055     -0.30566
```

Based on this, we assume r=1, that is, there is a single Cointegrating equation. One can also calculate the roots of companion matrix.

1.6.3 Diagnostic testing

It is possible to undertake diagnostic testing of each individual equation and of the system as a whole. Selecting Test yields Figure 9

Figure 9: Test box



The tests are relatively standard diagnostic tests, but can be reported for both each individual equation and for the system as a whole. Clicking Test Summary in Figure 5, yields:

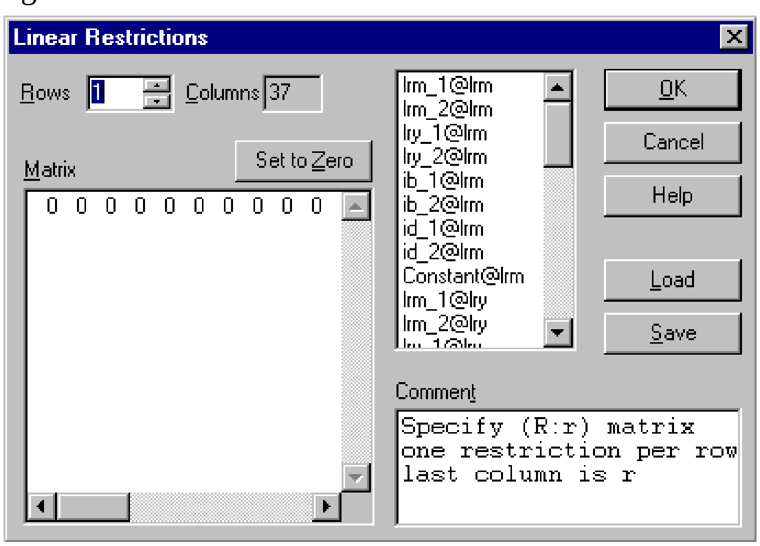
```
lrm          : Portmanteau( 6): 8.45597
lry          : Portmanteau( 6): 3.17245
ib           : Portmanteau( 6): 2.76536
id           : Portmanteau( 6): 3.98761
```

```
lrm          : AR 1-4 test:      F(4,40)   =   2.0439 [0.1065]
lry          : AR 1-4 test:      F(4,40)   =   1.6995 [0.1692]
ib           : AR 1-4 test:      F(4,40)   =   1.5547 [0.2051]
id           : AR 1-4 test:      F(4,40)   =  0.37572 [0.8246]
lrm          : Normality test:   Chi^2(2)  =   5.4278 [0.0663]
lry          : Normality test:   Chi^2(2)  =   4.3401 [0.1142]
ib           : Normality test:   Chi^2(2)  =   2.7268 [0.2558]
id           : Normality test:   Chi^2(2)  =   9.2094 [0.0100]*
lrm          : ARCH 1-4 test:    F(4,36)   =  0.24359 [0.9117]
lry          : ARCH 1-4 test:    F(4,36)   =  0.22883 [0.9204]
ib           : ARCH 1-4 test:    F(4,36)   =  0.35641 [0.8379]
id           : ARCH 1-4 test:    F(4,36)   =  0.63679 [0.6396]
lrm          : hetero test:      F(16,27)  =  0.83787 [0.6369]
lry          : hetero test:      F(16,27)  =   2.2422 [0.0311]*
ib           : hetero test:      F(16,27)  =   1.0152 [0.4714]
id           : hetero test:      F(16,27)  =  0.52207 [0.9118]
lrm          : Not enough observations for hetero-X test
lry          : Not enough observations for hetero-X test
ib           : Not enough observations for hetero-X test
id           : Not enough observations for hetero-X test

Vector Portmanteau( 6): 76.6655
Vector AR 1-4 test:       F(64,100)=   1.1662 [0.2429]
Vector Normality test:    Chi^2(8) =   30.172 [0.0002]**
Vector hetero test:       F(160,172)=  0.74870 [0.9680]
Not enough observations for hetero-X test
```

1.6.4 Restrictions

One can also test for restrictions within the system of equations you have estimated. The form of these restrictions is slightly different from that for single equation analysis (as discussed in section 2.3.4 p.20 in Givewin 2 and PcGive 10 document), as each variable appears in each equation. The notation used in PcGive is x1@y1, referring to the right hand side variable x1 in the y1 equation.

Figure 10: Linear restrictions

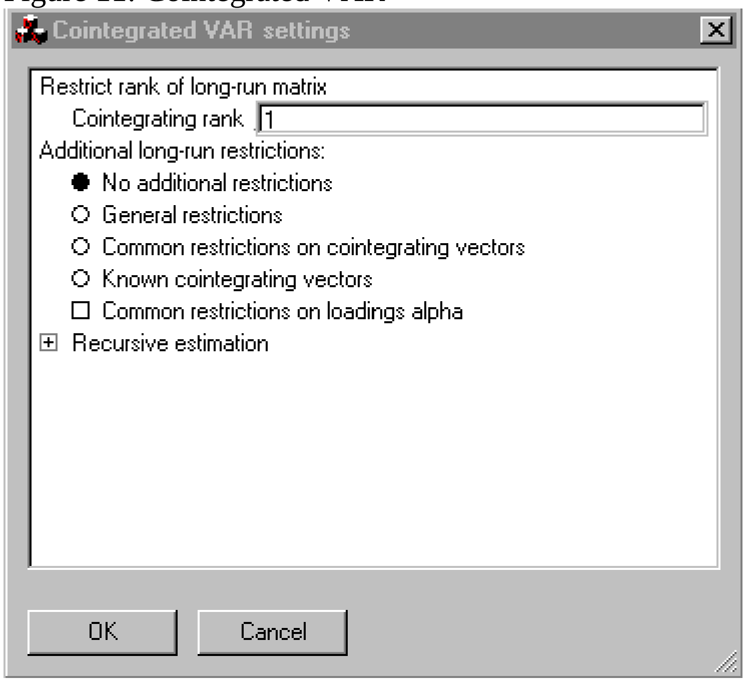


Given this new notation the exclusion restrictions and general restrictions follow the same for as for Single-equation estimation.

1.7 Model Setting: Cointegrated VAR

Having determined the satisfactory nature of your VAR model as well as the number of cointegrating vectors (r=1). Click on Model and Model Settings and get Figure 3 again. In Figure 3 select Cointegrated VAR and you get Figure 11

Figure 11: Cointegrated VAR



In this window you must specify the number of Cointegrating relations (in our case r=1), and whether you wish to impose any restrictions on the cointegrating relations. Initially we specify no restrictions and get the output:

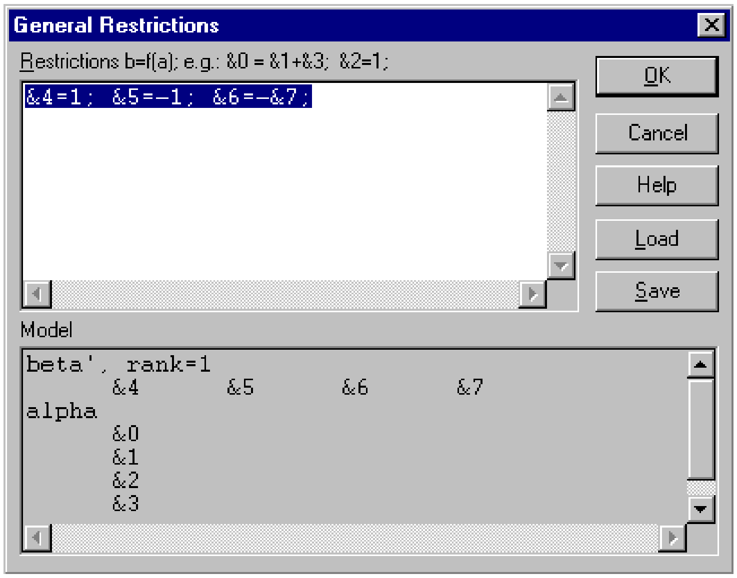
```
SYS( 2) Cointegrated VAR (using Damonew.in7)
        The estimation sample is: 74 (3) to 87 (3)
Cointegrated VAR (2) in:
[0] = lrm
[1] = lry
[2] = ib
[3] = id
Unrestricted variables:
[0] = Constant
Number of lags used in the analysis: 2

beta
lrm          1.0000
lry        -0.97586
ib           5.4079
id          -4.1611

alpha
lrm        -0.28151
lry        0.037477
ib       -0.0038990
id         0.019957

Standard errors of alpha
lrm        0.075290
lry        0.064869
ib         0.023662
id         0.015759

Restricted long-run matrix, rank 1
                lrm          lry           ib           id
lrm        -0.28151      0.27471      -1.5224       1.1714
lry        0.037477    -0.036572      0.20267     -0.15594
ib       -0.0038990    0.0038048    -0.021085     0.016224
id         0.019957    -0.019475      0.10792    -0.083041

Standard errors of long-run matrix
lrm        0.075290     0.073472      0.40716      0.31329
lry        0.064869     0.063303      0.35081      0.26993
ib         0.023662     0.023090      0.12796     0.098458
id         0.015759     0.015379     0.085226     0.065576

Reduced form beta
lry         0.97586
ib          -5.4079
id           4.1611
Moving-average impact matrix
      0.26450     0.067407      -4.8971       2.6477
     0.090606      0.86766      -1.2497     -0.59546
     0.017756      0.22119       1.1733     0.064311
     0.065392      0.10019      0.64103      0.85952

log-likelihood     644.743526  -T/2log|Omega|     945.558495
no. of observations        53  no. of parameters          27
rank of long-run matrix     1  no. long-run restrictions   0
beta is not identified
No restrictions imposed
```

The cointegrating β vector has the coefficients on lrm and lry nearly equal and opposite in sign, similarly the coefficients on ib and id are also equal and opposite in sign.

1.8 Model Setting: Cointegrated VAR with restrictions

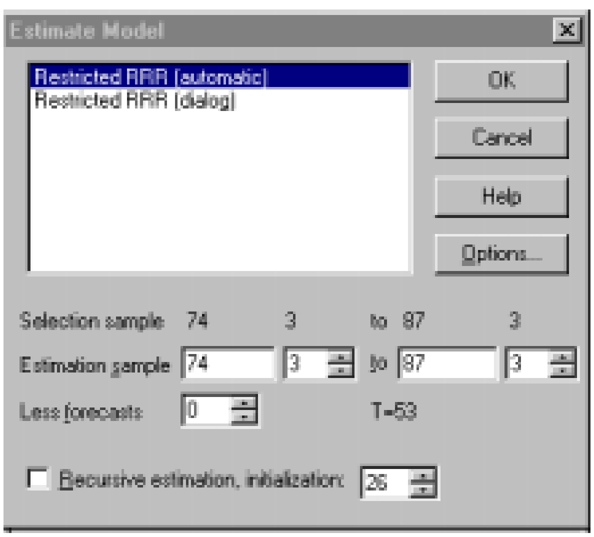
From Figure 11, specify the number of cointegrating relations as r=1 and select general restrictions yields, this produces Figure 12

Figure 12: General restrictions



In the box the beta parameters are denoted as &4-&7 and the alpha parameters are &0-&3. We have imposed that $\beta_1 = -\beta_2 = 1$ and $\beta_3 = -\beta_4$. There are 2 restrictions as $\beta_1 = 1$ is a simple normalisation and not a restriction. Clicking OK yields Figure 13:

Figure 13: Estimate Model box



Clicking OK yields the output:

```
SYS( 3) Cointegrated VAR (using Damonew.in7)
        The estimation sample is: 74 (3) to 87 (3)
Cointegrated VAR (2) in:
[0] = lrm
[1] = lry
[2] = ib
[3] = id
Unrestricted variables:
[0] = Constant
Number of lags used in the analysis: 2
General cointegration restrictions:
&4=1; &5=-1; &6=-&7;
beta
lrm          1.0000
lry         -1.0000
ib           6.0551
id          -6.0551
Standard errors of beta
lrm         0.00000
lry         0.00000
ib          0.00000
id          0.50498

alpha
lrm        -0.22864
lry        0.042244
ib       0.00041384
id         0.024902
Standard errors of alpha
lrm        0.068205
lry        0.057301
ib         0.020953
id         0.013715

Restricted long-run matrix, rank 1
                lrm          lry           ib           id
lrm        -0.22864      0.22864      -1.3844       1.3844
lry        0.042244    -0.042244      0.25579     -0.25579
ib       0.00041384  -0.00041384    0.0025058   -0.0025058
id         0.024902    -0.024902      0.15078     -0.15078
Standard errors of long-run matrix
lrm        0.068205     0.068205      0.41298      0.41298
lry        0.057301     0.057301      0.34696      0.34696
ib         0.020953     0.020953      0.12687      0.12687
id         0.013715     0.013715     0.083044     0.083044
Reduced form beta
lry          1.0000
ib          -6.0551
id           6.0551

Moving-average impact matrix
      0.37088     0.090826      -4.4098       3.3244
      0.10309      0.87068      -1.1932     -0.51072
     0.038378      0.21428       1.2948    -0.032655
     0.082605     0.085484      0.76357      0.60072

log-likelihood     644.080471  -T/2log|Omega|      944.89544
```

```
no. of observations         53  no. of parameters          25
rank of long-run matrix      1  no. long-run restrictions   2
beta is identified

LR test of restrictions: Chi^2(2) =   1.3261 [0.5153]

Switching (scaled linear) using analytical derivatives (eps1=0.0001;
eps2=0.005):
Strong convergence
```

Restrictions are easily accepted, with a $\chi^2(2)$ p-value of 51.53%, this implies that the cointegrating vector is:
$lrm = lry - 6.05(ib - id)$

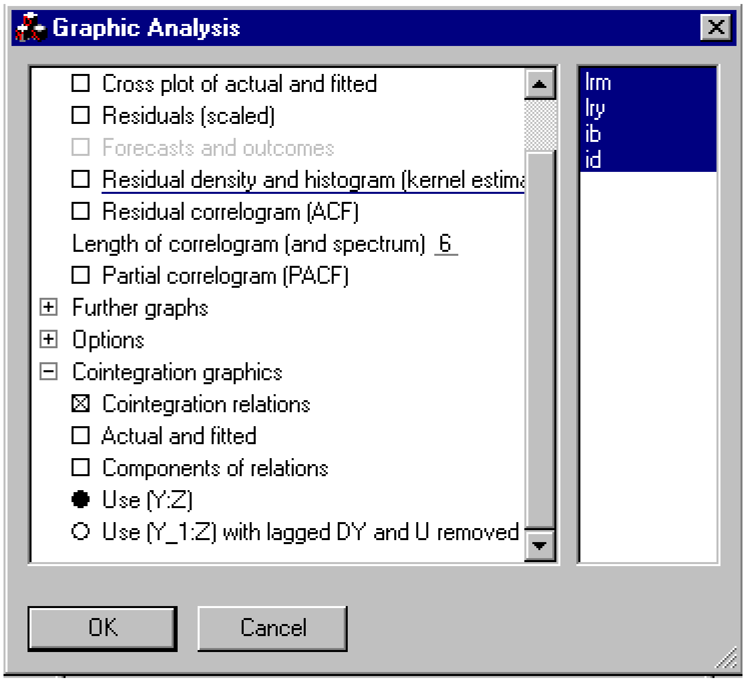
It is possible to impose other types of restrictions on the beta (and alpha) vectors, such as common restrictions across all beta vectors, such that $\beta = H\phi$, or for known cointegrating vectors. (we will not give further details on these restrictions).

1.9 Model testing

Returning to the Test options in Figure 5 and selecting graphical analysis you get Figure 14. This now includes options for plotting the cointegrating relations as $\beta' Y_t$ or $\beta' R_{pt}$

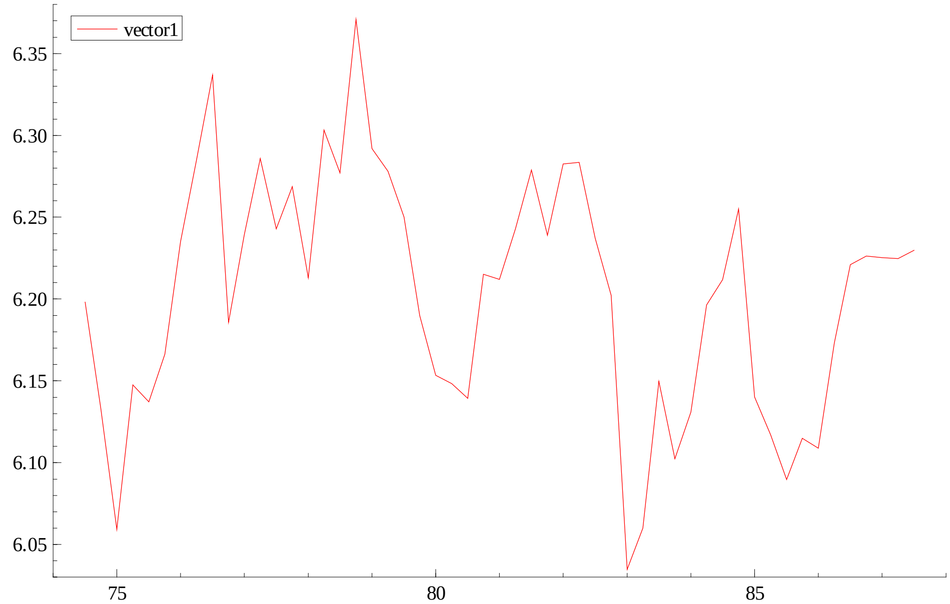
1.9.1 Graphical analysis

Figure 14: Graphical analysis



Selecting Cointegrating relations and Use (Y:Z), i.e., $\beta' Y_t$, you get Figure 15

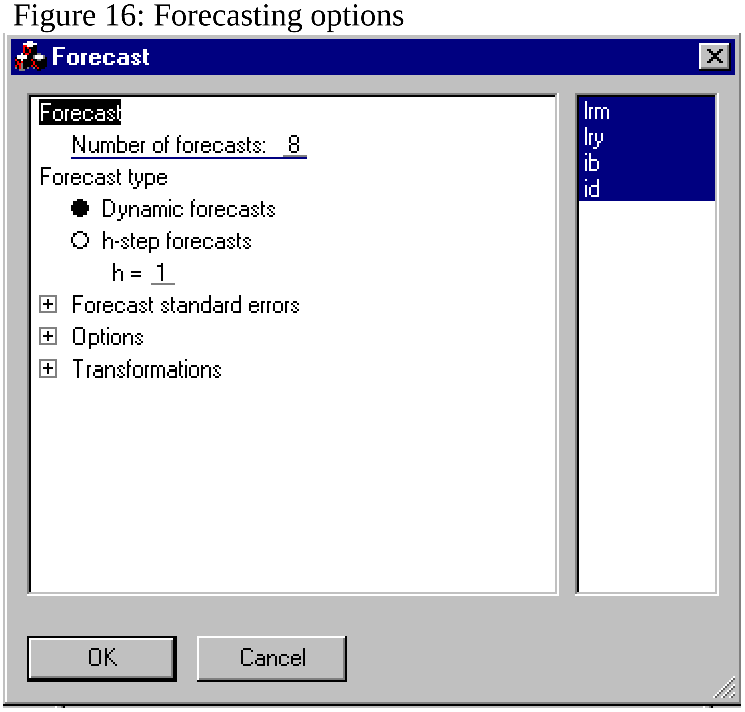
Figure 15: Plots of the 1st cointegrating relation



1.9.2 Forecasting

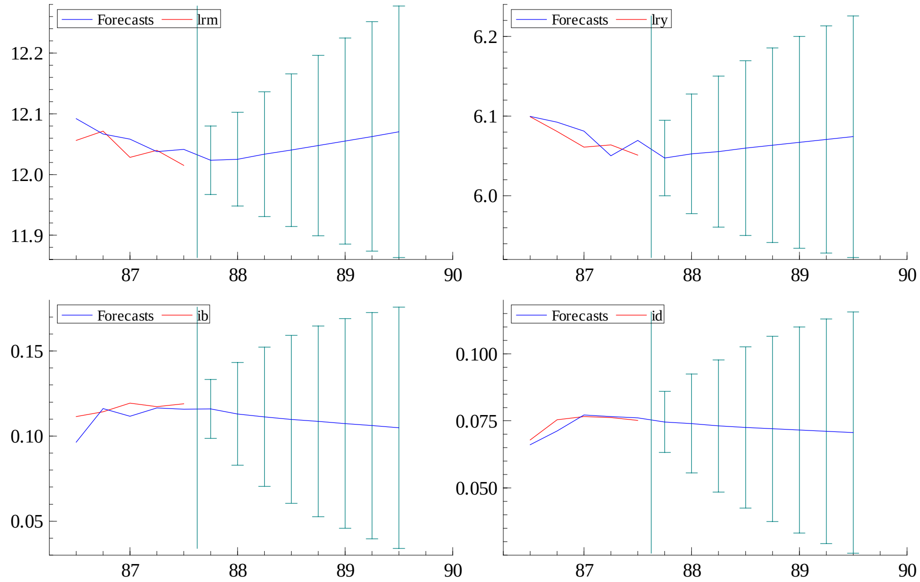
Clicking on forecasting in Figure 5 gives Figure 16. Note in the VAR we have estimated forecasting is possible even without having saved points for forecasting in Figure 4 as there are no exogenous variables in the system.

Figure 16: Forecasting options



Selecting Dynamic forecasts over 8 periods produces Figure 17 below

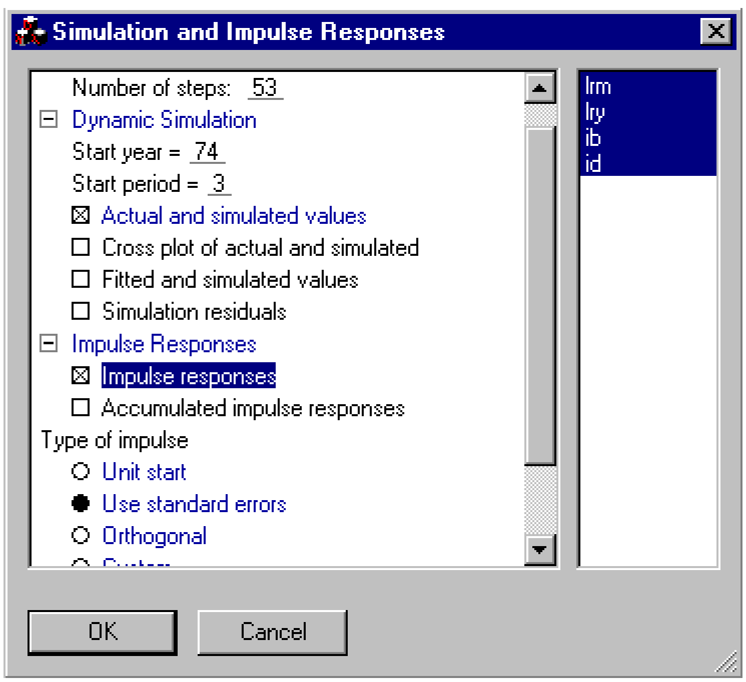
Figure 17: 8-period dynamic forecasts



1.9.3 Simulation and Impulse Responses

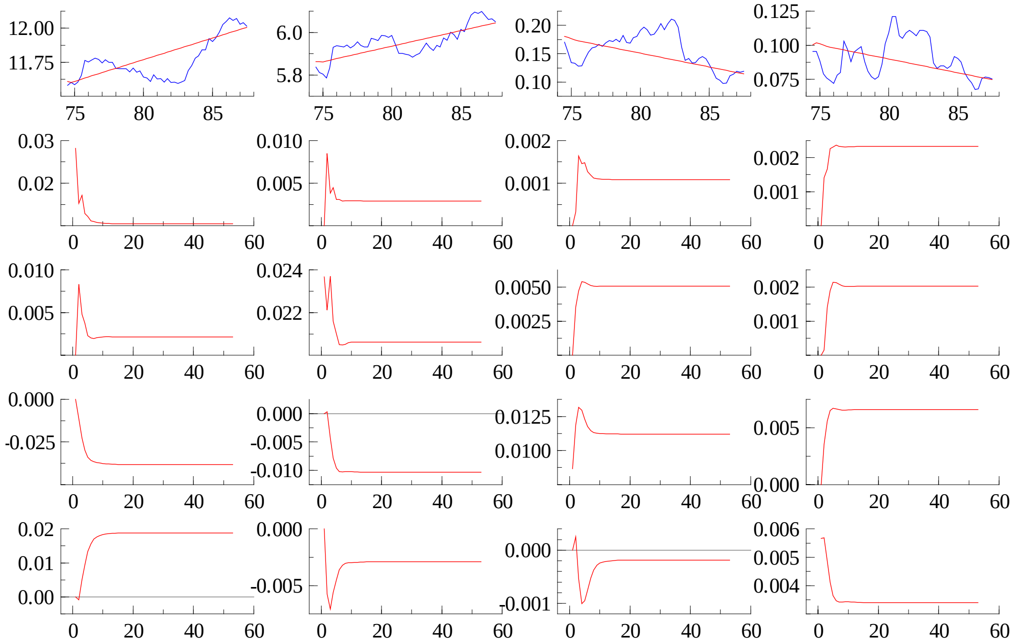
Clicking on this option gives Figure 18.

Figure 18 Simulation and Impulse Responses



It is possible to undertake a within sample simulation of your model. In Figure 19 we plot the simulated and actual values for the period from 1974Q3. In addition we report the 1-standard deviation impulse responses from a shock to every variable in every equation.

Figure 19: Simulation and Impulse response graphs



From this point you would need to respecify your reduced form Vector Error Correction Model (VECM) as a structural vector error correction model (SVECM). This would involve the identification and estimation of a system of equations including the error correction terms. Information on this is available in the PcGive manual.