Department of Economics

Econometric Analysis of Panel Data

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Assignment 3

Part I. Instrumental Variable Estimation

This exercise is based on Baltagi/Griffin's gasoline demand model, which we extend to the folowing random effects model:

$$\log G_{i,t} = \beta_1 + \beta_2 \log Y_{i,t} + \beta_3 \log P_{i,t} + \beta_4 \log C_{i,t} + \beta_5 \log G_{i,t-1} + u_i + \varepsilon_{i,t}$$

where G = per capita gasoline consumption, Y = income, P = price, C = cars per capita. (Use Baltagi's gasoline data posted on the course web site, for the computations.) Note the appearance of the lagged value of the dependent variable.

(1) Will the ordinary least squares estimator of β for this model be unbiased? Consistent? Efficient? Explain.

It will be neither. Efficiency is a moot point. (OLS would not even be the most efficient estimator of the thing that it does estimate because this is a generalized regression model.) The problem is the persistent correlation between $\log G_{i,t-1}$ and u_i.

(2) What about the GLS estimator? Consistent? Explain.

Inconsistent. Same reason as in (1).

(3) Estimate the model by OLS and report your results.

```
--> Sample;all$
--> Create;t=year-1959$
--> create;logg=lgaspcar ; logy=lincomep;logp=lrpmg$
--> create;logc=lcarpcap;logg1=logg[-1]$
--> reject;t=1$
--> names;x=one,logy,logp,logc,logg1$
--> regress;lhs=logg;rhs=x$
```

```
+----------------------------------------------------+
| Ordinary    least squares regression               |
| LHS=LOGG     Mean                 =   4.281163     |
|              Standard deviation   =   .5406116     |
| WTS=none     Number of observs.   =        324     |
| Model size   Parameters           =          5     |
|              Degrees of freedom   =        319     |
| Residuals    Sum of squares       =   1.217978     |
|              Standard error of e  =   .6179087E-01 |
| Fit          R-squared            =   .9870977     |
|              Adjusted R-squared   =   .9869359     |
| Model test   F[  4,   319] (prob) =6101.33 (.0000) |
| Diagnostic   Log likelihood       =   444.7993     |
|              Restricted(b=0)      =  -259.9578     |
|              Chi-sq [   4]  (prob) =1409.51 (.0000) |
| Info criter. LogAmemiya Prd. Crt. =  -5.552685     |
|              Akaike Info. Criter. =  -5.552687     |
|              Bayes Info. Criter.  =  -5.494343     |
| Autocorrel   Durbin-Watson Stat.  =  2.1877578     |
|              Rho = cor[e,e(-1)]   =  -.0938789     |
| Model was estimated Mar 23, 2009 at 09:36:56AM     |
+----------------------------------------------------+
```

Variable	Coefficient	Standard Error	t-ratio	P[|T|>t]	Mean of X
Constant	.25410***	.05155174	4.929	.0000	
LOGY	.06648***	.01792300	3.709	.0002	-6.1192275
LOGP	-.07827***	.01682261	-4.653	.0000	-.5325998
LOGC	-.04364***	.01371528	-3.182	.0016	-8.9901333
LOGG1	.92879***	.01615761	57.483	.0000	4.3065209

Note: ***, **, * = Significance at 1%, 5%, 10% level.

(4) Estimate the model by FGLS, ignoring its dynamic nature, and report your results. (Note that a year of data is lost because of the presence of the lagged dependent variable.)

--> regress;lhs=logg;rhs=x;str=country;panel;random effects$

```
+--------------------------------------------------+
| Random Effects Model: v(i,t) = e(i,t) + u(i)     |
| Estimates:  Var[e]              =   .273408D-02  |
|             Var[u]              =   .108403D-02  |
|             Corr[v(i,t),v(i,s)] =   .283918      |
| Lagrange Multiplier Test vs. Model (3) =   48.14 |
| ( 1 df, prob value =  .000000)                   |
| (High values of LM favor FEM/REM over CR model.) |
| Baltagi-Li form of LM Statistic =          48.14 |
|             Sum of Squares          .147022D+01  |
|             R-squared               .984426D+00  |
+--------------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
LOGY	.14792***	.02452234	6.032	.0000	-6.1192275
LOGP	-.16096***	.02127079	-7.567	.0000	-.5325998
LOGC	-.12603***	.01785398	-7.059	.0000	-8.9901333
LOGG1	.80548***	.02254132	35.734	.0000	4.3065209
Constant	.49875***	.07497369	6.652	.0000	

Note: ***, **, * = Significance at 1%, 5%, 10% level.

(5) Suitable instruments for this model, using data within the model, might include a time trend and lagged values of income, price and cars per capita. What are the explicit assumptions which would justify this suggestion.

The explicit assumptions would be that these variables are correlated with the lagged value of $\log G_{i,t}$ but they are uncorrelated with u_i and with ε_{it}.

(6) Compute the instrumental variable estimates for this model, ignoring the random effect term, u_i.

```
--> samp;all$
--> create;logy1=logy[-1];logp1=logp[-1];logc1=logc[-1]$
--> reject;t=1$
--> 2sls
    ;lhs=logg
    ;rhs=x
    ;inst=one,logy,logp,logc,t,logy1,logp1,logc1$
+----------------------------------------------------+
| Two stage   least squares regression               |
| LHS=LOGG     Mean                    =   4.281163   |
|              Standard deviation      =   .5406116   |
| WTS=none     Number of observs.      =        324   |
| Model size   Parameters              =          5   |
|              Degrees of freedom      =        319   |
| Residuals    Sum of squares          =   1.670324   |
|              Standard error of e     =   .7236107E-01
| Fit          R-squared               =   .9820286   |
|              Adjusted R-squared      =   .9818033   |
| Model test   F[  4,   319] (prob) =4357.86 (.0000)  |
| Diagnostic   Log likelihood          =   393.6355   |
|              Restricted(b=0)         =  -259.9578   |
|              Chi-sq [  4]  (prob) =1307.19 (.0000)  |
| Info criter. LogAmemiya Prd. Crt. =  -5.236859      |
|              Akaike Info. Criter. =  -5.236862      |
|              Bayes Info. Criter.  =  -5.178517      |
| Autocorrel   Durbin-Watson Stat.  =  1.1862635      |
|              Rho = cor[e,e(-1)]   =   .4068683      |
| Not using OLS or no constant. Rsqd & F may be < 0. |
| Model was estimated Mar 23, 2009 at 09:43:42AM     |
+----------------------------------------------------+
| Instrumental Variables:
|ONE      LOGY      LOGP      LOGC      T        LOGY1     LOGP1     LOGC1
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	.66980***	.15453441	4.334	.0000	
LOGY	.22631***	.05858391	3.863	.0001	-6.1192275
LOGP	-.23625***	.05753897	-4.106	.0000	-.5325998
LOGC	-.18348***	.05047775	-3.635	.0003	-8.9901333
LOGG1	.74790***	.06472725	11.555	.0000	4.3065209

Note: ***, **, * = Significance at 1%, 5%, 10% level.

(7) Under the assumptions made so far (presumably), this model can be viewed as a special case of the Hausman and Taylor model discussed in class. Show how this is the case, then propose how to estimate the parameters of the model.

The Hausman and Taylor formulation is a random effects model with

$x_{1,it}$ = time varying variables that are uncorrelated with u_i
$x_{2,it}$ = time varying variables that are correlated with u_i

$z_{1,it}$ = time invriant variables that are uncorrelated with u_i
$z_{1,it}$ = time invariant variables that are correlated with u_i

In the model in this exercise,
x_1 is everything save the lagged value of logG
x_2 is the lagged value of logG
z_1 is the constant term (in principle). There are no other variables in z_1
z_2 is empty.

The H&T estimator is a four step estimator discussed in class. The instrumental variables for lagged logG are the group means of the variables in x_1. There are three of them, so the identification issue is not a problem.

This model is also in the form of the Arellano and Bond formulation, so their method suggests another way to proceed. There are several different variations on the A&B method, depending on how many lags (and leads) of the exogenous variables should be used as instruments.

NOTE: Baltagi, Chapter 8, contains an application of this sort of model. (Ignore the λ_t term in his application.)

```
Sample   ; all $
Create   ; logg=lgaspcar ; logy=lincomep ; logp=lrpmg ;logc=lcarpcap$
Create   ; logg1 = logg[-1] $
Namelist ; x1 = logy, logp,logc  ; x2 = logg1  ; z1=one $
Calc     ; kx1 = col(x1) ; kx2 = col(x2) ; kz1 = col(z1) ; kz2=0$
Reject   ; year = 1960 $
Regress  ; lhs = logg ; rhs = x1,x2 ; pds=18 ; fixed ; panel $
Calc     ; s2e = ssqrd $
Namelist ; x = x1,x2 $
Create   ; dwit = logg - x'b $
Regress  ; lhs = dwit ; rhs = one ; pds = 18 ; panel ; keep = dwi $
2sls     ; lhs = dwi ; rhs=z1 ; inst = x1,z1 $
Calc     ; s2s = ssqrd $
Calc     ; s2u = s2s - s2e/18 $
Regress  ; lhs = logg  ; rhs = x1,x2,z1
; panel ; pds=18 ; random
; start=kx1,kx2,kz1,0,s2e,s2u$
```

```
+----------------------------------------------------+
| Random Effects Model: v(i,t) = e(i,t) + u(i)       |
| Estimates:  Var[e]              =   .273408D-02    |
|             Var[u]              =   .634650D-02    |
|             Corr[v(i,t),v(i,s)] =   .698909        |
| This is the Hausman and Taylor IV estimator.       |
| Variance components provided by ;START=values      |
| No time invariant vars. correlated with u(i)       |
+----------------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
+--------+
|LOGY    |     .16320***       .03275540     4.982   .0000  -6.1192275|
|LOGP    |    -.17093***       .02383122    -7.172   .0000   -.5325998|
|LOGC    |    -.15939***       .02114784    -7.537   .0000  -8.9901333|
+--------+
|LOGG1   |     .73368***       .02725711    26.917   .0000   4.3065209|
+--------+
|Constant|     .59621***       .10287641     5.795   .0000            |
+--------+------------------------------------------------------------+
| Note: ***, **, * = Significance at 1%, 5%, 10% level.               |
+---------------------------------------------------------------------+
```

Part II. A GMM Estimator

Continuing problem (1), with the model

$$\log G_{i,t} = \beta_1 + \beta_2 \log Y_{i,t} + \beta_3 \log P_{i,t} + \beta_4 \log C_{i,t} + \beta_5 \log G_{i,t-1} + u_i + \varepsilon_{i,t}$$

suppose it is proposed to estimate the model by relying on the following orthogonality conditions:

let $\mathbf{z}_{i,t} = (\log Y_{i,t}, \log P_{i,t}, \log C_{i,t})$

Then, we assume

$$E[\quad (u_i + \varepsilon_{i,t})] = 0,$$
$$E[\mathbf{z}_{i,t} \times (u_i + \varepsilon_{i,t})] = 0,$$
$$E[\mathbf{z}_{i,t-1} \times (u_i + \varepsilon_{i,t})] = 0,$$
$$E[\mathbf{z}_{i,t-2} \times (u_i + \varepsilon_{i,t})] = 0$$

(1) Show that this set of conditions is sufficient to estimate the model. Write out the 10 moment conditions. I.e., show precisely how to set up the moment conditions for estimation.

There are 9 variables plus the constant term listed in the set of condisions. For convenience, let Z_{it} denote them. Note also that two observations are lost when constructing the moments. In any event, based on these, we are looking for the 5 parameter values that satisfy the 10 equations

$$\left[\frac{1}{N(T-2)}\sum_{i,t=3...19} Z_{it}(\log G_{i,t} - \beta_1 - \beta_2 \log Y_{it} - \beta_3 \log P_{it} - \beta_4 \log C_{it} - \beta_5 \log G_{i,t-1})\right] = 0$$

There are too many equations, but obviously, the equations are sufficient to identify the parameters. Any 5 of them will do, and we have 10. The GMM estimator will use all 10 equations as efficiently as possible.

(2) Construct the GMM estimator.

See below.

(Looks like a typo. There is no part 3.)

(3) Compute the GMM estimator and test the overidentifying restrictions. Discuss the implications of the test results.

The program below computes several different estimates. The full GMM estimator is given last. The standard errors do seem to fall as more information is added. Note that the GMM estimator makes use of the correlation across years, while the other two do not.

```
Sample ; all $
Create ; g=lgaspcar ; g1 = g[-1] $
Create ; y=lincomep ; y1 = y[-1] ; y2 = y[-2] $
create ; p=lrpmg    ; p1 = p[-1] ; p2 = p[-2] $
Create ; c=lcarpcap ; c1 = c[-1] ; c2 = c[-2] $
Reject ; Year < 1962 $
Namelist ; x = one,y,p,c,g1$
Namelist ; z = one,y,p,c,y1,p1,c1,y2,p2,c2 $
2sls ; lhs = g ; rhs = x ; inst = z ; res = e $

Heteroscedasticity only
=======================
Create ; e2 = e*e $
Matrix ; W = <z'[e2]z> $
Matrix ; vgmm = x'z*w*z'x ; vgmm=<vgmm>
       ; bgmm = vgmm * x'z * w * z'g $
Matrix ; stat(bgmm,vgmm,x)$

Cross period correlation due to random effect
=============================================
Sample;all $
Reject ; Year < 1962 $
Matrix ; zeez = init(10,10,0)$
Proc = wmat $
Include ; new ; country = i  & year > 1961 $
Matrix  ; ze = z'*e ; zeez = zeez + ze*ze' $
Endproc$
Exec ; i=1,18$

Sample;all $
Reject ; Year < 1962 $
Matrix ; W = <zeez> $
Matrix ; vgmm = x'z*w*z'x ; vgmm=<vgmm>
       ; bgmm = vgmm * x'z * w * z'g $
Matrix ; stat(bgmm,vgmm,x)$

GMM Criterion
==============
Sample ; all $
Reject ; year < 1962 $
Matrix ; egmm = g - X*bgmm
  ; list ; q = egmm'Z * W * Z'egmm $

Matrix Q        has  1 rows and  1 columns.
               1
        +--------------
       1|   13.38767
```

2SLS

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	.62653***	.12012137	5.216	.0000	
Y	.20147***	.04519272	4.458	.0000	-6.0994603
P	-.21031***	.04432644	-4.745	.0000	-.5407110
C	-.15981***	.03880791	-4.118	.0000	-8.9402302
G1	.77503***	.04964613	15.611	.0000	4.2911591

Note: ***, **, * = Significance at 1%, 5%, 10% level.

Heteroscedasticity

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
Constant	.50891***	.12932957	3.935	.0001
Y	.11170**	.04692009	2.381	.0173
P	-.11452**	.04580170	-2.500	.0124
C	-.06671*	.04014253	-1.662	.0966
G1	.88009***	.05149707	17.090	.0000

Note: ***, **, * = Significance at 1%, 5%, 10% level.

GMM

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]
Constant	.67652***	.09446681	7.161	.0000
Y	.21347***	.03529008	6.049	.0000
P	-.20713***	.02343071	-8.840	.0000
C	-.15832***	.02473016	-6.402	.0000
G1	.78497***	.03505659	22.392	.0000

Note: ***, **, * = Significance at 1%, 5%, 10% level.

Part III. Minimum Distance Estimation

This exercise will be based on the Spanish dairy farm data. This is a panel data set of 247 individuals (farms) each observed 6 times, in years 1993, 1994, …, 1998. For this exercise, we will use 3 of the years, 1993, 1995, and 1997, which will be denoted t=1, t=2 and t=3 below.

Consider Chamberlain's formulation of the fixed effects model:

$$y_{it} = \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it},\ i = 1,\ldots,N;\ t = 1,2,3.$$

We parameterize the fixed effect here as

$$\alpha_i = \mathbf{x}_{i1}'\boldsymbol{\delta}_1 + \mathbf{x}_{i2}'\boldsymbol{\delta}_2 + \mathbf{x}_{i3}'\boldsymbol{\delta}_3 + u_i.$$

Making the substitution, we obtain the random effects model,

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \mathbf{x}_{i1}'\boldsymbol{\delta}_1 + \mathbf{x}_{i2}'\boldsymbol{\delta}_2 + \mathbf{x}_{i3}'\boldsymbol{\delta}_3 + u_i + \varepsilon_{it},\ i = 1,\ldots,N;\ t = 1,2,3.$$

(We note, this has some redundancies in it; in each specific period, t, x_{it} appears in the equation twice.) Now, consider how to estimate the parameters. We can estimate the parameters using the data for the three periods separately. For the three periods,

$$\begin{aligned}
y_{i1} &= \mathbf{x}_{i1}'(\boldsymbol{\beta}+\boldsymbol{\delta}_1) + \mathbf{x}_{i2}'\boldsymbol{\delta}_2 + \mathbf{x}_{i3}'\boldsymbol{\delta}_3 + u_i + \varepsilon_{i1},\ i = 1,\ldots,N.\\
y_{i2} &= \mathbf{x}_{i1}'\boldsymbol{\delta}_1 + \mathbf{x}_{i2}'(\boldsymbol{\beta}+\boldsymbol{\delta}_2) + \mathbf{x}_{i3}'\boldsymbol{\delta}_3 + u_i + \varepsilon_{i2},\ i = 1,\ldots,N.\\
y_{i3} &= \mathbf{x}_{i1}'\boldsymbol{\delta}_1 + \mathbf{x}_{i2}'\boldsymbol{\delta}_2 + \mathbf{x}_{i3}'(\boldsymbol{\beta}+\boldsymbol{\delta}_3) + u_i + \varepsilon_{i3},\ i = 1,\ldots,N.
\end{aligned}$$

Using the dairy data, let $\mathbf{x}_{it}$ = X1,X2,X3,X4 for the period. To make it a little more convenient, we will use y_{it} in deviations form and omit the constant term in each equation.

a. Using the data on YI1 = YIT for period 1 (1993), regress YI1 on $\mathbf{x}_{i1}$,, $\mathbf{x}_{i2}$, and $\mathbf{x}_{i3}$. That will be a regression of YI1 (1993) on three years of **x**s, 1993, 1995 and 1997. That will produce 12 estimated coefficients.

b. Repeat part a using data for YI2 and Yi3. Note that each regression produces 12 estimated coefficients.

These are the OLS coefficients. The program appears below.

```
Matrix C          has 12 rows and  3 columns.
                    1             2             3
        +-------------------------------------------
       1|      .67011        .03248        .00368
       2|     -.01313       -.01075        .04148
       3|     -.01889        .05185       -.04949
       4|      .42306        .05712        .00244
       5|      .00901        .55407       -.01453
       6|     -.02494        .02822       -.03758
       7|     -.10241       -.05939       -.08226
       8|      .00794        .28731        .03796
       9|     -.01082       -.06117        .56585
      10|      .00769        .04163        .03000
      11|      .13605        .01350        .17751
      12|     -.02583        .13682        .43877
```

c. Note that from the listing above, you can see that you have two direct estimates of $\boldsymbol{\delta}_1$. What are these? (I.e., specifically, what are the numerical values?)

The two estimates of δ_1 are bold in the matrix above.

```
--> Matrix    ; list ; delta12 = c(1:4,2:2)
    ; delta13 = c(1:4,3:3) $

Matrix DELTA12  has  4 rows and  1 columns.
                    1
        +--------------
       1|      .03248
       2|     -.01075
       3|      .05185
       4|      .05712

Matrix DELTA13  has  4 rows and  1 columns.
                    1
        +--------------
       1|      .00368
       2|      .04148
       3|     -.04949
       4|      .00244
```

d. Based on the three equations, you can see, by subtraction, that the results in part c., combined with your results from the first equation, provide two different estimates of $\boldsymbol{\beta}$. What are these two different estimates?

The estimator of $\beta+\delta_1$ are underlined in the matrix above. The two results of subtraction are shown below.

```
--> Matrix   ; list ; beta11 = c(1:4,1:1) - delta12
    ; beta12 = c(1:4,1:1) - delta13 $

Matrix BETA11   has  4 rows and  1 columns.
              1
        +--------------
       1|      .63763
       2|     -.00237
       3|     -.07074
       4|      .36595

Matrix BETA12   has  4 rows and  1 columns.
              1
        +--------------
       1|      .66643
       2|     -.05461
       3|      .03060
       4|      .42063
```

e. In fact, using the direct estimates of $\boldsymbol{\delta}_2$ and the second equation, you can obtain two more estimates of $\boldsymbol{\beta}$. What are these estimates? (I.e., give the values.) The third equation produces yet two more estimates of $\boldsymbol{\beta}$, for 6 estimates in total. Show the 6 sets of values.

Here are 4 more estimators of β

```
Matrix ; delta21 = c(5:8,1:1) ; delta23=c(5:8,3:3)
Matrix ; list ; beta21 = c(5:8,2:2) - delta21
              ; beta23 = c(5:8,2:2) - delta23 $

Matrix ; delta31 = c(9:12,1:1) ; delta32=c(9:12,2:2)
Matrix ; list ; beta31 = c(9:12,3:3) - delta31
              ; beta32 = c(9:12,3:3) - delta32 $
Matrix BETA21   has  4 rows and  1 columns.
               1
        +--------------
       1|      .54505
       2|      .05316
       3|      .04302
       4|      .27937

Matrix BETA23   has  4 rows and  1 columns.
               1
        +--------------
       1|      .56860
       2|      .06579
       3|      .02288
       4|      .24935

Matrix BETA31   has  4 rows and  1 columns.
               1
        +--------------
       1|      .57667
       2|      .02230
       3|      .04146
       4|      .46460

Matrix BETA32   has  4 rows and  1 columns.
               1
        +--------------
       1|      .62701
       2|     -.01164
       3|      .16401
       4|      .30194
```

f. Your three estimated equations provide a total of $3\times12 = 36$ estimates of parameters. Your model contains $4 + 3(4) = 16$ unique parameters. Describe a method that you can use to combine your different estimates of the parameters in an efficient manner.

We could use a minimum distance estimator. There are 3 least squares estimates of 12 parameters each. Denote the X matrices in each by X_1, X_2 and X_3. Each of these is 247 rows and 12 columns. The covariance matrix of the 36×1 long vector of estimates obtained by stacking the three estimates is a partitioned matrix whose each submatrix is

$$V_{l,m} = \sigma_{lm}(X_l'X_l)^{-1}X_l'X_m(X_m'X_m)^{-1}.$$

This makes a 36×36 covariance matrix. The 36×1 vector of least squares estimates is

$$b = [b_1', b_2', b_3']'.$$

The 36×1 vector of unknown parameters is the stack of the three parameter vectors shown above,

$$\Delta' = (\beta+\delta_1)', \delta_2', \delta_3', \delta_1', (\beta+\delta_2)', \delta_3', \delta_1', \delta_2', (\beta+\delta_3)'$$

The MDE would look for the 12 values of the unknowns that minimize

$$(b - \Delta)' V^{-1} (b - \Delta).$$

Wooldridge notes that there is a somewhat simpler way to formulate this problem. We can write the whole thing as a generalized regression model,

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{bmatrix} X_1 & X_1 & X_2 & X_3 \\ X_2 & X_1 & X_2 & X_3 \\ X_3 & X_1 & X_2 & X_3 \end{bmatrix} \begin{pmatrix} \beta \\ \delta_1 \\ \delta_2 \\ \delta_3 \end{pmatrix} + \begin{pmatrix} u_1+\varepsilon_1 \\ u_2+\varepsilon_2 \\ u_3+\varepsilon_3 \end{pmatrix}$$

There are a couple different ways this can be fit by GLS, either explicitly accounting for the random effects form, or treating it is a SUR model with free correlation across periods.

PROGRAMMING:

Using NLOGIT, we will do the computations using matrix algebra. You can do parts a. – d. using the following commands:

```
Create   ; Y = Dev(yit)$
Namelist ; X = x1,x2,x3,x4 $
Include  ; new ; year93=1 $
Matrix   ; x93 =  x ; y93 = y $
Include  ; new ; year95=1 $
Matrix   ; x95 =  x ; y95 = y $
Include  ; new ; year97=1 $
Matrix   ; x97 =  x ; y97 = y $
Matrix   ; allX = [x93,x95,x97] $
Matrix   ; ally = [y93,y95,y97] $
Matrix   ; list ; c = <allX'allX> * allX'ally $
? Estimates of delta 1. Note syntax c(rows r1:r2, columns c1:c2)
Matrix   ; list ; delta12 = c(1:4,2:2)
                ; delta13 = c(1:4,3:3) $
? Estimates of beta using delta1
Matrix   ; list ; beta11 = c(1:4,1:1) - delta12
                ; beta12 = c(1:4,1:1) - delta13 $
Matrix ; delta21 = c(5:8,1:1) ; delta23=c(5:8,3:3)
Matrix ; list ; beta21 = c(5:8,2:2) - delta21
              ; beta23 = c(5:8,2:2) - delta23 $

Matrix ; delta31 = c(9:12,1:1) ; delta32=c(9:12,2:2)
Matrix ; list ; beta31 = c(9:12,3:3) - delta31
              ; beta32 = c(9:12,3:3) - delta32 $
```

Now, add the necessary instructions to do the rest of the computations. We will pursue the actual estimation of the parameters and the appropriate asymptotic covariance matrix in class.