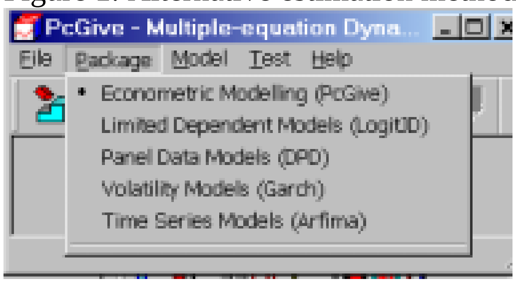
PcGive 10:0 Alternative estimation packages

Index:

Introduction

This document follows on from the document Givewin 2 and PcGive 10. That document discussed the option Econometric Modelling (PcGive). In this document we discuss the other options available for estimation. Figure 1 reports the range of estimation methods available within PcGive, which are obtained by clicking on Package.

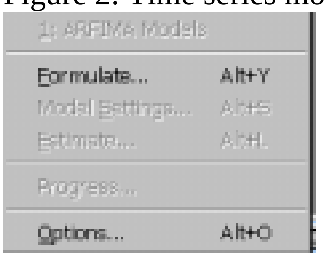
Figure 1: Alternative estimation methods available in PcGive



1.0 Time Series Models (Arfima)

Choosing Time Series Models (Arfima) you get Figure 2.

Figure 2: Time series models options



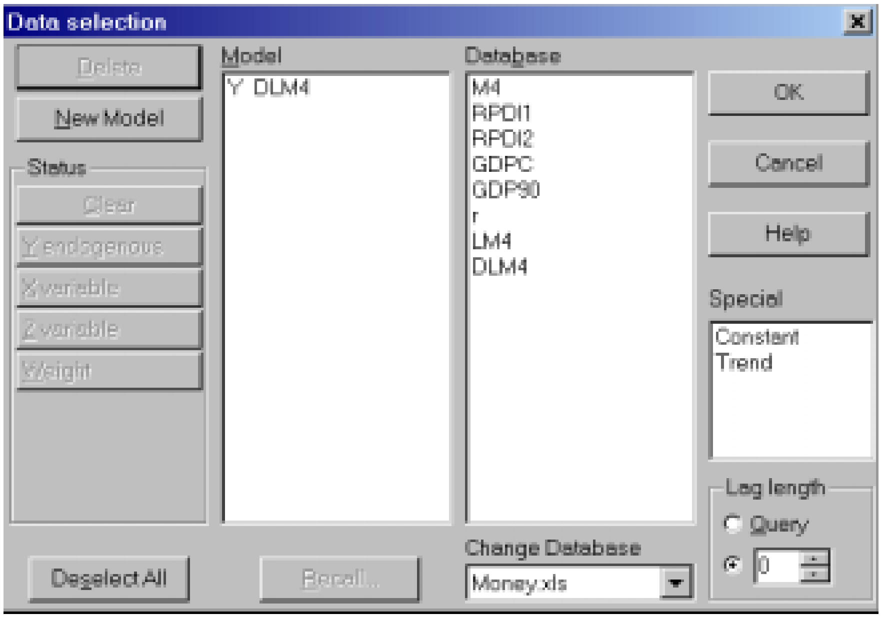
Clicking on Formulate you get Figure 3. This is the formulate window observed in Single-equation Dynamic Modelling (see Figure ? in the document Givewin 2 and PcGive 10). To move a variable from the Database box to the Model box, click on the variable and click <<Add.
Consider estimating the ARMA(1,1) model for the variables DLM4, written as:

$$(1-\phi L)DLM4_t = \mu + (1+\theta L)\varepsilon_t$$

The data selection box therefore appears as Figure 3.

1.1 Model formulation

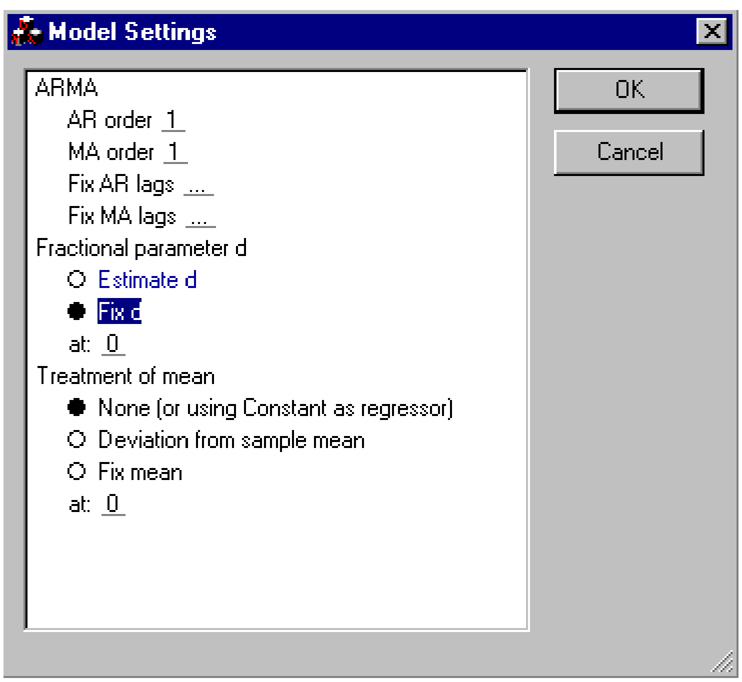
Figure 3: Model selection window



Clicking OK you get Figure 4 and are required to specify the order of the AR and MA elements.

1.2 Model setting

Figure 4: Model setting window

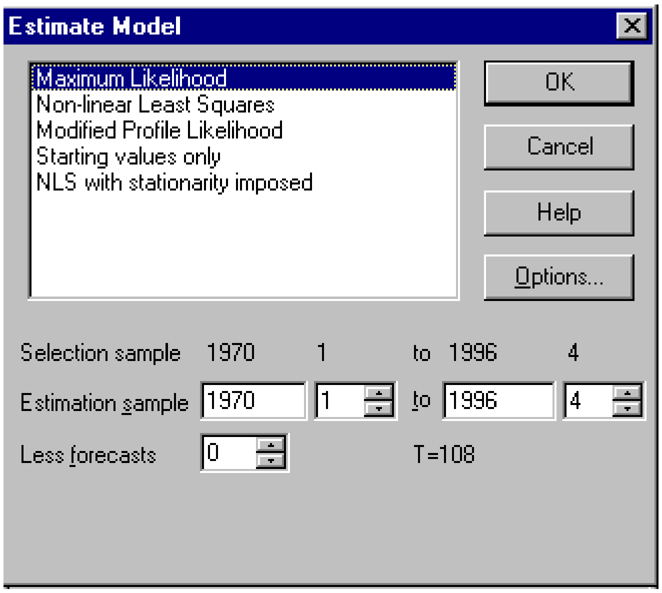


I specify the AR order at 1 and the MA order at 1. Additionally, within the selection of the Fractional parameter d, select Fix d and ensure it is fixed at 0 (the fractional parameter refers to the number of times you wish your underlying series to be differenced to induce stationarity as DLM$ is the first difference of he log of M4, we believe d=0).

1.3 Model estimation

Clicking OK in Figure 4 you get Figure 5. This requires you to specify the estimation method. In general Maximum Likelihood would appear the best option:

Figure 5: Estimation options



In addition to choosing the estimation method, you must select he sample period over which you wish to estimate the model. While recursive options are not available, it is still possible to save some of the data points for forecasting. Clicking OK gives you the results below:

```
---- Maximum likelihood estimation of ARFIMA(1,0,1) model ----
The estimation sample is:  1970 (2) - 1996 (4)
The dependent variable is: DLM4  (Money.xls)

                  Coefficient  Std.Error  t-value  t-prob
AR-1                 0.892437    0.05999     14.9   0.000
MA-1                -0.481616     0.1247    -3.86   0.000
Constant            0.0307707   0.004264     7.22   0.000

log-likelihood     343.092885
no. of observations       107  no. of parameters           4
AIC.T              -678.18577  AIC                -6.33818477
mean(DLM4)          0.0311847  var(DLM4)          0.000178658
sigma              0.00976613  sigma^2            9.53772e-005

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence
Used starting values:
      0.84885     -0.30387     0.031185
```

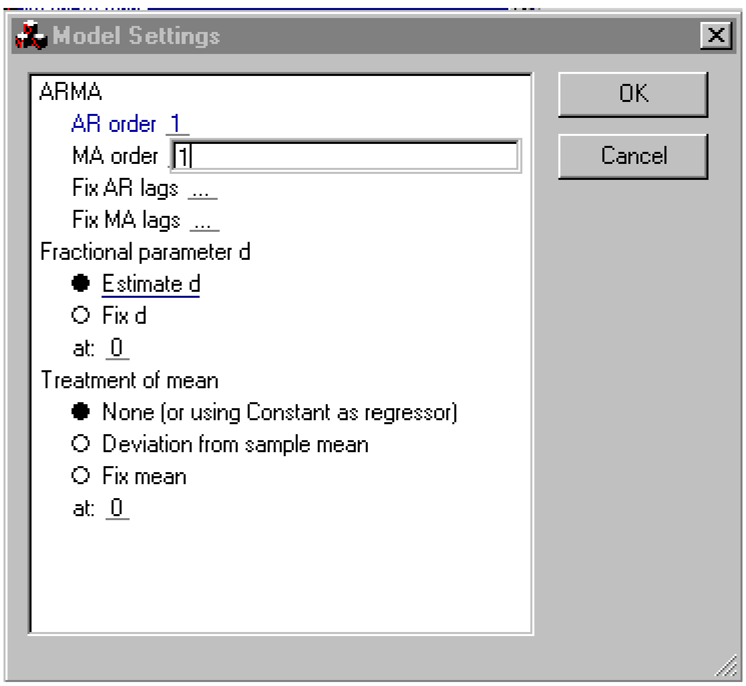
in which $\hat{\phi} = 0.892$ and $\hat{\theta} = -0.482$ and both parameters are highly significant.

To estimate an ARFIMA(1,d,1) model, which is written as:

$$(1-L)^d (1-\phi L) DLM4_t = \mu + (1+\theta L)\varepsilon_t$$

in which d is a fractional parameter and for stationarity is assumed hat –0.5<d<0.5 In this case I feel that the unit difference imposed in creating DLM4 is not precisely correct and I have either under-differences and 0.0<d<0.5 or I have over-differenced and –0.<d<0.0. To estimate this model we have the same model formulation window (see Figure 3) and in Figure 4, you choose the Estimate d option (see Figure 6 below)

Figure 6: Model settings window



Clicking OK and in Figure 5 clicking OK and using maximum likelihood, you estimate the ARFIMA(1,d,1) model, the results are reported below.

```
---- Maximum likelihood estimation of ARFIMA(1,d,1) model ----
The estimation sample is:  1970 (2) - 1996 (4)
The dependent variable is: DLM4  (Money.xls)

                  Coefficient  Std.Error  t-value  t-prob
d parameter        0.00613175     0.7064  0.00868   0.993
AR-1                 0.891442     0.1300     6.85   0.000
MA-1                -0.486757     0.6007   -0.810   0.420
Constant            0.0307653   0.004301     7.15   0.000

log-likelihood     343.092921
no. of observations       107  no. of parameters           5
AIC.T             -676.185841  AIC                 -6.31949384
mean(DLM4)          0.0311847  var(DLM4)           0.000178658
sigma                0.009766  sigma^2            9.53748e-005
```

```
BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence
Used starting values:
      0.40000      0.89971     -0.44404     0.031185
```

From these results we have $\hat{d} = 0.006$ and this is insignificantly different from zero at all conventional levels of significance, in which case the ARMA(1,1) model for DLM seems a better model.

1.4 Model testing

Clicking on Test you get Figure 7.

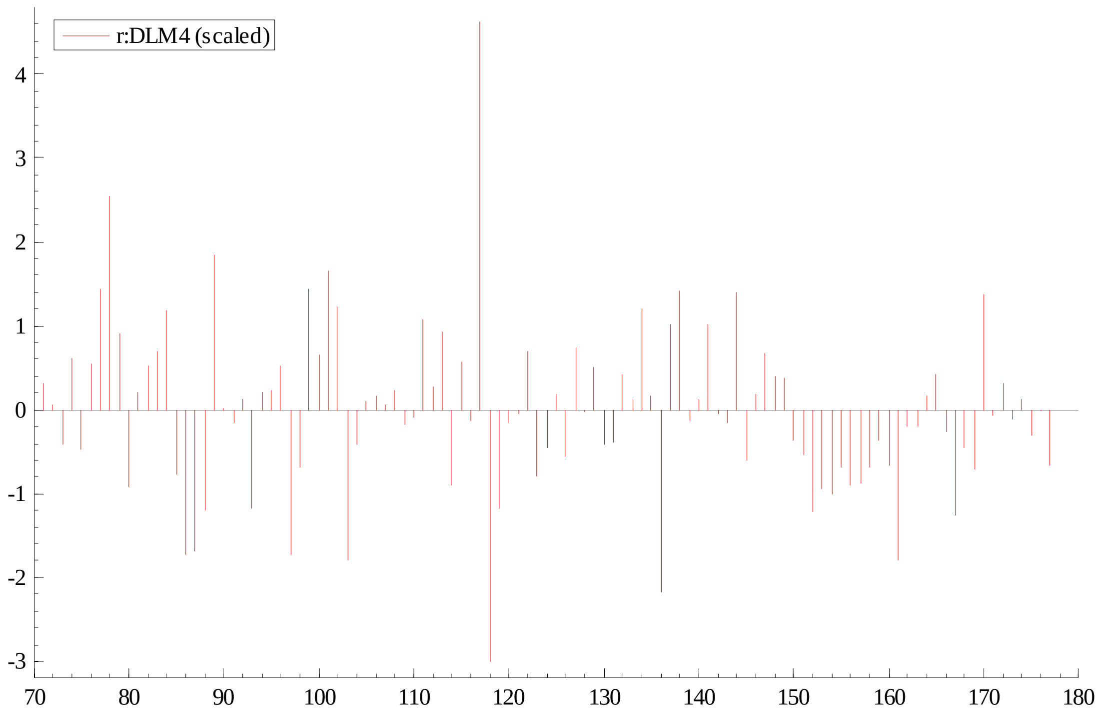
Figure 7: Testing window

The options here are very similar to those for Single-equation Dynamic Analysis (see section ? in the document Givewin 2 and PcGive 10 for a discussion of these options). Clicking on Test Summary, you get the results below, which suggest that the ARMA(1,1) model has severe non-normality problems as well s evidence of ARCH errors. The test of additional serial correlation in the error term is only just accepted at the 5% significance level.

```
Descriptive statistics for residuals:
Normality test:   Chi^2(2) =   30.023 [0.0000]**
ARCH 1-1 test:    F(1,102) =   8.8584 [0.0036]**
Portmanteau(10):  Chi^2(8) =   14.223 [0.0761]
```

The plot of the residuals suggests that at least the non-normality problem is due to the existence of outliers, which may also account for the ARCH errors

Figure 8: Residuals for the ARMA(1,1) model



[Further investigation discovered that both the non-normality and ARCH resultsare produced by the two outlier points – although serial correlation remains a problem].

2 Volatility models (Garch)

To estimate models from the ARCH family, in Figure 1 choose Volatility models. Then in PcGive select Model and then Formulate to get Figure 2. Specify the linear levels models you wish to estimate. For interest rates (r) we are wish to estimate the model:

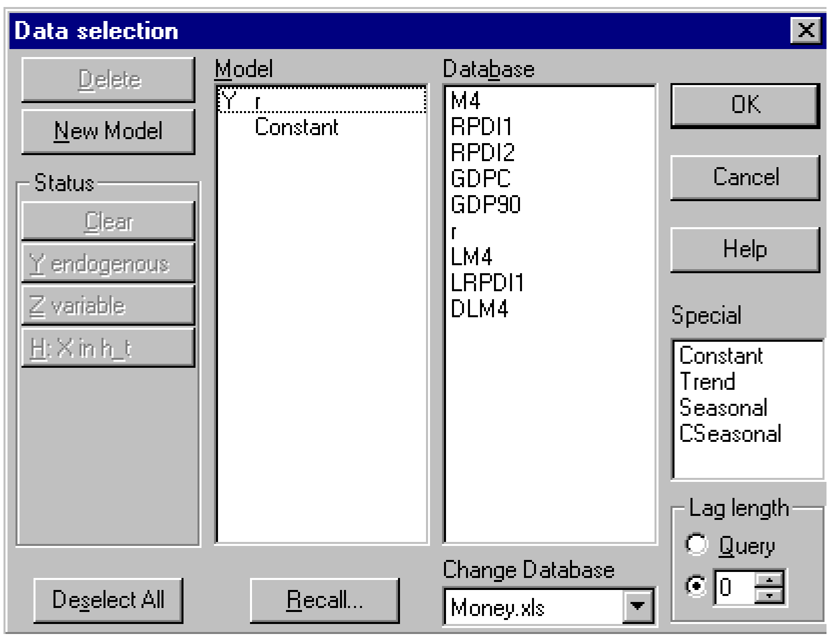
$$r_t = \mu + \varepsilon_t \quad z_t \sim II(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}$$

which is a simple GARCH(1,1) model.

2.1 Model formulation

Select r as the dependent variable and use a constant as the only explanatory variable, and you get Figure 9.

Figure 9: Model formulation window

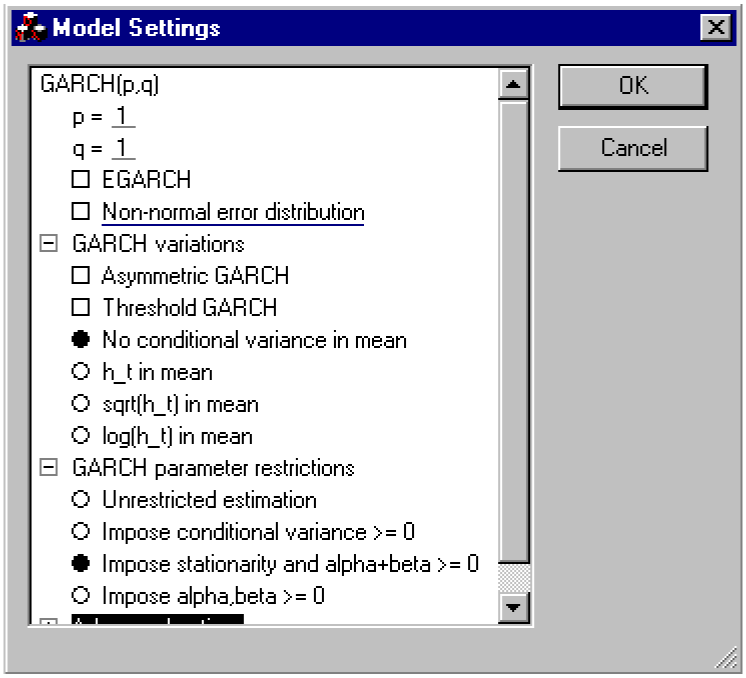


2.2 Model settings

Clicking OK you get Figure 10. From this Figure it is clear there are many estimation options available. In PcGive you can estimate (i) ARCH models (set q=0), (ii) GARCH models (p>0 and q>0), (iii) EGARCH models, (iv) Threshold GARCH models, and a variety of (v) GARCH in mean models. Additionally you are able to impose parameter restrictions on the ARCH-type models as well as allow non-normality in the error term.

From Figure 10, we estimate a GARCH(1,1) model (imposing stationarity, that is, $0 < \alpha_1 + \beta < 1$, with normal errors and with no feedback from the error variance model to the mean model

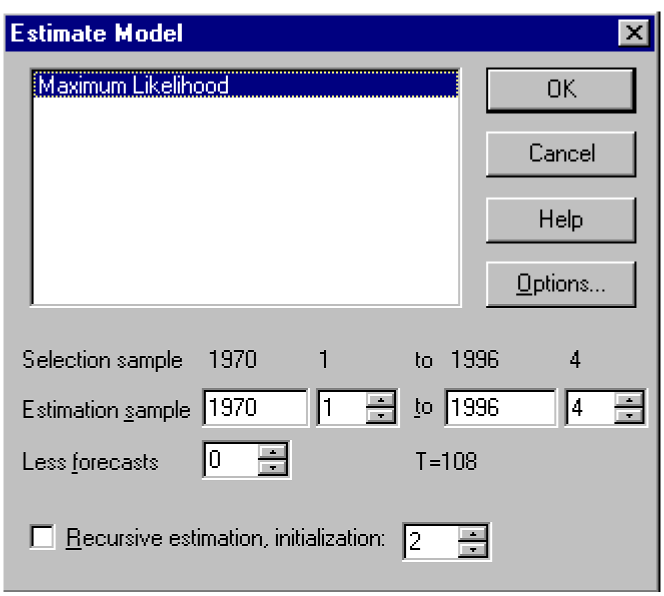
Figure 10: Model settings window



2.3 Model estimation

Setting p=1 and q=1 and selecting No conditional variance in mean and then selecting OK you get Figure 11.

Figure 11: Model estimation window



Here you choose the sample size (and select some observations for forecasting or select recursive estimation). Selecting OK produces the results below:

```
VOL( 1) Modelling r by restricted GARCH(1,1) (Money.xls)
        The estimation sample is: 1970 (1) to 1996 (4)

                  Coefficient  Std.Error  robust-SE  t-value  t-prob
Constant      X       6.92391     0.1082    0.07689     90.0   0.000
alpha_0       H      0.568883     0.2463     0.1931     2.95   0.004
alpha_1       H      0.955098
beta_1        H     0.0449017    0.08368    0.08454    0.531   0.596

log-likelihood    -239.035403  HMSE                 0.750458
mean(h_t)               14.08  var(h_t)              734.956
no. of observations       108  no. of parameters           4
AIC.T              486.070805  AIC                4.50065561
mean(r)                8.2537  var(r)                11.6063
alpha(1)+beta(1)            1  alpha_i+beta_i>=0, alpha(1)+beta(1)<1

Initial terms of alpha(L)/[1-beta(L)]:
      0.95510     0.042886    0.0019256  8.6464e-005  3.8824e-006
1.7433e-007
  7.8275e-009  3.5147e-010  1.5782e-011  7.0862e-013  3.1818e-014
1.4287e-015

Used sample mean of squared residuals to start recursion
Robust-SE based on analytical Information matrix and analytical OPG
matrix
BFGS using analytical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence
Used starting values:
       8.2537       2.3472      0.64847      0.14929
```

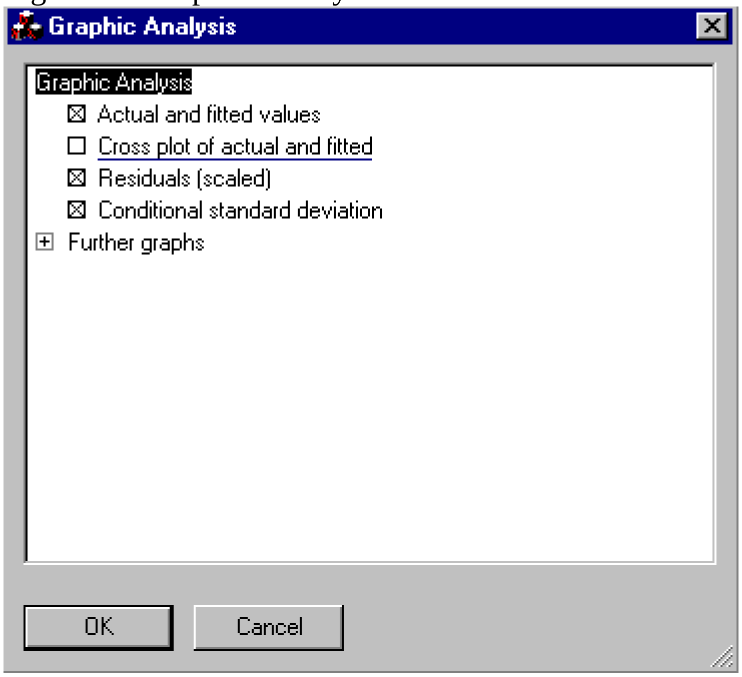
2.4 Model Testing

Clicking Test you get Figure 12.choosing Test Summary you get all but the Portmanteau test of squared residuals, that is:

```
Descriptive statistics for scaled residuals:
Normality test:   Chi^2(2) =   14.269 [0.0008]**
ARCH 1-2 test:    F(2,98)  =  0.24172 [0.7857]
Portmanteau(10):  Chi^2(10)=   223.87 [0.0000]**
```

Which indicates that the mean model is mis-specified and there is non-normality. Selecting graphical analysis produces Figure 13

Figure 13: Graphical analysis



Selecting Residuals and Conditional standard deviation produces Figure 14.

Figure 14

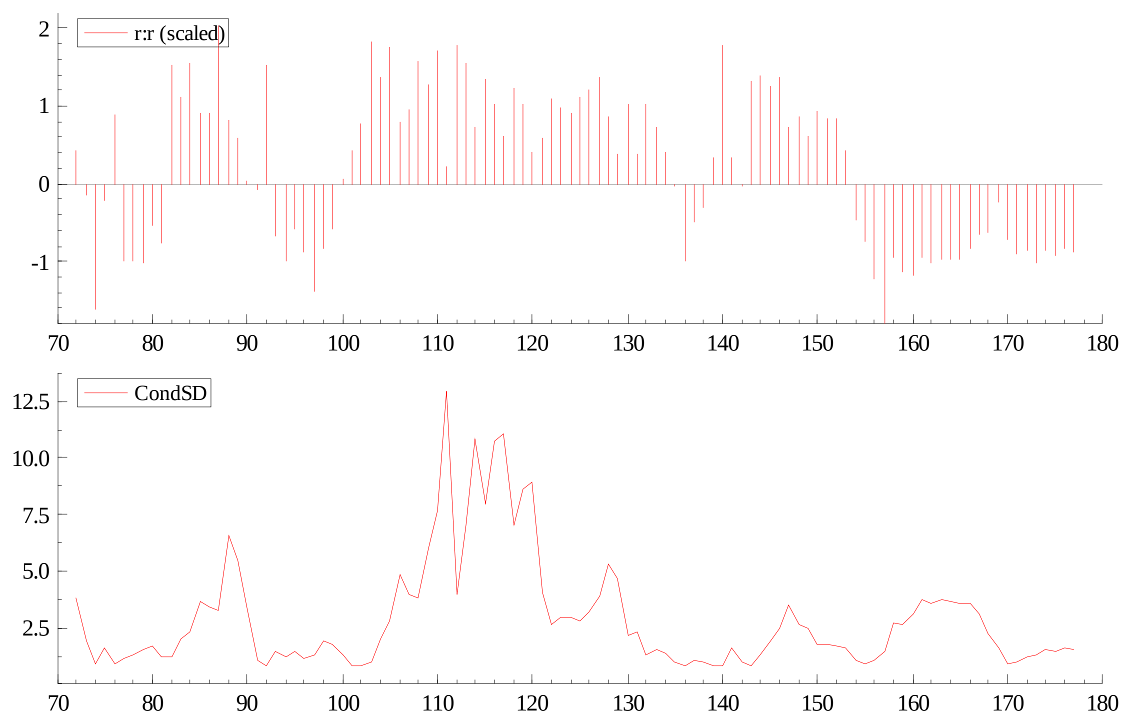
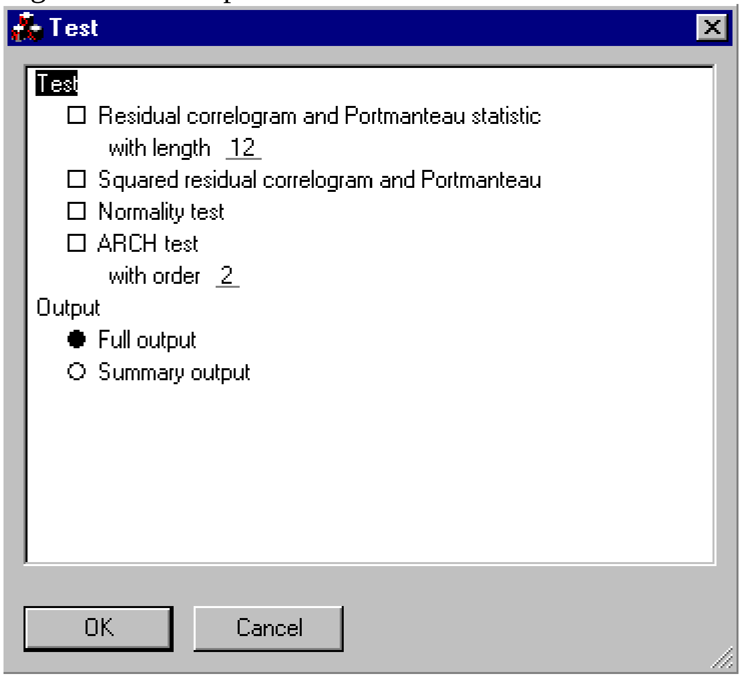


Figure 12: Test options

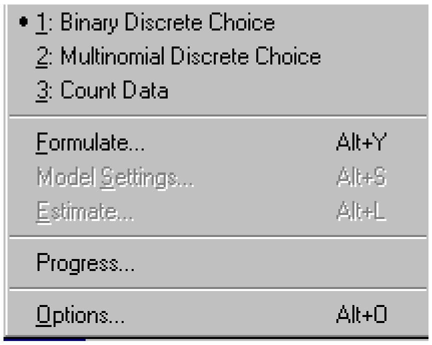


Selecting test options it is possible to undertake some basic tests of the mean model as well as the variance equation of this model.

3. Limited Dependent Models (LOGITJD)

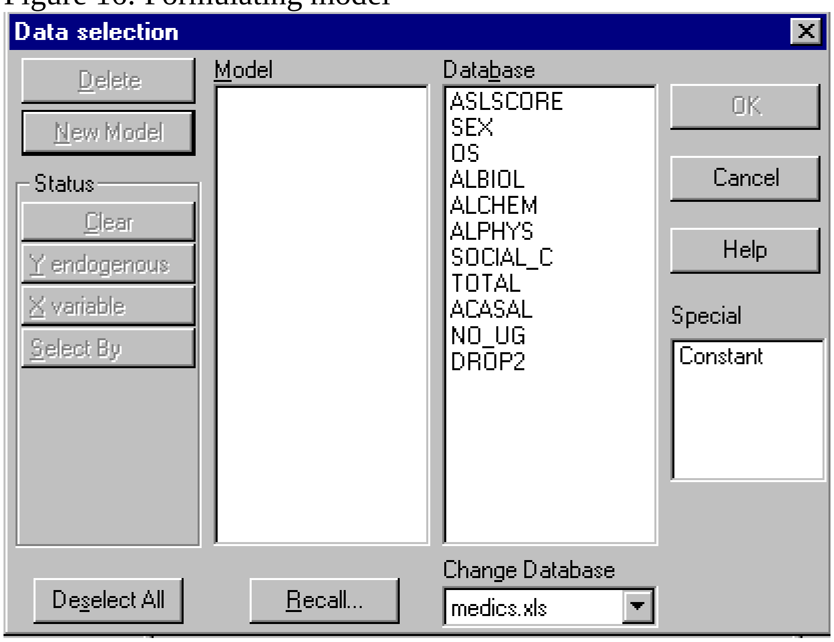
Prior to formulating the model you must specify the nature of your dependent variables as either a Binary Discrete Choice (two possible outcomes, for example, Success vs Failure); Multinomial Discrete Choice (many outcomes of the dependent variable – no ordering, for example, Mode of transport, e.g. walking, car, bus, train, bicycle), Count Data (for example, number of times…). We will only discuss the first of these options Binary Discrete Choice.

Figure 15: Estimation options in LOGITJD



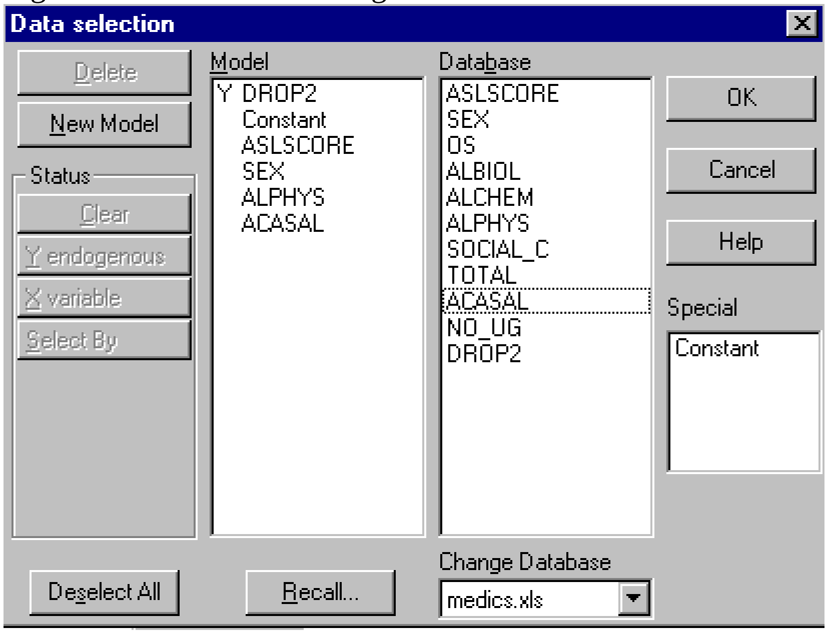
3.1 Model formulation

Figure 16: Formulating model



No lag options choose variables for the model in an identical fashion as elsewhere. We are interested in estimating a model of what determines whether students dropout of university. Figure 17 has the dependent variable as DROP2 and a series of 4 explanatory variables (excluding the intercept).

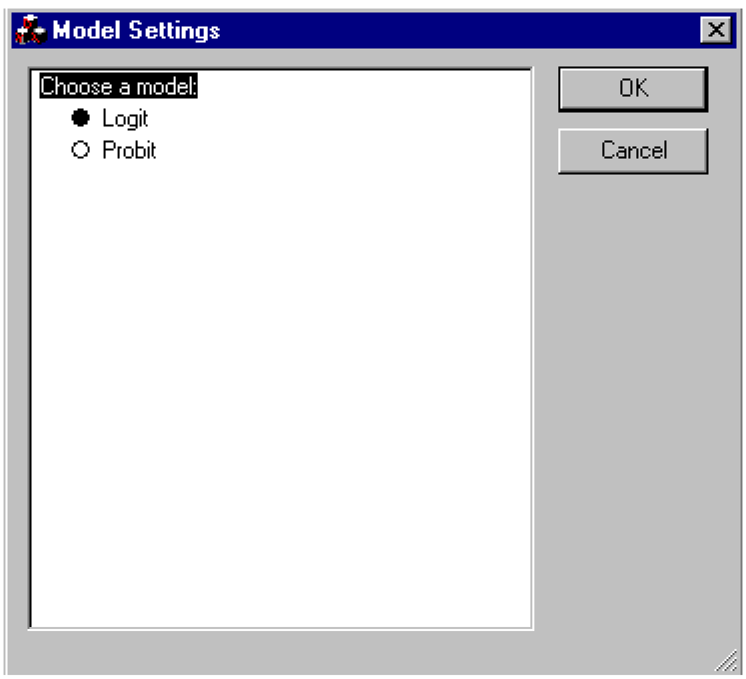
Figure 17: Model formulating



3.2 Model settings

Clicking OK in Figure 17, produces Figure 18.

Figure 18: Model settings

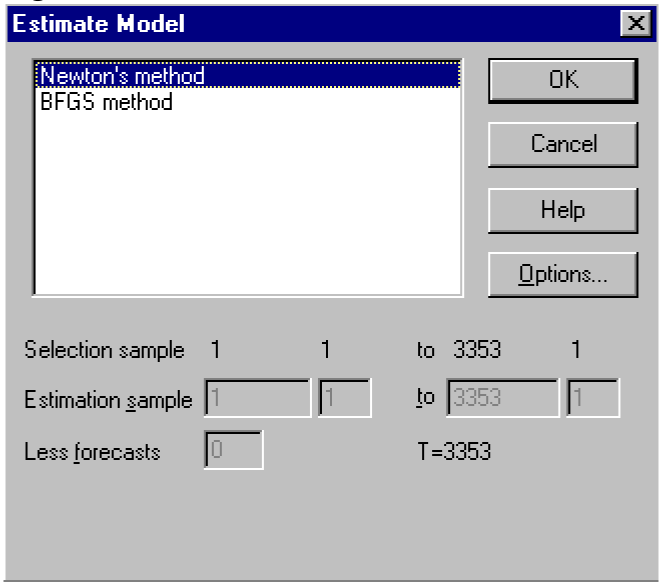


A probit model assumes that the error distribution is normal, whereas the logit model assumes the error distribution is logistic (which has fatter tails than the normal). Evidence shows that there is often little difference between the two sets of results.

3.3 Model estimation

Clicking OK produces the estimation model window (see Figure 19).

Figure 19: Model estimation



In addition, you must also select the estimation sample. Clicking OK produces the output below:

```
CS( 1) Modelling DROP2 by Logit
       The estimation sample is 1 - 3353

                  Coefficient  Std.Error  t-value  t-prob
Constant              5.02067     0.3120     16.1   0.000
ASLSCORE            -0.338614    0.01422    -23.8   0.000
SEX                  0.101642     0.1568    0.648   0.517
ALPHYS              0.0452791    0.02239     2.02   0.043
ACASAL            5.66246e-005 9.475e-006    5.98   0.000

log-likelihood    -646.986183  no. of states              2
no. of observations      3353  no. of parameters          5
baseline log-lik    -1084.941  Test: Chi^2(  4)      875.91 [0.0000]**
AIC                1303.97237  AIC/T             0.388897216
mean(DROP2)          0.099314  var(DROP2)          0.0894508
Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

              Count   Frequency Probability    loglik
State 0        3020     0.90069     0.90069    -201.4
State 1         333     0.09931     0.09931    -445.6
Total          3353     1.00000     1.00000    -647.0
```

In the sample some 9.9% of observations are dropouts (DROP2=1) and 90.9% are non-dropouts (DROP2=0). All variables with the exception of sex are significant at the 5% level.

3.4 Testing

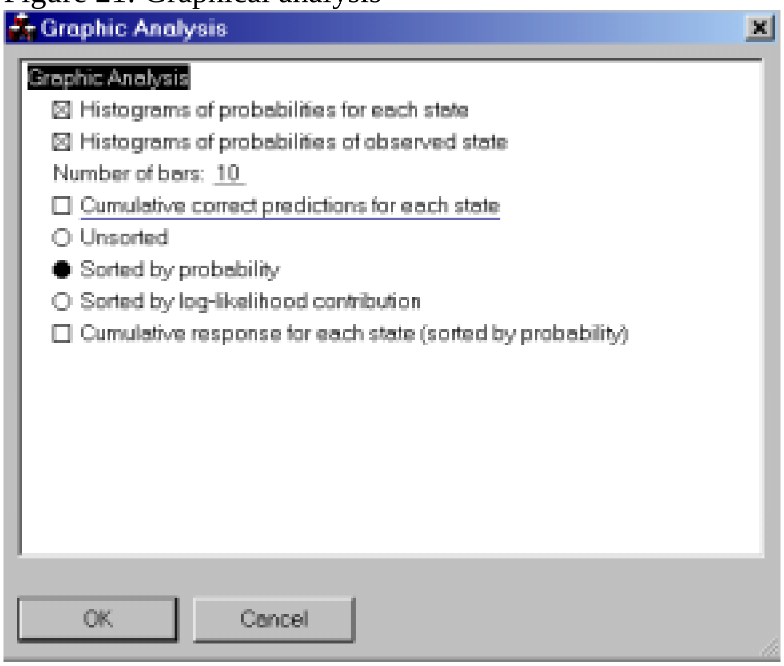
Clicking on Test you get Figure 20.

Figure 20: Test window

3.4.1 Graphical analysis

The graphical analysis available for these limited dependent variable models is different from those seen elsewhere.

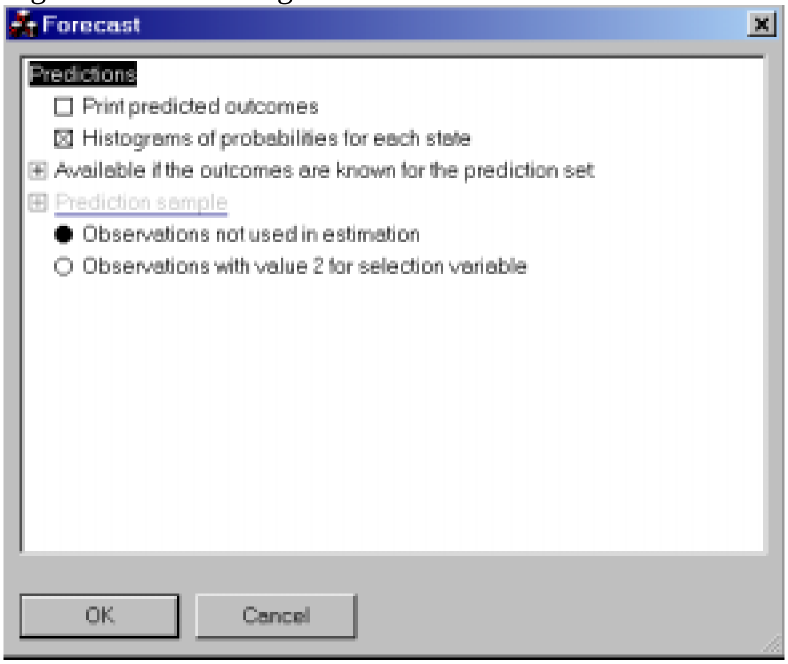
Figure 21: Graphical analysis



The graphs available are not particularly useful.

3.4.2 Forecasting

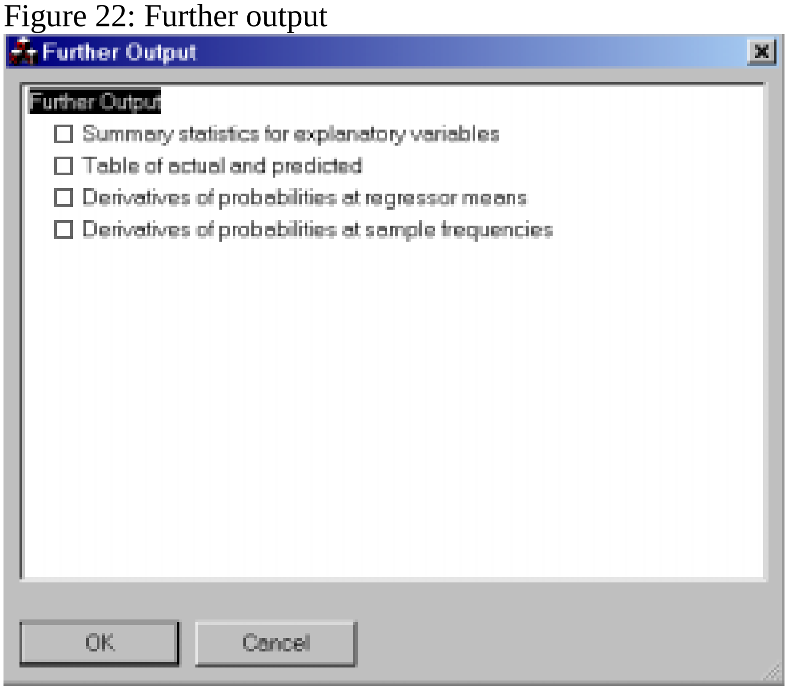
Figure 22: Forecasting



I don't know what these are

3.4.3 Further output

Figure 22: Further output



Putting a cross in the second and third boxes you get the output below:

```
Table of actual and predicted
          State 0  State 1  Sum actual
State 0      2982       38     3020
State 1       122      211      333
Sum pred     3104      249     3353

Derivatives of probabilities at regressor means
Probabilities:
State 0             0.95698
State 1            0.043017
Derivatives:
                       mean      State 0      State 1
Constant             1.0000     -0.20668      0.20668
ASLSCORE             25.599     0.013940    -0.013940
SEX                 0.54578   -0.0041843    0.0041843
ALPHYS               6.2368   -0.0018640    0.0018640
ACASAL               3660.7 -2.3310e-006  2.3310e-006
Quasi-elasticities:
                    State 0      State 1
Constant           -0.20668      0.20668
ASLSCORE            0.35683     -0.35683
SEX              -0.0022837    0.0022837
ALPHYS            -0.011625     0.011625
ACASAL           -0.0085332    0.0085332
Elasticities:
                    State 0      State 1
Constant           -0.19779    0.0088909
ASLSCORE            0.34148    -0.015350
SEX              -0.0021854  9.8237e-005
ALPHYS            -0.011125   0.00050008
ACASAL           -0.0081662   0.00036707
t-values:
                    State 0      State 1
Constant            -16.093       16.093
ASLSCORE             23.810      -23.810
SEX                -0.64840      0.64840
ALPHYS              -2.0223       2.0223
ACASAL              -5.9763       5.9763
```

Initially we have a cross-tabulation of actual and predicted values and we can see that whereas the were 333 dropouts, we only predict 249 dropouts. Of the 249 predicted 211 actually did drop out and 38 continued their studies. The model fails to identify 122 individuals who did dropout and the model predicts would continue.

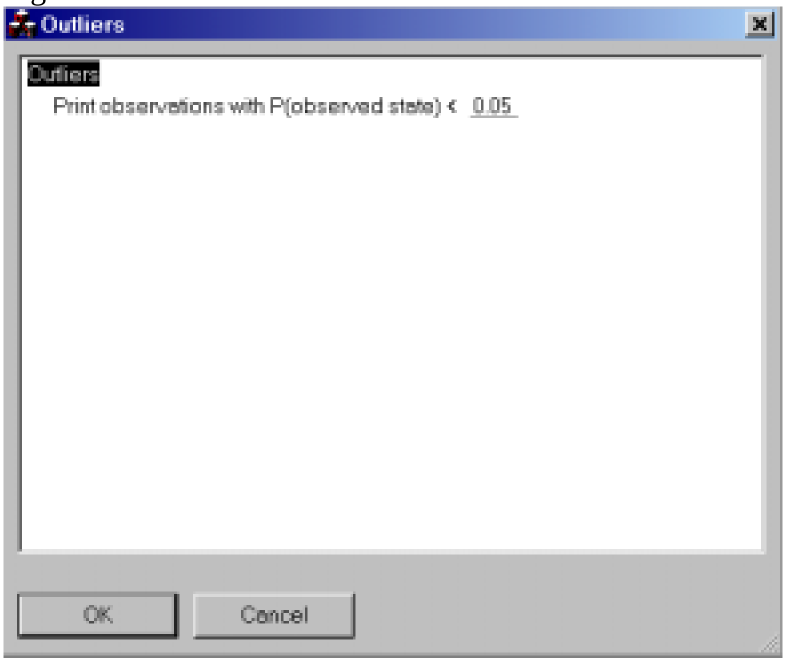
The output the reports the derivatives of probabilities at regressor means and the derivatives. These derivatives for State 1 represent a change in the probability of (DROP2=1) for a unit change in x. Below this are reported quasi-elsticities and elasticities.

3.4.4 Norm observations

This produces identical output to that in Further output (see section 3.4.3).

3.4.5 Outliers

Figure 23: Outliers



This lists those cases where the probability of being in State 1 (DROP2=1) is less han 0.05 (5%).

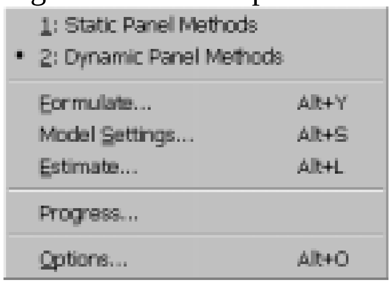
3.4.6 Store in database

This option allows you to store Probabilities (for State 1 and State 2) the log likelihood and the Prediction set probabilities.

4. Panel Data Models (DPD)

Selecting DPD in Figure 1 and then in Model you have Figure 24. Select Static Panel Methods.

Figure 24: Model options

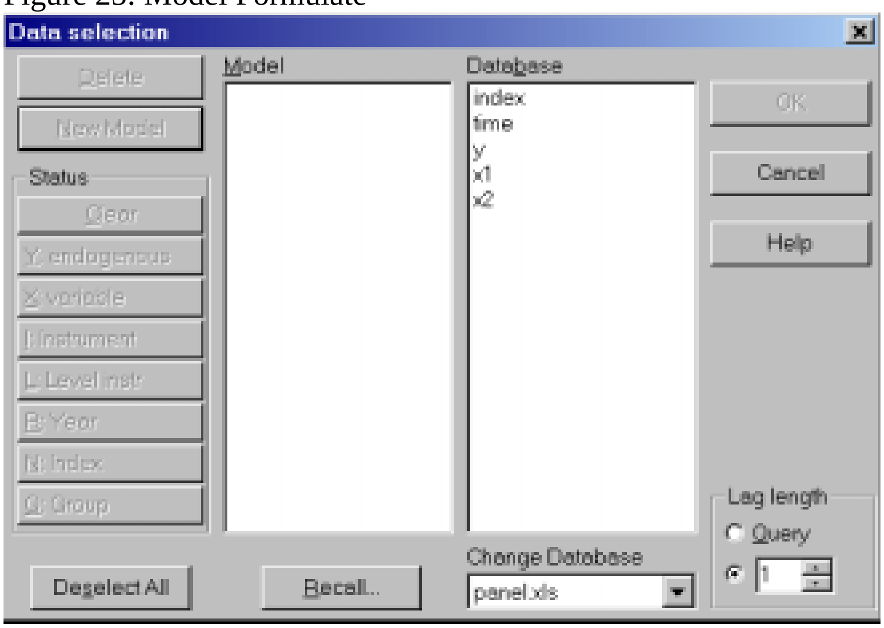


Clicking on Formulate you get Figure 25, which requires you to specify the panel model you are estimating.

4.1 Model formulation

In this you select variables from the Database box and include them into the Model box. As this is a Static Panel Methods set the lag length at zero. The dependent variable will be denoted as Y, other variables are assumed to be explanatory variables. However, for panel estimation it is essential to have a variable which tells the computer the unit of observation for the individual or firm or country. In addition, it is essential to have a further variable denoting the period of observation, e.g. year.

Figure 25: Model Formulate



I used an excel database which looked like Figure 26.

Figure 26: Excel spreadsheet for the panel database

	A	B	C	D	E
1	index	time	y	x1	x2
2	1	1	4.138105	2.438337	0
3	1	2	3.195262	2.472945	0
4	1	3	7.174431	2.930174	1
5	1	4	5.201367	1.924894	0
6	1	5	7.391777	2.193426	1
7	1	6	4.806744	1.073611	0
8	2	1	2.360313	2.543901	0
9	2	2	5.560429	1.79461	1
10	2	3	8.669472	3.57445	1
11	2	4	5.504351	2.591052	1
12	2	5	8.427841	3.118046	2
13	2	6	2.681069	2.371502	0
14	3	1	2.065898	1.912809	0
15	3	2	2.489945	1.467574	0

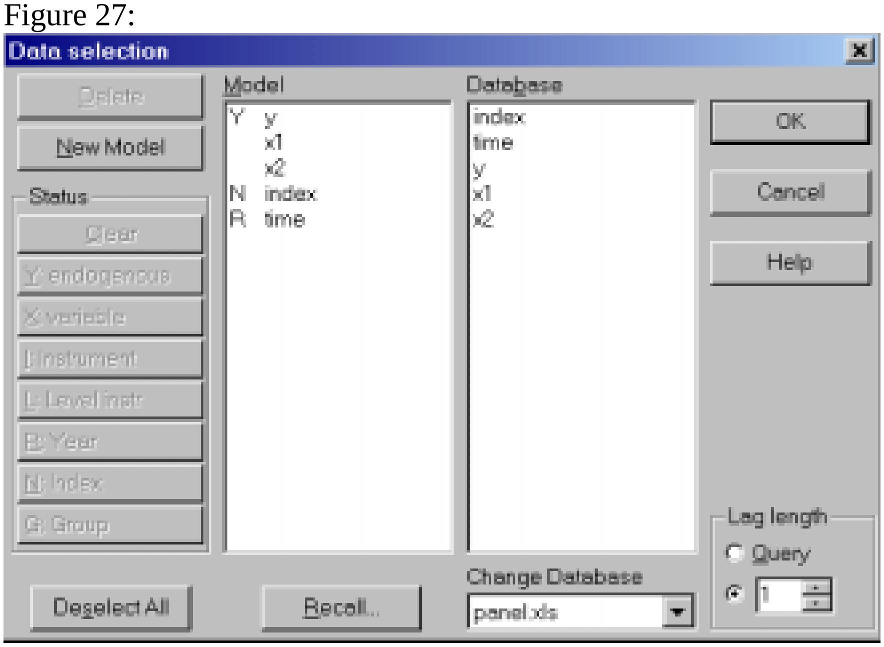
Where column A indicates the country (1=Australia, 2=Brazil, 3=Canada etc) and column B indicates the time period (1=1980, 2=1981 etc). PcGive needs to have this information in order to be able to construct time dummies and individual dummies as well as for constructing lags.

In Figure 27 we estimate a simple model

$$y_{it} = \alpha_i + \delta_t + \beta_1 x1_{it} + \beta_2 x2_{it} + u_{it}$$

Selecting the variables, we have

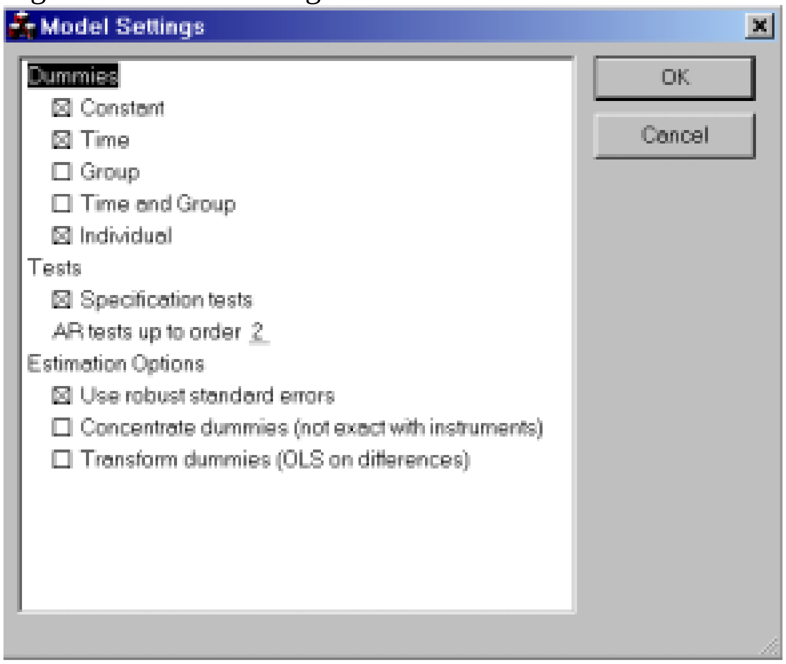
Figure 27:



where you must also have the two variables index and time included in the Model box. Highlight index variable in the Model box and click N:Index button and then highlight in the model box and click the R: Year button. Clicking OK gives Figure 28

4.2 Model settings

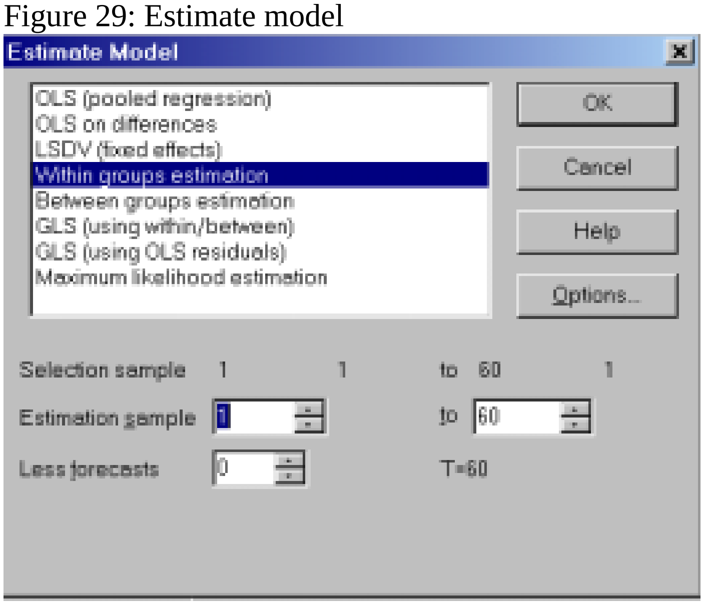
Figure 28: Model settings



Here you choose the nature of the fixed effect dummy variables: whether you want time dummies (δ_t) or individual dummies (α_i) or both or neither. In addition, within this window you select the diagnostic tests you require to be reported. Clicking OK gives Figure 29

4.3 Model estimation

Figure 29: Estimate model



In this box there are a series of alternative estimation methods. A good discussion of the various alternatives is in Greene, W. H. (2000) *Econometric Analysis*, Prentice Hall). Given the model we have specified in Figures 27 and 28) OLS (pooled regression) and LSDV (fixed effects) will give the same answer. Choosing LSDV the output is:

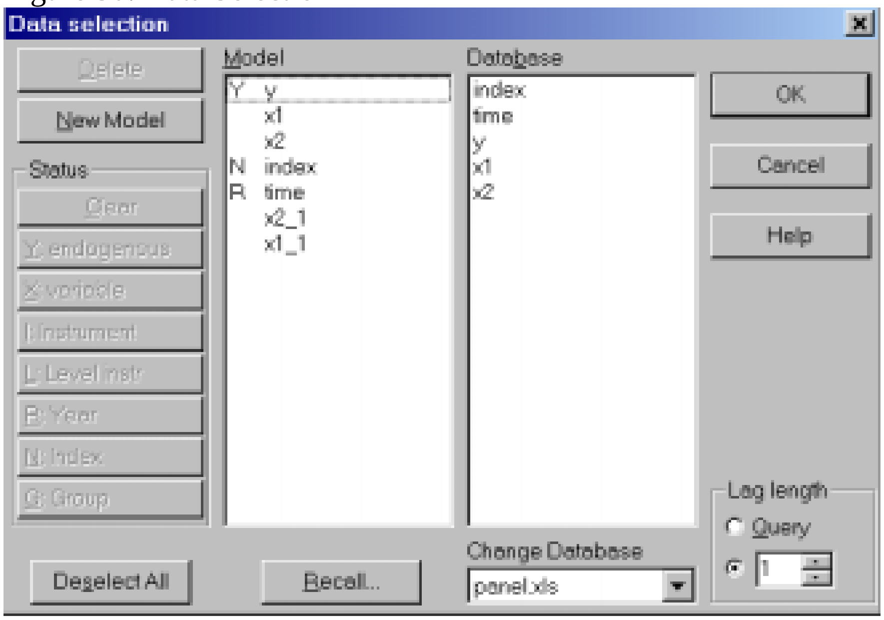
```
DPD( 1) Modelling y by LSDV (using panel.xls)

                  Coefficient  Std.Error  t-value  t-prob
x1                    1.06617     0.1537     6.94   0.000
x2                    2.18986     0.2170     10.1   0.000
Constant              1.90528     0.3973     4.80   0.000
T2                  0.0603626     0.4817    0.125   0.901
T3                   0.512915     0.3993     1.28   0.206
T4                   0.727171     0.3690     1.97   0.055
T5                   0.531014     0.5132     1.03   0.307
T6                   0.368951     0.5200    0.709   0.482
I1                   -1.40497     0.1636    -8.59   0.000
I2                   -1.57171    0.02998    -52.4   0.000
I3                  -0.407746    0.03807    -10.7   0.000
I4                   0.151752    0.02882     5.26   0.000
I5                  0.0599882    0.03498     1.71   0.094
I6                  -0.820595     0.1105    -7.43   0.000
I7                  -0.669321     0.2528    -2.65   0.011
I8                   -1.44334    0.09427    -15.3   0.000
I9                  -0.499907    0.08120    -6.16   0.000

sigma                1.117822  sigma^2             1.249525
R^2                 0.8003609
RSS              53.729589851  TSS             269.13362677
no. of observations        60  no. of parameters         17
Using robust standard errors

Transformation used:     none

constant:                 yes  time dummies:              5
group dummies:              0  time*group:                0
individual:                 9
number of individuals      10
longest time series         6 [1 - 6]
shortest time series        6 (balanced panel)

Wald (joint):    Chi^2(2) =     104.2 [0.000] **
Wald (dummy):   Chi^2(15) =     174.1 [0.000] **
Wald (time):     Chi^2(5) =     6.503 [0.260]
AR(1) test:        N(0,1) =    -1.312 [0.190]
AR(2) test:        N(0,1) =   -0.2098 [0.834]
```

Note: T2 through to T6 reflect the time dummy variables and I1 through to I9 reflect the individual dummy variables. The diagnostic test indicate the joint significance of all dummy variables, but suggest the time dummies are insignificant. There is no evidence of either AR(1) or AR(2) behaviour in the error term.

4.4 Dynamic Model

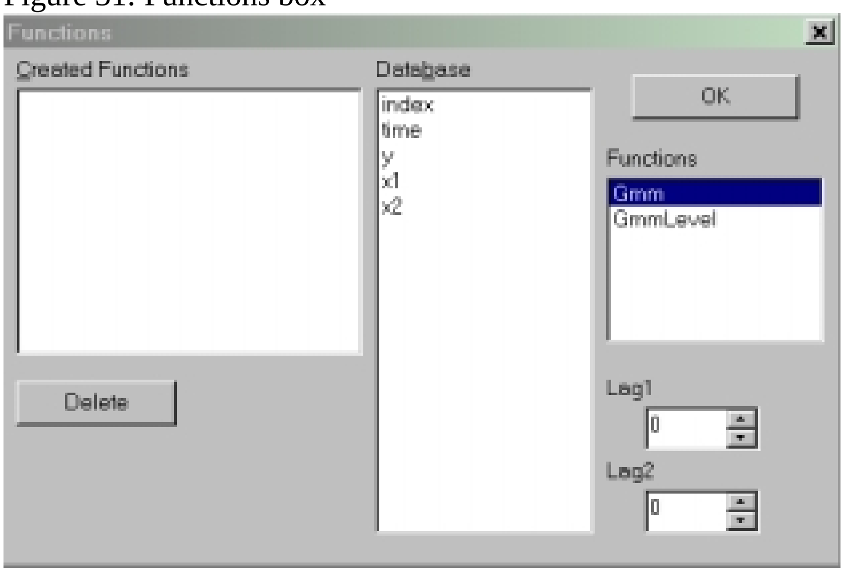
In Figure 24 clicking on Dynamic model, and assuming we wish to estimate the model
$y_{it} = \alpha_i + \delta_t + \beta_1 x1_{it} + \beta_2 x1_{it-1} + \beta_3 x2_{it} + \beta_4 x2_{it-1} + u_{it}$
we get from clicking Formulate Figure 30

Figure 30: Data Selection



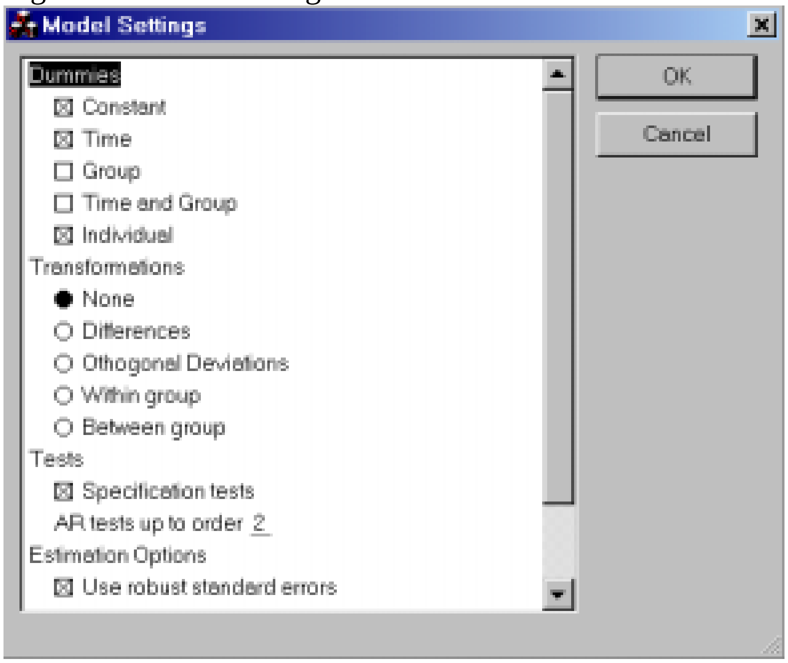
Clicking OK yields Figure 31,

Figure 31: Functions box



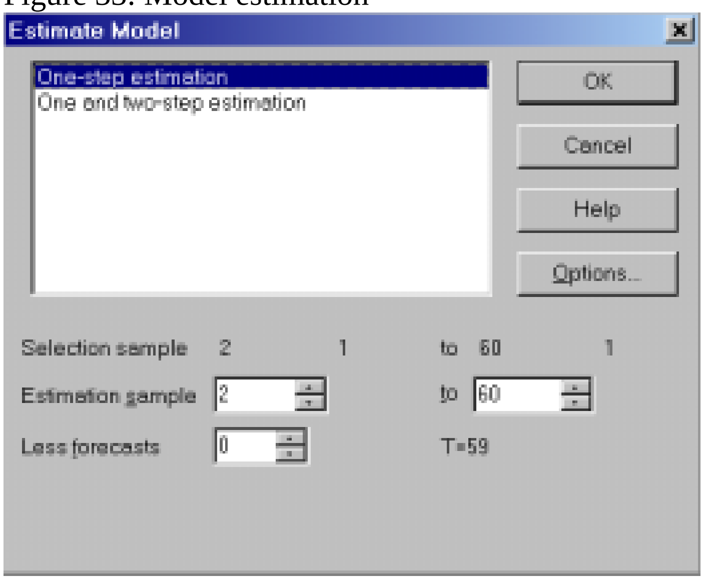
For this simple model there are no created functions and so clicking OK yields the Model setting window in Figure 32

Figure 32: Model settings window



Again select the types of dummy variables you wish to include as well as the type of transformations as specified in Figure 31. Clicking OK yields Figure 33:

Figure 33: Model estimation



Selecting One and two-step estimation and clicking OK , this gives the output:

```
DPD( 8) Modelling y by 1 and 2 step (using panel.xls)

                  ----   1-step estimation using DPD ----
                  Coefficient  Std.Error  t-value  t-prob
x1                   0.964864     0.1927     5.01   0.000
x2                    2.05568     0.2137     9.62   0.000
x2(-1)              0.0647789     0.2870    0.226   0.823
x1(-1)              -0.204478     0.2985   -0.685   0.498
```

Constant	2.68701	0.8600	3.12	0.004
T3	0.466145	0.5365	0.869	0.391
T4	0.865348	0.5101	1.70	0.100
T5	0.600639	0.7277	0.825	0.415
T6	0.384191	0.5746	0.669	0.509
I1	-1.14044	0.2910	-3.92	0.000
I2	-1.53650	0.1257	-12.2	0.000
I3	-0.756884	0.2508	-3.02	0.005
I4	0.142443	0.07619	1.87	0.071
I5	-0.210862	0.1883	-1.12	0.271
I6	-0.711124	0.3064	-2.32	0.027
I7	-0.247149	0.4131	-0.598	0.554
I8	-1.30884	0.2348	-5.58	0.000
I9	-0.679173	0.1355	-5.01	0.000

```
sigma                 1.196984  sigma^2              1.432772
R^2                  0.7915696
RSS               45.848693703  TSS              219.97120713
no. of observations         50  no. of parameters          18
Using robust standard errors

Wald (joint):    Chi^2(4) =     113.7 [0.000] **
Wald (dummy):   Chi^2(14) =     1245. [0.000] **
Wald (time):     Chi^2(4) =     3.322 [0.505]
AR(1) test:        N(0,1) =    -1.216 [0.224]
AR(2) test:        N(0,1) =   -0.2481 [0.804]
```

---- 2-step estimation using DPD ----

	Coefficient	Std.Error	t-value	t-prob
x1	1.15526	0.1431	8.07	0.000
x2	2.13731	0.1510	14.2	0.000
x2(-1)	0.0707533	0.2043	0.346	0.731
x1(-1)	0.175055	0.08677	2.02	0.052
Constant	0.422824	0.09269	4.56	0.000
T3	0.691457	0.3923	1.76	0.088
T4	0.736456	0.3650	2.02	0.052
T5	0.648314	0.5547	1.17	0.251
T6	0.429357	0.4146	1.04	0.308
I1	-0.00407564	0.1056	-0.0386	0.969
I2	0.0218380	0.07776	0.281	0.781
I3	0.459037	0.2342	1.96	0.059
I4	0.137315	0.05339	2.57	0.015
I5	0.107467	0.05484	1.96	0.059
I6	-0.242633	0.09781	-2.48	0.019
I7	-0.0992556	0.2012	-0.493	0.625
I8	-0.0569096	0.1041	-0.547	0.588
I9	-0.0589598	0.06322	-0.933	0.358

```
sigma                 1.414495  sigma^2              2.000796
R^2                  0.7089371
RSS               64.025459373  TSS              219.97120713
no. of observations         50  no. of parameters          18
Using robust standard errors

Transformation used:      none

constant:                  yes  time dummies:               4
```

```
group dummies:              0  time*group:                  0
individual:                 9
number of individuals      10
longest time series         5 [2 - 6]
shortest time series        5 (balanced panel)

Wald (joint):    Chi^2(4) =     306.8 [0.000] **
Wald (dummy):   Chi^2(14) =2.137e+005 [0.000] **
Wald (time):     Chi^2(4) =     8.448 [0.076]
AR(1) test:        N(0,1) =     1.025 [0.305]
AR(2) test:        N(0,1) =     1.621 [0.105]
```