PcGive 10:0 Alternative estimation packages

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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 <u>P</u>ackage.

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 <u>F</u>ormulate 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

Data selection			×
Delete	Model	Database	
NewHendel	Y DLM4	M4 BPD/1	OK
Mew woder		RPDI2	
Status		GDPC	Cancel
Çlear		r GDP30	
Yendogenous		LM4	Help
Sverisble		DLM4	Special
Zvariable			Constant
V/sight			Trend
			Lag length
	I		C Query
		Change Database	- 0 ÷
Degelect All	Herall	Moneyxis	

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

🎄 Model Settings	×
ARMA AR order <u>1</u> MA order <u>1</u> Fix AR lags <u></u> Fix MA lags <u></u> Fractional parameter d O Estimate d Fix <u>0</u> Treatment of mean None (or using Constant as regressor) O Deviation from sample mean O Fix mean at: <u>0</u>	OK Cancel
	11.

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

Estimate Model	×
Maximum Likelihood	OK
Modified Profile Likelihood Starting values only	Cancel
TALS With stationality imposed	Help
	Options
Selection sample 1970 1 to 199	64
Estimation sample 1970 1 🚊 to 199	6 4 🗧
Less forecasts 0 📩 T=108	

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
                        0.892437 0.05999 14.9 0.000
-0.481616 0.1247 -3.86 0.000
AR-1
MA-1
                       0.0307707 0.004264 7.22 0.000
Constant
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)



💑 Model Settings	×
ARMA AR order 1 MA order 1 Fix AR lags Fix AR lags Fix MA lags Fractional parameter d • Estimate d • O Fix d at: 0 Treatment of mean • None (or using Constant as regressor) • Deviation from sample mean • Fix mean at: 0	OK Cancel

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 -0.486757 0.6007 -0.810 0.420 MA-1 0.0307653 0.004301 7.15 0.000 Constant 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 0.009766 sigma² 9.53748e-005 sigma

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 <u>T</u>est 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 <u>Model</u> and then <u>F</u>ormulate to get Figure 2. Specify the linear levels models you wish to estimate. For interest rates (r) we are wish to estimate the model:

$$\begin{split} r_t &= \mu + \epsilon_t \quad z_t \sim II(0, h_t) \\ h_t &= \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1} \end{split}$$

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.

Data selection X <u>M</u>odel Data<u>b</u>ase M4 ΟK Г RPDI1 Constant New Model RPDI2 GDPC Cancel Status GDP90 Help LM4 LRPDI1 DLM4 Special H:X in h_t Constant Trend Seasonal CSeasonal | -Lag length O Query Change Database • 0 ÷ Deselect All Recall... Money.xls

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

Estimate Model	×
Maximum Likelihood	ОК
	Cancel
	Help
	Options
Selection sample 1970 1	to 1996 4
Estimation <u>s</u> ample 1970 1 🛨	to 1996 🛛 🕹 🚔
Less <u>f</u> orecasts 0	T=108
<u>Recursive estimation, initialization</u> :	2 -

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 ConstantX6.923910.10820.0768990.00.000alpha_0H0.5688830.24630.19312.950.004alpha_1H0.955098beta_1H0.04490170.083680.084540.5310.596 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 8.2537 var(r) mean(r) 11.6063 mean(r)
alpha(1)+beta(1) 1 alpha i+beta i>=0, alpha(1)+beta(1)<1</pre> 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 <u>Test</u> you get Figure 12.choosing Test <u>S</u>ummary 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

💑 Graphic Analysis	×
Graphic Analysis	
OK Cancel	

Selecting Residuals and Conditional standard deviation produces Figure 14.

Figure 14



Figure 12: Test options

ð	Test 🗙
	Image: Second Structure Residual correlogram and Portmanteau statistic with length 12 Image: Squared residual correlogram and Portmanteau Image: Normality test Image: ARCH test with order 2 Output Image: Full output Image: Summary output
	OK Cancel

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

<u>1</u> : Binary Discrete Choice <u>2</u> : Multinomial Discrete Choice <u>3</u> : Count Data		
Eormulate Model <u>S</u> ettings Estimate	Alt+Y Alt+S Alt+L	
Progress		
Options	Alt+0	

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

Data selection			×
<u>D</u> elete <u>New Model</u> Status <u>Clear</u> <u>Y</u> endogenous <u>X</u> variable <u>S</u> elect By	Model Y DROP2 Constant ASLSCORE SEX ALPHYS ACASAL	Database ASLSCORE SEX OS ALBIOL ALCHEM ALPHYS SOCIAL_C TOTAL ACASAL NO_UG DROP2	OK Cancel Help Special Constant
De <u>s</u> elect All	<u>R</u> ecall	medics.xls]

<u>3.2 Model settings</u> Clicking OK in Figure 17, produces Figure 18.

Figure 18: Model settings

🚠 Model Settings	×
Choose a model:	OK
O Probit	Cancel

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

Estimate Model	×	(
Newton's method BFGS method	ОК	
	Cancel	
	Help	
	Options	
Selection sample 1 1	to 3353 1	
Estimation <u>s</u> ample 1	<u>t</u> o 3353 1	
Less forecasts	T=3353	

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
              0.0452791 0.02239 2.02 0.043
5.66246e-005 9.475e-006 5.98 0.000
                  0.0452791 0.02239
ALPHYS
ACASAL
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 O
            3020 0.90069 0.90069
                                        -201.4
State 1
             333
                     0.09931
                                0.09931
                                           -445.6
             3353 1.00000
Total
                                1.00000
                                          -647.0
```

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

3.4 Testing

Clicking on <u>T</u>est you get Figure 20.



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

÷ G	raphic Analysis	x
	 phic Analysis Histograms of probabilities for each state Histograms of probabilities of observed state Number of bars: <u>10</u> <u>Cumulative correct predictions for each state</u> Unsorted Sorted by probability Sorted by log-likelihood contribution Cumulative response for each state (sorted by probability) 	
	OK Cancel	

The graphs available are not particularly useful.

3.4.2 Forecasting

Figure 22: Forecasting

🚰 Forecast	×
Predictions	1
Print predicted outcomes	1
Histograms of probabilities for each state	1
Available if the outcomes are known for the prediction set	1
Prediction sample	
 Observations not used in estimation 	
O Observations with value 2 for selection variable	
	1
	1
	1
1	d.
OK. Cancel	

I don't know what these are

3.4.3 Further output



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

Table of	actual ar	nd predict	ted	
	State 0	State 1	Sum actual	
State 0	2982	38	3020	
State 1	122	211	333	
Sum pred	3104	249	3353	
Derivativ	ves of pro	babiliti	es at regress	or means
Probabil	ities:			
State 0		0.95698		
State 1		0.043017		
Derivati	ves:			
		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
Ouasi-ela	asticities	3:		
~		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	
Elastici	cies:			
		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

- Outliers	×
Outiers	-1
Print observations with P(observed state) < 0.05	
J	
OK Cancel	

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 \underline{M} odel you have Figure 24. Select Static Panel Methods.

Figure 24: Model options

1: Static Panel Methods 2: Dynamic Panel Methods			
Eormulate Model Settings Estimate	Alt+Y Alt+S Alt+L		
Progress			
Options	Alt+O		

Clicking on <u>F</u>ormulate 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 Formulat	e
---------------------------	---

Data selection			×
Delete	Model	Database	
		index	0K
New Model		time v	
Status		x1	Cancel
Geor		×2	
Y. endoursecus			Help
Vundekle			
≥ vuriusie			
) instrument			
L: Level instr			
B:Year			
N: Index			
G: Graun			Lag length
			C Query
I management		Change Database	01-
Deselect All	Becall	panel.xls 💌	

I used an excel database which looked like Figure 26.

	А		В		С	D		E
1	index	time	;	у	>	(1	x2	
2		1		1	4.138105	2.43833	7	0
3		1		2	3.195262	2.47294	5	0
4		1		3	7.174431	2.93017	4	1
5		1		4	5.201367	1.92489	4	0
6		1		5	7.391777	2.19342	6	1
7		1		6	4.806744	1.07361	1	0
8		2		1	2.360313	2.54390	1	0
9		2		2	5.560429	1.7946	1	1
10		2		3	8.669472	3.5744	5	1
11		2		4	5.504351	2.59105	2	1
12		2		5	8.427841	3.11804	6	2
13		2		6	2.681069	2.37150	2	0
14		3		1	2.065898	1.91280	9	0
15		3		2	2.489945	1.46757	4	0

Figure 26: Excel spreadsheet for the panel database

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

 $y_{it} = \alpha_i + \delta_t + \beta_1 x \mathbf{1}_{it} + \beta_2 x \mathbf{2}_{it} + u_{it}$

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

i iguie 20. mouel settings	Figure	28:	Model	settings
----------------------------	--------	-----	-------	----------

Model Settings	×
Dummies	ОК
Constant	
🖾 Time	Cancel
Group	
Time and Group	
⊠ Individual	
Tests	
Specification tests	
AR tests up to order 2	
Estimation Options	
Use robust standard errors	
Concentrate dummies (not exact with instruments)	
 Transform dummies (OLS on differences) 	
1	

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	
Estimate Model	×
OLS (pooled regression) OLS on differences	OK
LSDV (fixed effects) Within groups estimation	Cancel
Between groups estimation GLS (using within/between) GLS (using OLS residuals)	Help
Maximum likelihood estimation	Options
Selection sample 1 1 to 60	1
Estimation sample	-
Less jorecasts 0 📩 T=60	

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:

	Coefficient	Std.Error	t-value	t-prob
xl	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
Т2	0.0603626	0.4817	0.125	0.901
Т3	0.512915	0.3993	1.28	0.206
Т4	0.727171	0.3690	1.97	0.055
Т5	0.531014	0.5132	1.03	0.307
Тб	0.368951	0.5200	0.709	0.482
I1	-1.40497	0.1636	-8.59	0.000
12	-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
15	0.0599882	0.03498	1.71	0.094
IG	-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
19	-0.499907	0.08120	-6.16	0.000
sigma	1.117822	sigma^2		1.249525
R^2	0.8003609			
RSS	53.729589851	TSS	26	9.13362677
no. of observatio	ons 60	no. of par	ameters	17
Using robust stan	dard errors			
Transformation us	ed: none			
constant:	ves	time dummi	es:	5
group dummies:	0	time*group	:	0
individual:	9	ormo group		C C
number of individ	uals 10			
longest time seri	es 6	[1 - 6]		
shortest time ser	ies 6	(balanced p	anel)	
		(,	
Wald (joint):	Chi^2(2) =	104.2 [0.	000] **	
Wald (dummy): C	hi^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]	

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

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 $y_{it} = \alpha_i + \delta_t + \beta_1 x 1_{it} + \beta_2 x 1_{it-1} + \beta_3 x 2_{it} + \beta_4 x 2_{it-1} + u_{it}$ we get from clicking Formulate Figure 30

Figure 30:	Data	Selection
------------	------	-----------

Data selection			×
Qelete	Model	Database	
New Model	x1	time	OK
Status	N index	×1	Cancel
Gear	R time x2_1	×2	
⊻ endogencus	×1_1		Help
≚ voriokle			
): Instrument			
L'Level instr			
<u>B</u> :Year			
N: Index			
<u>G</u> : Group]		Lag length
		Change Database	C Query
Deselect All	<u>B</u> ecall	panelxis	



Figure	31:	Functions	box
1 15010	51.	1 unetions	004

Functions		×
Greated Functions	Database	
	index time y x1 x2	OK Functions Gmm GmmLevel
Delete		Leg1 Leg2 0 ×

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

Estimate Model	×
One-step estimation One and two-step estimation	OK
	Cancel
	Help
	Options
Selection sample 2 1	to 60 1
Estimation sample 2	to 60 😐
Less forecasts 0	T=59

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-ste	p estimatio	n using D	PD
	Coefficient	Std.Error	t-value	t-prob
xl	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
Т3	0.466145	0.5365	0.869	0.391
Т4	0.865348	0.5101	1.70	0.100
Т5	0.600639	0.7277	0.825	0.415
тб	0 384191	0 5746	0 669	0 509
т1	-1 14044	0 2910	-3 92	0 000
TT TO	1 52650	0.2010	10 0	0.000
12	-1.53050	0.1257	-12.2	0.000
13	-0.756884	0.2508	-3.02	0.005
I4	0.142443	0.07619	1.87	0.071
15	-0.210862	0.1883	-1.12	0.271
IG	-0.711124	0.3064	-2.32	0.027
I7	-0.247149	0.4131	-0.598	0.554
18	-1.30884	0.2348	-5.58	0.000
т9	-0.679173	0.1355	-5.01	0.000
giama	1 196984	gioma^2		1 430770
	0 7015606	SIGMA Z		1.132//2
R Z	0.7913090	m 00	0.1	0 09100910
RSS	45.848693/03	TSS	21	9.9/120/13
no. of observat	cions 50	no. of para	ameters	18
Using robust st	andard errors			
Wald (joint):	Chi^2(4) =	113.7 [0.0)00] **	
Wald (dummy):	Chi^2(14) =	1245. [0.0)00] **	
Wald (time):	$Chi^{2}(4) =$	3.322 [0.5	5051	
AR(1) test:	N(0, 1) =	-1 216 [0 2	2241	
AR(2) test:	N(0, 1) =	-0 2481 [0 8	2041	
AR(Z) CCSC.	N(0,1) -	0.2101 [0.0	01]	
		n ogtimation	uning D	מח
				PD
_	Coefficient	Sta.Error	t-value	t-prob
xl	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
т3	0.691457	0.3923	1.76	0.088
т4	0 736456	0 3650	2 02	0 052
т. т.	0 648314	0 5547	1 17	0 251
т <u>с</u>	0 420257	0.3317	1 04	0.201
10	0.429337	0.4140	1.04	0.300
11	-0.0040/564	0.1056	-0.0386	0.969
12	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
15	0.107467	0.05484	1.96	0.059
IG	-0.242633	0.09781	-2.48	0.019
I7	0 0000556	0 2012	-0.493	0.625
т8	-0.0992556	0.2012		
10	-0.0992556 -0.0569096	0.2012	-0 547	0 588
	-0.0992556 -0.0569096 -0.0589598	0.1041	-0.547	0.588
19	-0.0569096 -0.0569598	0.1041 0.06322	-0.547 -0.933	0.588 0.358
	-0.0992556 -0.0569096 -0.0589598	0.1041 0.06322	-0.547 -0.933	0.588 0.358
sigma	-0.0992556 -0.0569096 -0.0589598 1.414495	0.1041 0.06322 sigma^2	-0.547 -0.933	0.588 0.358 2.000796
sigma R^2	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371	0.1041 0.06322 sigma^2	-0.547 -0.933	0.588 0.358 2.000796
sigma R^2 RSS	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373	0.1041 0.06322 sigma ²	-0.547 -0.933 21	0.588 0.358 2.000796 9.97120713
sigma R^2 RSS no. of observat	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373 tions 50	0.1041 0.06322 sigma ² TSS no. of para	-0.547 -0.933 21 ameters	0.588 0.358 2.000796 9.97120713 18
sigma R^2 RSS no. of observat Using robust st	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373 tions 50 candard errors	0.1041 0.06322 sigma^2 TSS no. of para	-0.547 -0.933 21 ameters	0.588 0.358 2.000796 9.97120713 18
sigma R^2 RSS no. of observat Using robust st	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373 tions 50 tandard errors	0.1041 0.06322 sigma^2 TSS no. of para	-0.547 -0.933 21 ameters	0.588 0.358 2.000796 9.97120713 18
sigma R^2 RSS no. of observat Using robust st Transformation	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373 tions 50 tandard errors used: none	0.1041 0.06322 sigma^2 TSS no. of para	-0.547 -0.933 21 ameters	0.588 0.358 2.000796 9.97120713 18
sigma R^2 RSS no. of observat Using robust st Transformation	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373 tions 50 tandard errors used: none	0.1041 0.06322 sigma^2 TSS no. of para	-0.547 -0.933 21 ameters	0.588 0.358 2.000796 9.97120713 18
sigma R^2 RSS no. of observat Using robust st Transformation	-0.0992556 -0.0569096 -0.0589598 1.414495 0.7089371 64.025459373 tions 50 tandard errors used: none	0.1041 0.06322 sigma^2 TSS no. of para	-0.547 -0.933 21 ameters	0.588 0.358 2.000796 9.97120713 18

group dummies:	0 time*group:
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]