STATA Commands for Unobserved Effects Panel Data

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Contents

1	Introduction	1
2	Examining Panel Data	4
3	Estimation using xtreg 3.1 Introduction	
	3.2 Pooled of Stacked OLS3.3 Fixed Effects Estiamator	
	3.4 Between Effects Estimator	
4	Testing after xtreg	15
5	Prediction after xtreg	16
6	Other Stata Panel estimators	17
	6.1 Faster estimation of alternative models using xtdata	17
	6.2 More general error structures	17
	6.3 Dynamic panel data	17
	6.4 Limited Dependent Variables in Panel Data	17

1 Introduction

Panel data, cross-sectional timeseries or longitudinal data are observations on a panel of i units or cases over t time periods. Most panel data commands start with **xt** For an overview of panel data type **help xt**. A typical panel data might record data on the income and expenditure of a group of individuals repeated over a number of years.

These notes present the annotated log of a STATA session demonstrating the use of many of these commands. The data sets used are those used in the STATA cross-sectional time series reference manual. This note should be regarded as an introduction to that manual and to the STATA on-line help files which give comprehensive descriptions of the facilities in STATA for cross-sectional time series analysis.

To obtain the optimum benefit from these notes I would recommend that one should work through the STATA session with a copy of Wooldridge (2002) (or Cameron and Trivedi

(2005) or your favourite text) available for reference. The emphasis here is on the implementation of the methods described in Chapter 10 of Wooldridge (2002) Wooldridge and no attempt is made to explain the theory set out there¹. Note the different fonts used for comments (this font), instructions in these comments (**help xt**) and for computer input/output (help xt).

help xt dialogs: xtset

Title

[XT] xt -- Introduction to xt commands

Syntax

xtcmd ... [, i(varname_i) t(varname_t) ...]

Description

The xt series of commands provide tools for analyzing panel data (also known as longitudinal data or in some disciplines as cross-sectional time series when there is an explicit time component):

<pre>xtline Line plots with xt data xtreg Fixed-, between- and random-effects, and</pre>	xtset xtdescribe xtsum xttab xtdata	Declare a dataset to be panel data Describe pattern of xt data Summarize xt data Tabulate xt data Faster specification searches with xt data
population-averaged linear modelsxtregarFixed- and random-effects linear models with an AR(1) disturbancextmixedMultilevel mixed-effects linear regressionxtglsPanel-data models using GLSxtpcseOLS or Prais-Winsten models with panel-corrected standard errorsxtrcRandom coefficients modelsxtivregInstrumental variables and two-stage least squares for panel-data modelsxtabondArellano-Bond linear dynamic panel-data estimatorxtdpdsysArellano-Bond/Blundell-Bond estimationxttobitRandom-effects tobit modelsxtintregRandom-effects, random-effects, & population-averaged logit modelsxtlogitFixed-effects, and population-averaged probit models	xtline	Line plots with xt data
<pre>xtregar Fixed and random-effects linear models with an AR(1) disturbance xtmixed Multilevel mixed-effects linear regression xtgls Panel-data models using GLS xtpcse OLS or Prais-Winsten models with panel-corrected standard errors xtrc Random coefficients models xtivreg Instrumental variables and two-stage least squares for panel-data models xtabond Arellano-Bond linear dynamic panel-data estimator xtdpdsys Arellano-Bond/Blundell-Bond estimation xtdpd Linear dynamic panel-data estimation xttobit Random-effects tobit models xtintreg Random-effects, & population-averaged logit models xtprobit Random-effects and population-averaged probit models</pre>	xtreg	
<pre>xtmixed Multilevel mixed-effects linear regression xtgls Panel-data models using GLS xtpcse OLS or Prais-Winsten models with panel-corrected standard errors xtrc Random coefficients models xtivreg Instrumental variables and two-stage least squares for panel-data models xtabond Arellano-Bond linear dynamic panel-data estimator xtdpdsys Arellano-Bond/Blundell-Bond estimation xtdpd Linear dynamic panel-data estimator xttobit Random-effects tobit models xtintreg Random-effects, a population-averaged logit models xtprobit Random-effects and population-averaged probit models</pre>	xtregar	Fixed- and random-effects linear models with an AR(1)
<pre>xtpcse OLS or Prais-Winsten models with panel-corrected standard errors xtrc Random coefficients models xtivreg Instrumental variables and two-stage least squares for panel-data models xtabond Arellano-Bond linear dynamic panel-data estimator xtdpdsys Arellano-Bond/Blundell-Bond estimation xtdpd Linear dynamic panel-data estimation xttobit Random-effects tobit models xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit models xtprobit Random-effects and population-averaged probit models</pre>	xtmixed	Multilevel mixed-effects linear regression
errors xtrc Random coefficients models xtivreg Instrumental variables and two-stage least squares for panel-data models xtabond Arellano-Bond linear dynamic panel-data estimator xtdpdsys Arellano-Bond/Blundell-Bond estimation xtdpd Linear dynamic panel-data estimation xttobit Random-effects tobit models xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit models xtprobit Random-effects and population-averaged probit models	xtgls	Panel-data models using GLS
<pre>xtivreg Instrumental variables and two-stage least squares for</pre>	xtpcse	•
panel-data models xtabond Arellano-Bond linear dynamic panel-data estimator xtdpdsys Arellano-Bond/Blundell-Bond estimation xtdpd Linear dynamic panel-data estimation xttobit Random-effects tobit models xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit models xtprobit Random-effects and population-averaged probit models	xtrc	Random coefficients models
<pre>xtdpdsys Arellano-Bond/Blundell-Bond estimation xtdpd Linear dynamic panel-data estimation xttobit Random-effects tobit models xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit</pre>	xtivreg	
<pre>xtdpd Linear dynamic panel-data estimation xttobit Random-effects tobit models xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit</pre>	xtabond	Arellano-Bond linear dynamic panel-data estimator
<pre>xttobit Random-effects tobit models xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit</pre>	xtdpdsys	Arellano-Bond/Blundell-Bond estimation
<pre>xtintreg Random-effects interval data regression models xtlogit Fixed-effects, random-effects, & population-averaged logit</pre>	xtdpd	Linear dynamic panel-data estimation
<pre>xtlogit Fixed-effects, random-effects, & population-averaged logit models xtprobit Random-effects and population-averaged probit models</pre>	xttobit	Random-effects tobit models
models xtprobit Random-effects and population-averaged probit models	xtintreg	Random-effects interval data regression models
	xtlogit	
	xtprobit	Random-effects and population-averaged probit models
	xtcloglog	

¹The references at the end of this note are to books on panel data analysis or on the use of Stata in econometrics. These panel data books are not always easy going and are are suitable for those undertaking quantitative research using panel data. If you have problems you might consult one of the more general texts recommended for your course as an introduction to the topic.

xtpoisson	Fixed-effects, random-effects, & population-averaged
	Poisson models
xtnbreg	Fixed-effects, random-effects, & population-averaged
	negative binomial models
xtmelogit	Multilevel mixed-effects logistic regression
xtmepoisson	Multilevel mixed-effects Poisson regression
•	

xtgee Population-averaged panel-data models using GEE

Panel datasets have the form x_it, where x_it is a vector of observations for unit i and time t. The particular commands (such as xtdescribe, xtsum, and xtreg) are documented in their own help file entries. This entry deals with concepts common across commands.

The xtset command sets the panel variable and the time variable. Most xt commands require that the panel variable be specified, and some require that the time variable also be specified. Once you xtset your data, you need not do it again. The xtset information is stored with your data.

If you have previously tsset your data by using both a panel and a time variable, these settings will be recognized by xtset, and you need not xtset your data.

Example

An xt dataset:

pid	yr_visit	fev	age	sex	height	smokes
 1071	1991	1.21	 25	1	 69	0
1071	1992	1.52	26	1	69	0
1071	1993	1.32	28	1	68	0
1072	1991	1.33	18	1	71	1
1072	1992	1.18	20	1	71	1
1072	1993	1.19	21	1	71	0

The other xt commands need to know the identities of the variables identifying patient and time. You could type

. xtset pid yr_visit

Also see

Manual: [XT] xt Online: [XT] xtset

Load the data set nlswork.dta.

. use nlswork, clear

. describe

Contains data

National Longitudinal Survey. Young Women 14-26 years of age in 1968

obs: vars: size: 1,0	28,534 21)55,758		18 Feb 2005 22:17
		display format	variable label
<pre>idcode year idcode year birth_yr age race msp nev_mar grade collgrad not_smsa c_city south ind_code occ_code union wks_ue ttl_exp tenure hours wks_work ln_wage</pre>	byte byte byte byte byte byte byte byte	%8.0g %8.0g	NLS id interview year birth year age in current year 1=white, 2=black, 3=other 1 if married, spouse present 1 if never yet married current grade completed 1 if college graduate 1 if college graduate 1 if not SMSA 1 if central city 1 if south industry of employment occupation 1 if union weeks unemployed last year total work experience job tenure, in years usual hours worked weeks worked last year ln(wage/GNP deflator)

Sorted by: idcode year

To start one must set the indices i (units) and t (time). As already described this can be done in Stata 10 using the **xtset** command.² Examples of the commands follow.

. tsset idcode year panel variable: idcode, 1 to 5159 time variable: year, 68 to 88, but with gaps . tsset panel variable: idcode, 1 to 5159 time variable: year, 68 to 88, but with gaps

2 Examining Panel Data

The instructions in this section may be used to extract various panel properties of a panel data set. The temptation may be to skip this material and move to the estimation instructions in the next section. You should, at least, have a look at it as these instructions may be very useful in examining the kind of panel data found in real examples.

xtdescribe describes the participation pattern in panel data. We have 4711 women in the survey. The maximum number of years over which any women is observed is 15. The most common pattern is participation in only the first year (136 or 2.89% are observed in this pattern). The bottom line of the table give the totals for participation patterns not observed. The **pattern(#)** option allows one to increase the number of patterns shown.

 $^{^{2}}$ In earlier versions of Stata one used the **iis tis** commands, the **i() t()** options or the **tsset** command. While these can still be used it is recommended that one use the newer version 10 methods.

. xtdes

idcode: year:		, 88 r) = 1;	(88-68)+1 uely ident		each obse	-	η = Γ =	4	711 15
Distributi	on of T_i:	min 1	5% 1	25% 3	50% 5	759	% 9	95% 13	max 15
Freq.	Percent	Cum.	Pattern						
136	2.89	2.89	r						
114	2.42	5.31			1				
89	1.89	7.20			1.11				
87	1.85	9.04			11				
86	1.83	10.87	•		11.1.11				
61	1.29	12.16			11.1.11				
56	$1.19 \\ 1.15$	13.35	•		.1.1.11				
54 54	1.15	14.50 15.64	-		11.1.11				
3974	84.36		(other p						
4711	100.00		+ XXXXXX.	x.xx.x.					
. xtdes, p	attern(20)								
idcode: year:		, 88 r) = 1;	(88-68)+1 uely ident		each obse	-	η = Γ =	43	711 15
Distributi	on of T_i:		5% 1	25%	50% 5	75%		95% 13	max
		1	1	3	50% 5		% 9	95% 13	max 15
Distributi Freq.			1	3					
		1	1 Pattern +	3					
Freq. 136 114	Percent 2.89 2.42	1 Cum. 2.89 5.31	1 Pattern + 1 	3	5				
Freq. 136 114 89	Percent 2.89 2.42 1.89	1 Cum. 2.89 5.31 7.20	1 Pattern 1 	3	5				
Freq. 136 114 89 87	Percent 2.89 2.42 1.89 1.85	1 Cum. 2.89 5.31 7.20 9.04	1 Pattern 1 	3	5				
Freq. 136 114 89 87 86	Percent 2.89 2.42 1.89 1.85 1.83	1 Cum. 2.89 5.31 7.20 9.04 10.87	1 Pattern 1 111111.	3	5 				
Freq. 136 114 89 87 86 61	Percent 2.89 2.42 1.89 1.85 1.83 1.29	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16	1 Pattern 1 111111. 	3	5 1 11 11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35	1 Pattern 1 111111. 11	3	5 1 11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61	Percent 2.89 2.42 1.89 1.85 1.83 1.29	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50	1 Pattern 1 111111. 11 	3	5 1 11 11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35	1 Pattern 1 111111 11 	3	5 1 11 11.1.11 11.1.11 				
Freq. 136 114 89 87 86 61 56 54 54	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64	1 Pattern 1 111111. 11 11	3	5 				
Freq. 136 114 89 87 86 61 56 54 54 49	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15 1.04	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55	1 Pattern 1 111111. 111 11 1111	3	5 				
Freq. 136 114 89 87 86 61 56 54 54 49 45 43 42	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15 1.04 0.96 0.91 0.89	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44	1 Pattern 1 111111. 	3	5 1 1 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54 54 49 45 43 42 40	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15 1.04 0.96 0.91 0.89 0.85	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29	1 Pattern 1 111111. 11 1111 1	3 1.11.1. 1.11.1. 1.11.1	5 1 1 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54 49 45 43 42 40 38	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15 1.04 0.96 0.91 0.89 0.85 0.81	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29 21.10	1 Pattern 1	3 1.11.1. 11.1. 11.1. 11.1. 11.1. 1.11.1	5 1 1 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54 49 45 43 42 40 38 38	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15 1.04 0.96 0.91 0.89 0.85 0.81 0.81	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29 21.10 21.91	1 Pattern 1 1 1 1 1 1 1 1.11111 1 1 1 1.1111 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	3	5 1 1 1.1.1 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54 49 45 43 42 40 38 38 34	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.15 1.04 0.96 0.91 0.89 0.85 0.81 0.81 0.72	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29 21.10 21.91 22.63	1 Pattern 1 1 1 1 1 1 1 111111 1 1 1 11111 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	3 1.11.1. 1.11.1. 1.11.1. 1.11.1	5 1 1 1.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54 49 45 43 42 40 38 38 34 31	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.04 0.96 0.91 0.89 0.85 0.81 0.81 0.72 0.66	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29 21.10 21.91 22.63 23.29	1 Pattern 1 1 1 1 1 1 1 1 1 111111	3 1.11.1. 1.11.1. 1.11.1. 1.11.1	5 1 1 1.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11 11.1.11				
Freq. 136 114 89 87 86 61 56 54 49 45 43 42 40 38 38 34	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.04 0.96 0.91 0.89 0.85 0.81 0.81 0.72 0.66 0.64	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29 21.10 21.91 22.63 23.29 23.92	1 Pattern 1	3 	5 				
Freq. 136 114 89 87 86 61 56 54 54 49 45 43 42 40 38 38 34 31 30	Percent 2.89 2.42 1.89 1.85 1.83 1.29 1.19 1.15 1.04 0.96 0.91 0.89 0.85 0.81 0.81 0.72 0.66	1 Cum. 2.89 5.31 7.20 9.04 10.87 12.16 13.35 14.50 15.64 16.68 17.64 18.55 19.44 20.29 21.10 21.91 22.63 23.29 23.92	1 Pattern 1 1 1 1 1.111111 1 1.1111 1111 1 11111 11111	3 1.11.1. 1.11.1. 1.11.1. 1.11.1	5 				

xtsum generalizes summarize by reporting means and standard for panel data. It differs from summarize in that it decomposes the standard deviation into between and within components. The between figures refers to the standard deviation, minimum and maximum of the averages for each individual (\bar{x}_i) (4710 individuals). The within figure calculates the statistics for the deviations of each individual from his own average ($x_{ij} - \bar{x}_i + \bar{x}$) 28467 observations. Thus is for each person you calculate the average hours worked and then calculate the standard deviation of these averages you will get 7.846585. If, for each time period and each person you calculate his deviation from his own average and then calculate the standard deviation of all these 28467 adjusted observations yo get 7.520712. (The addition of an overall average to the individual deviations does not change the variance but does impinge on the explanation of the maximum and minimum. If you find the meaning of between and within a bit difficult leave it and return to it later)

. summ hours

Variable					
-	28467 36				
. xtsum hours					
Variable					Observations
hours overall between	36.55956 	9.869623 7.846585	1 1	168 83.5	
. xtsum birth_yr	/∗ Time inva	riant vari	able */		
Variable					
birth_yr overall between	48.08509	3.012837 3.051795	41 41	54 54	

xttab generalises tabulate by performing one-way tabulations and giving details of between and within frequencies. 3113 in the between category is the number of women who showed a 0 in some year in the sample while 3643 is the number who showed a 1. As there were only 4711 in the sample we can see that many changed status during the sample period. The 55.06% is the fraction of time, on average, a women recorded 0 under msp given that she recorded 0 in some period. Similarly 71.90 is the fraction of time, on average, that a woman recorded 1 given that she recorded 1 in some period. For comparison purposes **xttab** is repeated for race, a characteristic which does not change over the period.

. summ msp

Variable	Obs	Mean	Std. Dev.	Min	Max
msp	28518	.6029175	.4893019	0	1
. tab msp					
1 if married, spouse					

present	Freq.	Percent	Cum.
0 1	11,324 17,194	39.71 60.29	39.71 100.00
Total	28,518	100.00	

. xttab msp

	0verall		Bet	Within	
msp	•	Percent	•	Percent	Percent
+					
0	11324	39.71	3113	66.08	55.06
1	17194	60.29	3643	77.33	71.90
+					
Total	28518	100.00	6756	143.41	64.14
		((n = 4711)		

xttrans looks at transitions from on state to another over time. Thus 80.49% of the women who were 0 in one year were also zero in the next recorded year while 19.51% changed to 1. As we have seen above this data set is not balanced (i.e. There are not observations for all persons for all years. Thus some of the transitions may be over a period of years. To solve this problem we need to fill in the missing observations with NAs. This is accomplished by the **fillin** command. Rerunning the **xttrans** command gives appropriate estimates of the transition probabilities.

. xttrans msp

1 if married, spouse present	 1 if marrie pres 0		Total
	+		+
0 1	80.49 7.96	19.51 92.04	100.00 100.00
Total	37.11	62.89	100.00

. xttrans msp, freq /* Does not normalize for missing time periods */

1 if married,	 1 if married,	spouse	
spouse	preser	it	
present	0	1	Total
	+		+
0	7,697	1,866	9,563
	80.49	19.51	100.00
	+		+
1	1,133	13,100	14,233
	7.96	92.04	100.00
	+		+
Total	8,830	14,966	23,796
	37.11	62.89	100.00
	•		

. * Rectangularize the data

. fillin idcode year

. xttrans m	sp, freq		
1 if married, spouse present	 1 if marri pre 0	ed, spouse esent 1	Total
0	6,792 82.45	1,446 17.55	. ,
1	813 6.91	10,954 93.09	. ,
Total	7,605 38.02	12,400 61.98	

At this stage we might mention the **reshape** command. To illustrate this we load a small artificial data set which is listed in the computer output below. This is in what is known as long format. In long format each record has two identifiers. Here the identifiers are the idcode and the year. There are two variables, wage and tax, and 12 observations on each variable. In wide format as shown in the second list command there are three records indexed by idcode. There are four wage (wage2001, wage2002, wage2003 and wage2004) and four tax variables. This allows one to summarise data for each year if required. On some occasions one may find panel data on an excel spreadsheet in this format and may need to transform it to long format for analysis. Transfer from long to wide format is accomplished by **reshape wide** and the refverse transfer by **reshape long** In Stata 10 details of the **reshape** command are given in the Data manual.

xtline draws line plots for panel data. detail of wide and long

```
//
insheet using long.csv, comma clear
xtset idcode year
describe
summarize
list
// Switch to wide format
reshape wide wage tax , i(idcode) j(year)
describe
summarize
list
// Switch back to narrow format
reshape long wage tax , i(idcode) j(year)
describe
summarize
list
//
```

3 Estimation using xtreg

3.1 Introduction

The basic linear unobserved effects panel data model is

$$y_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + c_i + u_{it} \tag{1}$$

(For a full explanation of the symbols see Wooldridge page 251, etc.). In equation (1) c_i is the unit specific residual and differs *between* units but not across time *within* units. Averaging equation 1 over time we get

$$\bar{y}_i = \bar{\mathbf{X}}_i \boldsymbol{\beta} + c_i + \bar{u}_i \tag{2}$$

Subtracting equation (2) from equation (1) gives equation (3) which does not include the unit specific effect.

$$(\mathbf{y}_{it} - \bar{\mathbf{y}}_i) = (\mathbf{X}_{it} - \bar{\mathbf{X}}_i)\boldsymbol{\beta} + (u_{it} - \bar{u}_i)$$
(3)

These three equations form the basis for the various ways of estimating β .

xtreg ..., **fe** gives the fixed effects or within estimator of β and is derived from equation (3). It is equivalent to performing *OLS* on equation (3).

xtreg ..., **be** gives the between effects and corresponds to *OLS* estimation of equation (2).

xtreg ..., **re** gives the random effects estimator and is a weighted average of the within and between effects estimator. The random effects estimator is equivalent to estimating

$$(\gamma_{it} - \theta \bar{\gamma}_i) = (\mathbf{X}_{it} - \theta \bar{\mathbf{X}}_i) \boldsymbol{\beta} + (1 - \theta) c_i + (u_{it} - \theta \bar{u}_i)$$
(4)

where θ is a function of σ_c^2 and σ_u^2 .

xtreg ...,**mle** produces maximum liklihood estimates of the random effects estimator.

For additional options available with the **xtreg** command see the on-line help files or the STATA manuals.

```
. //
. // Using xtreg
. //
. use nlswork, clear
(National Longitudinal Survey. Young Women 14-26 years of age in 1968)
. generate age2 = age^2
(24 missing values generated)
. generate ttl_exp2 = ttl_exp^2
. generate tenure2 = tenure^2
(433 missing values generated)
. generate byte black = race==2
```

3.2 Pooled of Stacked OLS

For comparison purposes, we first estimate the model using OLS. Some might refer to this model as a stacked or pooled OLS estimate.

```
. //
. // OLS
. //
. regress ln_wage grade age* ttl_exp* tenure* black not_smsa south
```

Source Model Residual Total	4011.63592	10 240 28080 .14	42864527		Number of obs F(10, 28080) Prob > F R-squared Adj R-squared Root MSE	= 1681.47 = 0.0000 = 0.3745 = 0.3743
]n_wage	Coef.	Std. Err	. t	P> t	[95% Conf.	Interval]
grade	.0629238	.0010313	61.01	0.000	.0609024	.0649452
age	.038598	.003467	11.13	0.000	.0318025	.0453935
age2	0007082	.0000563	-12.57	0.000	0008186	0005978
ttl_exp	.0211279	.002335	9.05	0.000	.0165511	.0257046
ttl_exp2	.0004473	.0001246	3.59	0.000	.0002031	.0006916
tenure	.0473687	.0019626	24.14	0.000	.0435219	.0512156
tenure2	002027	.0001338	-15.15	0.000	0022893	0017648
black	0699386	.0053207	-13.14	0.000	0803673	0595098
not_smsa	1720455	.0051675	-33.29	0.000	182174	161917
south	1003387	.0048938	-20.50	0.000	1099308	0907467
_cons	.2472833	.0493319	5.01	0.000	.1505903	.3439762

. estimates store m_ols

3.3 Fixed Effects Estiamator

Next we have a fixed effects estimator first assuming heteroscedasticity and then with a robust estimator of the variance covariance matrix. Note at the bottom of the the first table the F-test that all the fixed effects are zero. This test is not given in the table containing the results of the robust estimation procedure as the equivalent robust statistic is difficult to calculate. Finally there is a table summarising the results of the OLS and fixed effects estimator. There is also a Stata command **areg** which may be used for OLS estimation when one has a large number of dummy variables. **areg** is designed for datasets with many groups, but not a number of groups that increases with the sample size. xtreg, fe can handle the case in which the number of groups increases with the sample size. With the addition of the vce() options to the **xtreg**, **fe** command access to the **areg** command is not now required for that purpose.

. // . //Fixed Effects . // . xtreg ln_wage grade age* ttl_exp* tenure* bl	ack not_smsa south, fe
Fixed-effects (within) regression Group variable: idcode	Number of obs = 28091 Number of groups = 4697
R-sq: within = 0.1727 between = 0.3505 overall = 0.2625	Obs per group: min = 1 avg = 6.0 max = 15
corr(u_i, Xb) = 0.1936	F(8,23386) = 610.12 Prob > F = 0.0000
ln_wage Coef. Std. Err. t	P> t [95% Conf. Interval]

ttl_exp ttl_exp2 tenure tenure2 black not_smsa south _cons	.035998 00072 .033466 .000216 .035753 001970 (dropped 089010 060630	7 .00333 3 .0000 8 .00296 3 .00012 9 .00184 1 .0007 8 .0095 9 .0109 2 .0485	533 -13.58 553 11.29 277 1.69 487 19.34 125 -15.76 316 -9.34 319 -5.55	0.000 0.000 0.090 0.000 0.000 0.000 0.000	.0293611 0008274 .0276545 0000341 .0321303 0022151 1076933 0820582 .9421496	.0426362 0006186 .039279 .0004666 .0393775 0017251 0703282 0392036 1.13249
sigma_u sigma_e rho	.2906892	3	tion of varia	ance due t	o u_i)	
F test that a	ll u_i=0:	F(4696	, 23386) =	5.13	Prob >	F = 0.0000
. estimates s	tore m_fe					
. // . qui xtreg lu	n_wage grad	e age* tt [.]	l_exp* tenur	e∗ black n	ot_smsa soutl	h, fe vce(ro
> bust)	5 5	5	·			
. estimates s	tore m fe re	0				
		-				
. estimates ta	able m_ols ı	m_fe m_fe_	_ro m_fe_cl,	b(%7.3g)	se(%7.3g)	
	m_ols					
grade		0	0			
	.00103	0				
age		.036 .00339	.036			
age?		00072	00072			
5	5.6e-05	5.3e-05	8.5e-05			
ttl_exp		.0335	.0335			
	.00234	.00297	.00407			
ttl_exp2			.00022			
	.00012	.00013	.00018			
tenure		.0358	.0358			
tonuno	.00196 00203	.00185	.00247			
cenure2		00197 .00012	00197 .00017			
black		.00012	00017			
bruck	.00532	0	0			
not_smsa	172	089	089			
	.00517	.00953	.0138			
south	1	0606	0606			
	.00489	.0109	.0163			
_cons	.247	1.04	1.04			
	.0493	.0486	.074			
		10	egend: b/se			

3.4 Between Effects Estimator

We now calculate a between effects estimator.

. // . // Betweeen E . // . xtreg ln_wage			nure* bla	ick not_s	msa south, be	
Between regress Group variable:		sion on grou	p means)		of obs = of groups =	
	= 0.1591 = 0.4900 = 0.3695			Obs per	5	1 6.0 15
sd(u_i + avg(e_	_i.))= .3030	5114		F(10,46 Prob >	586) = F =	450.23 0.0000
ln_wage	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
age age2 ttl_exp ttl_exp2	.0138853 .0007342 .0698419 0028756 0564167 1860406	.0087251 .0001429 .0056749 .0003267 .0060729 .0004098 .0105131 .0112495 .010136	30.37 3.70 -4.20 2.45 2.25 11.50 -7.02 -5.37 -16.54 -9.80 2.76	0.000 0.000 0.014 0.025 0.000 0.000 0.000 0.000		.0494211 0003194 .0250108 .0013747 .0817476 0020722 0358061 1639862

3.5 Random Effects Estimator

Four examples of the random effects estimator follow - random effects, random effects with robust errors, Maximum likelihood. Note that the maximum likelihood estimator give a test for zero variance of the random effects.

1

6.0

15

```
. //
. // Random Effects Estimators
. //
. xtreg ln_wage grade age* ttl_exp* tenure* black not_smsa south, re
Random-effects GLS regression
                                        Number of obs
                                                              28091
                                                         =
Group variable: idcode
                                        Number of groups =
                                                               4697
R-sq: within = 0.1715
                                        Obs per group: min =
     between = 0.4784
                                                     avg =
     overall = 0.3708
                                                     max =
Random effects u_i ~ Gaussian
                                        Wald chi2(10)
                                                            9244.87
                                                        =
             = 0 (assumed)
corr(u_i, X)
                                        Prob > chi2
                                                        =
                                                             0.0000
    _____
   ln_wage | Coef. Std. Err. z P>|z| [95% Conf. Interval]
   _____
     grade | .0646499 .0017811 36.30 0.000 .0611589
age | .036806 .0031195 11.80 0.000 .0306918
                                                           .0681408
                        .0031195
                                                           .0429201
      age2 | -.0007133
                        .00005 -14.27 0.000
                                                -.0008113
                                                           -.0006153
                                               .0242737
             .0290207
    ttl_exp |
                        .0024219
                                 11.98
                                        0.000
                                                           .0337676
                                       0.009
   ttl_exp2 |
              .0003049
                        .0001162
                                  2.62
                                                  .000077
                                                           .0005327
```

black not_smsa south _cons	0020035 0530532 1308263 0868927 .2387209	.0073031 .0494688	-16.80 -5.31 -18.23 -11.90 4.83	0.000 0.000 0.000	0022373 0726379 1448891		
sigma_u sigma_e rho	.25790313 .29069544 .44043812	(fraction			o u_i)		
. estimates st	core m_re						
. qui xtreg lr > bust)	n_wage grade a	uge* ttl_exp)∗ tenure∗	e black ne	ot_smsa sou [.]	th, re vce(ro	
. estimates st	core m_re_ro						
. xtreg ln_wag	ge grade age*	ttl_exp* te	enure* bla	ack not_s	msa south, r	nle	
Fitting consta Iteration 0: Iteration 1: Iteration 2: Iteration 3: Iteration 4: Iteration 5:	log likeliho log likeliho log likeliho	pod = -13690 pod = -12819 pod = -12662 pod = -12649 pod = -12649	9.317 2.039 9.744 9.614				
Fitting full model: Iteration 0: log likelihood = -8922.145 Iteration 1: log likelihood = -8853.6409 Iteration 2: log likelihood = -8853.4255 Iteration 3: log likelihood = -8853.4254							
Random-effects Group variable		n			of obs of groups		
Random effects u_i ~ Gaussian C						= 1 = 6.0 = 15	
Log likelihood	d = -8853.425	4		LR chi2 Prob >	(10) chi2	= 7592.38 = 0.0000	
ln_wage	Coef.	Std. Err.				f. Interval]	
grade age	.0368531	.0017372 .0031226	37.19 11.80	0.000 0.000	.0612044 .030733	.0680142 .0429732	
age2		.0000501	-14.24	0.000	0008113	000615	
ttl_exp ttl_exp2		.0024143 .0001163	11.94 2.66	0.000 0.008	.0240877	.0335515 .0005369	
tenure		.0017604	2.66	0.008	.0359868	.0428875	
tenure2		.0001195	-16.77	0.000	0022395	0017709	
black	0533394	.0097338	-5.48	0.000	0724172	0342615	
not_smsa	1323433	.0071322	-18.56	0.000	1463221	1183644	
south _cons		.0072143 .0491902	-12.14 4.86	0.000 0.000	1016998 .1426727	0734201 .3354947	
/sigma_u /sigma_e		.0035017 .001352			.2417863 .289208	.2555144 .2945076	

rho	.4204033	.0074828	. 4057959	.4351212

Likelihood-ratio test of sigma_u=0: chibar2(01)= 7339.84 Prob>=chibar2 = 0.000

. estimates store m_mle

. estimates table m_re m_re_ro m_mle, b(%7.3g) se(%7.3g)

Variable	m_re	m_re_ro	m_mle
grade	.0646	.0646	
5	.00178	.00193	
age	.0368	.0368	
	.00312	.00354	
age2	00071	00071	
_	5.0e-05	5.8e-05	
ttl_exp	.029	.029	
	.00242	.00261	
ttl_exp2	.0003	.0003	
tenure	00012 .0393	.00013 .0393	
Lenure	00176	.00185	
tenure2	002	002	
centre ce	.00012	.00013	
black	0531	0531	
brach	.00999	.00983	
not_smsa	131	131	
	.00718	.00772	
south	0869	0869	
	.0073	.00772	
_cons	.239	.239	
	.0495	.0549	
	+		
ln_wage grade			.0646
yi aue			.00174
age	l İ		.0369
uge			.00312
age2	İ		00071
5	l		5.0e-05
ttl_exp	l		.0288
			.00241
ttl_exp2			.00031
			.00012
tenure			.0394
			.00176
tenure2			00201
h] a cli			.00012
black	1		0533 .00973
not_smsa	1		132
110 c_3113 d	1		.00713
south			0876
504.01			.00721
_cons			.239
			.0492
	+		
sigma_u			2.40
_cons			.249



Note that STATA has no direct command for two way fixed effects. If you wish to also introduce a second set of fixed effects for, say, time periods create a set of appropriate dummy variables for inclusion in your regressions and use a one way estimator.

4 Testing after xtreg

Note that the post estimation commands **test**, **testn1**, **estimates**, **lincom**, **lrtest**, **mfx**, **nlcom**, **predict**, **predictn1** and **hausman** are also available after **xtreg**. The command **xttest0** is the Breusch and Pagan LM test for random effects. We can also do a Hausman test. When the common effects are orthogonal to the regressors both fixed and random effect estimators are consistent (but fixed effects are not efficient) under the alternative fixed effects are consistent whereas random effects are not. The Hausman test looks at the difference between the coefficients estimated using a random effects estimator and a fixed effects estimator. Roughly speaking in both estimates are similar we can use a random effects estimator. If they are different one may use the fixed effects estimator. The format of the hausman instruction is

hausman m_consistent m_efficient

where *m_consistent* and *m_efficient* are estimates of two models that have been estimated and saved (**estimates store**). *m_consistent* is the estimate that is consistent in both cases but not efficient and *m_efficient* is efficient where the first model is not efficient. In this case the estimates are significantly different and we reject the random effects estimator.

. /* After xtreg, re */
// After the random effects estimate

```
. \star Breusch & Pagan score test for random effects . <code>xttest0</code>
```

Breusch and Pagan Lagrangian multiplier test for random effects:

ln_wage[idcode,t] = Xb + u[idcode] + e[idcode,t] Estimated results: sd = sqrt(Var)Var .4778416 ln_wage | .2283326 .0845038 .2906954 e | u | .066514 .2579031 Test: Var(u) = 0chi2(1) = 14779.98Prob > chi2 = 0.0000

. * Hausman specification test (compares fe and re)

.qui xtreg ln_wage grade age age2 ttl_exp ttl_exp2 tenure tenure2 not_smsa south,fe

F(4696, 23386) = 5.19 Prob > F = 0.0000

. estimates store fe

. qui xtreg ln_wage grade age age2 ttl_exp ttl_exp2 tenure tenure2 not_smsa south, re

. estimates store re

. hausman fe re

	Coeffi	cients		
	(b)	(B)	(b-B)	<pre>sqrt(diag(V_b-V_B))</pre>
 	fe	re	Difference	S.E.
age	.0359987	.0363062	0003075	.0013183
age2	000723	000705	000018	.0000184
ttl_exp	.0334668	.0292321	.0042347	.0017085
ttl_exp2	.0002163	.0002946	0000783	.0000529
tenure	.0357539	.0390983	0033444	.0005789
tenure2	0019701	0020014	.0000313	.0000372
not_smsa	0890108	1268961	.0378853	.0063038
south	0606309	094716	.0340851	.008259

b = consistent under Ho and Ha; obtained from xtreg B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(8)	=	$(b-B)'[(V_b-V_B)^{-1}](b-B)$
	=	142.53
Prob>chi2	=	0.0000

5 Prediction after xtreg

After **xtreg** the **predict** command has the following options

xb $x_j b$, fitted values

stdp standard error of the fitted values

ue $\hat{c}_i + \hat{u}_{it}$, combined residual

xbu $\boldsymbol{x}_{i}\boldsymbol{b} + c_{i}$, prediction including effect

 $u c_i$, The fixed or random effect component

 $e u_{it}$, the error component

The last three of these are only available within sample

6 Other Stata Panel estimators

Here we mention some more detail regarding other Stata panel data commands. A complete list has already been given in Section (1). Details are given in the manuals of the help files. Before using any of these commands one should be familiar with the theory involved.

6.1 Faster estimation of alternative models using xtdata

xtdata varlist ... produces a converted data set of the variables specified or, if varlist is not specified, all the variables in the data. Once converted, Stata's ordinary regress command may be used to perform various panel data regressions more quickly than using **xtreg**. Before using **xdata** you must eliminate any variables that you do not intend to use and that have missing values. After converting the data, with **xdata** you may form linear transformations of the regressors. All nonlinear transformations of the data must be done before conversion. The gain in this instruction is where one needs to do a large specification search. The following stata commands illustrate this procedure. Output is suppressed.

qui xtdata ln_wage grade age* ttl_exp* tenure* black not_smsa south, fe clear
qui regress ln_wage grade age ttl_exp tenure black not_smsa south
qui regress ln_wage grade age* ttl_exp* tenure* black not_smsa south
qui xtdata ln_wage grade age* ttl_exp* tenure* black not_smsa south, re ratio(.95) clear
qui regress ln_wage constant grade age ttl_exp tenure black not_smsa south, noconstant
qui regress ln_wage grade age* ttl_exp* tenure* black not_smsa south, noconstant
qui regress ln_wage constant grade age* ttl_exp* tenure* black not_smsa south, noconstant
qui xtdata ln_wage grade age* ttl_exp* tenure* black not_smsa south, fe clear
qui regress ln_w grade age ttl_exp tenure black not_smsa south

6.2 More general error structures

xtregar fits fixed affects and random effects models where the disturbance follows an AR(1) process i.e.

$$y_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + c_i + u_{it}$$
$$u_{it} = \rho u_{i,t-1} + \eta_{it}$$

and η_{it} are independent $N(0, \sigma_n^2)$.

xtpcse and **xtgls** estimate panel models under various assumptions about heterogeneity of variances across panels and possible serial correlation.

6.3 Dynamic panel data

The commands of interest here are **xtabond**, **xtdpsys** and **xtdpd**. There are considerable changes here relative to earlier versions of Stata.

6.4 Limited Dependent Variables in Panel Data

There are a variety of LDV estimation commands corresponding to the standard methods. These include **xttobit**, **xtintreg**, **xtlogit**, **xtprobit**, **xtclogit**, **xtpoisson**, **xtnbreg**, **xtmelogit** and **xtmepoisson**.

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