

**xt** — Introduction to xt commands

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## Description

The `xt` series of commands provides 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). Panel datasets have the form  $\mathbf{x}_{it}$ , where  $\mathbf{x}_{it}$  is a vector of observations for unit  $i$  and time  $t$ . The particular commands (such as `xtdescribe`, `xtsum`, and `xtreg`) are documented in alphabetical order in the entries that follow this entry. If you do not know the name of the command you need, try browsing the second part of this description section, which organizes the `xt` commands by topic. The next section, [Remarks and examples](#), describes concepts that are common across commands.

The `xtset` command sets the panel variable and the time variable; see [XT] [xtset](#). 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.

If your interest is in general time-series analysis, see [U] [27.14 Time-series models](#) and the [Time-Series Reference Manual](#). If your interest is in multilevel mixed-effects models, see [U] [27.16 Multilevel mixed-effects models](#) and the [Multilevel Mixed-Effects Reference Manual](#). If you are interested in SAR (spatial autoregressive or simultaneously autoregressive) models for panel data, see [SP] [spxtregress](#). If you are interested in extended panel-data regression models that address endogenous covariates, nonrandom treatment assignment, and endogenous sample selection, see the [Extended Regression Models Reference Manual](#).

## Setup

`xtset`      Declare data to be panel data

## Data management and exploration tools

`xtdescribe`    Describe pattern of `xt` data  
`xtsum`        Summarize `xt` data  
`xttab`        Tabulate `xt` data  
`xtdata`       Faster specification searches with `xt` data  
`xtline`       Panel-data line plots

### Linear regression estimators

<code>xtreg</code>	Fixed-, between-, and random-effects, and population-averaged linear models
<code>xtregar</code>	Fixed- and random-effects linear models with an AR(1) disturbance
<code>xtgls</code>	Fit panel-data models by using GLS
<code>xtpcse</code>	Linear regression with panel-corrected standard errors
<code>xthtaylor</code>	Hausman–Taylor estimator for error-components models
<code>xtfrontier</code>	Stochastic frontier models for panel data
<code>xtrc</code>	Random-coefficients model
<code>xtivreg</code>	Instrumental variables and two-stage least squares for panel-data models
<code>xtheckman</code>	Random-effects regression with sample selection
<code>xtdidregress</code>	Fixed-effects difference-in-differences estimation
<code>xteregress</code>	Random-effects models with endogenous covariates, treatment, and sample selection

### Unit-root tests

<code>xtunitroot</code>	Panel-data unit-root tests
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### Cointegration tests

<code>xtcointtest</code>	Panel-data cointegration tests
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### Dynamic panel-data estimators

<code>xtabond</code>	Arellano–Bond linear dynamic panel-data estimation
<code>xtdpd</code>	Linear dynamic panel-data estimation
<code>xtdpdsys</code>	Arellano–Bover/Blundell–Bond linear dynamic panel-data estimation

### Censored-outcome estimators

<code>xttobit</code>	Random-effects tobit models
<code>xtintreg</code>	Random-effects interval-data regression models
<code>xteintreg</code>	Random-effects interval-data regression models with endogenous covariates, treatment, and sample selection

### Binary-outcome estimators

<code>xtlogit</code>	Fixed-effects, random-effects, and population-averaged logit models
<code>xtprobit</code>	Random-effects and population-averaged probit models
<code>xtcloglog</code>	Random-effects and population-averaged cloglog models
<code>xteprobit</code>	Random-effects probit models with endogenous covariates, treatment, and sample selection

### Ordinal-outcome estimators

<code>xtologit</code>	Random-effects ordered logistic models
<code>xtoprobit</code>	Random-effects ordered probit models
<code>xteoprobit</code>	Random-effects ordered probit models with endogenous covariates, treatment, and sample selection

### Categorical-outcome estimators

<code>xtmlgit</code>	Fixed-effects and random-effects multinomial logit models
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### Count-data estimators

<code>xtpoisson</code>	Fixed-effects, random-effects, and population-averaged Poisson models
<code>xtnbreg</code>	Fixed-effects, random-effects, & population-averaged negative binomial models

## Survival-time estimators

`xtstreg` Random-effects parametric survival models

## Generalized estimating equations estimator

`xtgee` Population-averaged panel-data models by using GEE

## Utility

`quadchk` Check sensitivity of quadrature approximation

## Remarks and examples

[stata.com](https://www.stata.com)

Consider having data on  $n$  units—individuals, firms, countries, or whatever—over  $T$  periods. The data might be income and other characteristics of  $n$  persons surveyed each of  $T$  years, the output and costs of  $n$  firms collected over  $T$  months, or the health and behavioral characteristics of  $n$  patients collected over  $T$  years. In panel datasets, we write  $x_{it}$  for the value of  $x$  for unit  $i$  at time  $t$ . The xt commands assume that such datasets are stored as a sequence of observations on  $(i, t, x)$ .

For a discussion of panel-data models, see Baltagi (2013), Greene (2018, chap. 11), Hsiao (2014), and Wooldridge (2010). Cameron and Trivedi (2010) illustrate many of Stata's panel-data estimators.

For an introduction to linear, nonlinear, and dynamic panel-data analysis in Stata, we offer NetCourse 471, *Introduction to Panel Data Using Stata*; see <https://www.stata.com/netcourse/panel-data-intro-nc471/>.

### ► Example 1

If we had data on pulmonary function (measured by forced expiratory volume, or FEV) along with smoking behavior, age, sex, and height, a piece of the data might be

```
. list in 1/6, separator(0) divider
```

	pid	yr_visit	fev	age	sex	height	smokes
1.	1071	1991	1.21	25	1	69	0
2.	1071	1992	1.52	26	1	69	0
3.	1071	1993	1.32	28	1	68	0
4.	1072	1991	1.33	18	1	71	1
5.	1072	1992	1.18	20	1	71	1
6.	1072	1993	1.19	21	1	71	0

The xt commands need to know the identity of the variable identifying patient, and some of the xt commands also need to know the identity of the variable identifying time. With these data, we would type

```
. xtset pid yr_visit
```

If we resaved the data, we need not respecify `xtset`.

## □ Technical note

Panel data stored as shown above are said to be in the long form. Perhaps the data are in the wide form with 1 observation per unit and multiple variables for the value in each year. For instance, a piece of the pulmonary function data might be

pid	sex	fev91	fev92	fev93	age91	age92	age93
1071	1	1.21	1.52	1.32	25	26	28
1072	1	1.33	1.18	1.19	18	20	21

Data in this form can be converted to the long form by using `reshape`; see [D] [reshape](#). □

## ▷ Example 2

Data for some of the periods might be missing. That is, we have panel data on  $i = 1, \dots, n$  and  $t = 1, \dots, T$ , but only  $T_i$  of those observations are defined. With such missing periods—called unbalanced data—a piece of our pulmonary function data might be

```
. list in 1/6, separator(0) divider
```

	pid	yr_visit	fev	age	sex	height	smokes
1.	1071	1991	1.21	25	1	69	0
2.	1071	1992	1.52	26	1	69	0
3.	1071	1993	1.32	28	1	68	0
4.	1072	1991	1.33	18	1	71	1
5.	1072	1993	1.19	21	1	71	0
6.	1073	1991	1.47	24	0	64	0

Patient ID 1072 is not observed in 1992. The `xt` commands are robust to this problem. ◀

## □ Technical note

In many of the entries in [XT], we will use data from a subsample of the NLSY data ([Center for Human Resource Research 1989](#)) on young women aged 14–24 years in 1968. Women were surveyed in each of the 21 years 1968–1988, except for the six years 1974, 1976, 1979, 1981, 1984, and 1986. We use two different subsets: `nlswork.dta` and `union.dta`.

For `nlswork.dta`, our subsample is of 4,711 women in years when employed, not enrolled in school and evidently having completed their education, and with wages in excess of \$1/hour but less than \$700/hour.

```
. use https://www.stata-press.com/data/r17/nlswork, clear
(National Longitudinal Survey of Young Women, 14-24 years old in 1968)
. describe
Contains data from https://www.stata-press.com/data/r17/nlswork.dta
Observations:      28,534      National Longitudinal Survey of
                        Young Women, 14-24 years old in
                        1968
Variables:         21         27 Nov 2020 08:14
                        (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
idcode	int	%8.0g		NLS ID
year	byte	%8.0g		Interview year
birth_yr	byte	%8.0g		Birth year
age	byte	%8.0g		Age in current year
race	byte	%8.0g	racelbl	Race
msp	byte	%8.0g		1 if married, spouse present
nev_mar	byte	%8.0g		1 if never married
grade	byte	%8.0g		Current grade completed
collgrad	byte	%8.0g		1 if college graduate
not_smsa	byte	%8.0g		1 if not SMSA
c_city	byte	%8.0g		1 if central city
south	byte	%8.0g		1 if south
ind_code	byte	%8.0g		Industry of employment
occ_code	byte	%8.0g		Occupation
union	byte	%8.0g		1 if union
wks_ue	byte	%8.0g		Weeks unemployed last year
ttl_exp	float	%9.0g		Total work experience
tenure	float	%9.0g		Job tenure, in years
hours	int	%8.0g		Usual hours worked
wks_work	int	%8.0g		Weeks worked last year
ln_wage	float	%9.0g		ln(wage/GNP deflator)

Sorted by: idcode year

```
. summarize
```

Variable	Obs	Mean	Std. dev.	Min	Max
idcode	28,534	2601.284	1487.359	1	5159
year	28,534	77.95865	6.383879	68	88
birth_yr	28,534	48.08509	3.012837	41	54
age	28,510	29.04511	6.700584	14	46
race	28,534	1.303392	.4822773	1	3
msp	28,518	.6029175	.4893019	0	1
nev_mar	28,518	.2296795	.4206341	0	1
grade	28,532	12.53259	2.323905	0	18
collgrad	28,534	.1680451	.3739129	0	1
not_smsa	28,526	.2824441	.4501961	0	1
c_city	28,526	.357218	.4791882	0	1
south	28,526	.4095562	.4917605	0	1
ind_code	28,193	7.692973	2.994025	1	12
occ_code	28,413	4.777672	3.065435	1	13
union	19,238	.2344319	.4236542	0	1
wks_ue	22,830	2.548095	7.294463	0	76
ttl_exp	28,534	6.215316	4.652117	0	28.88461
tenure	28,101	3.123836	3.751409	0	25.91667
hours	28,467	36.55956	9.869623	1	168
wks_work	27,831	53.98933	29.03232	0	104
ln_wage	28,534	1.674907	.4780935	0	5.263916

Many of the variables in the `nlswork` dataset are indicator variables, so we have used factor variables (see [U] 11.4.3 **Factor variables**) in many of the examples in this manual. You will see terms like `c.age#c.age` or `2.race` in estimation commands. `c.age#c.age` is just `age` interacted with `age`, or `age-squared`, and `2.race` is just an indicator variable for black (`race = 2`).

Instead of using factor variables, you could type

```
. generate age2 = age*age
. generate black = (race==2)
```

and substitute `age2` and `black` in your estimation command for `c.age#c.age` and `2.race`, respectively.

There are advantages, however, to using factor variables. First, you do not actually have to create new variables, so the number of variables in your dataset is less.

Second, by using factor variables, we are able to take better advantage of postestimation commands. For example, if we specify the simple model

```
. xtreg ln_wage age age2, fe
```

then `age` and `age2` are completely separate variables. Stata has no idea that they are related—that one is the square of the other. Consequently, if we compute the average marginal effect of `age` on the log of wages,

```
. margins, dydx(age)
```

then the reported marginal effect is with respect to the `age` variable alone and not with respect to the true effect of `age`, which involves the coefficients on both `age` and `age2`.

If instead we fit our model using an interaction of `age` with itself for the square of `age`,

```
. xtreg ln_wage age c.age#c.age, fe
```

then Stata has a deep understanding that the coefficients `age` and `c.age#c.age` are related. After fitting this model, the marginal effect reported by `margins` includes the full effect of age on the log of income, including the contribution of both coefficients.

```
. margins, dydx(age)
```

There are other reasons for preferring factor variables; see [R] [margins](#) for examples.

For `union.dta`, our subset was sampled only from those with union membership information from 1970 to 1988. Our subsample is of 4,434 women. The important variables are `age` (16–46), `grade` (years of schooling completed, ranging from 0 to 18), `not_smsa` (28% of the person-time was spent living outside a standard metropolitan statistical area (SMSA), and `south` (41% of the person-time was in the South). The dataset also has variable `union`. Overall, 22% of the person-time is marked as time under union membership, and 44% of these women have belonged to a union.

```
. use https://www.stata-press.com/data/r17/union
(NLS Women 14-24 in 1968)
```

```
. describe
```

```
Contains data from https://www.stata-press.com/data/r17/union.dta
Observations:      26,200      NLS Women 14-24 in 1968
Variables:         8          4 May 2020 13:54
                        (_dta has notes)
```

Variable name	Storage type	Display format	Value label	Variable label
<code>idcode</code>	int	%8.0g		NLS ID
<code>year</code>	byte	%8.0g		Interview year
<code>age</code>	byte	%8.0g		Age in current year
<code>grade</code>	byte	%8.0g		Current grade completed
<code>not_smsa</code>	byte	%8.0g		1 if not SMSA
<code>south</code>	byte	%8.0g		1 if south
<code>union</code>	byte	%8.0g		1 if union
<code>black</code>	byte	%8.0g		Race black

```
Sorted by: idcode year
```

```
. summarize
```

Variable	Obs	Mean	Std. dev.	Min	Max
<code>idcode</code>	26,200	2611.582	1484.994	1	5159
<code>year</code>	26,200	79.47137	5.965499	70	88
<code>age</code>	26,200	30.43221	6.489056	16	46
<code>grade</code>	26,200	12.76145	2.411715	0	18
<code>not_smsa</code>	26,200	.2837023	.4508027	0	1
<code>south</code>	26,200	.4130153	.4923849	0	1
<code>union</code>	26,200	.2217939	.4154611	0	1
<code>black</code>	26,200	.274542	.4462917	0	1

In many of the examples where the `union` dataset is used, we also include an interaction between the `year` variable and the `south` variable—`south#c.year`. This interaction is created using factor-variables notation; see [U] [11.4.3 Factor variables](#).

With both datasets, we have typed

```
. xtset idcode year
```

□

## □ Technical note

The `xtset` command sets the  $t$  and  $i$  index for **xt** data by declaring them as characteristics of the data; see [P] [char](#). The panel variable is stored in `_dta[iis]` and the time variable is stored in `_dta[tis]`. □

## □ Technical note

Throughout the entries in [XT], when random-effects models are fit, a likelihood-ratio test that the variance of the random effects is zero is included. These tests occur on the boundary of the parameter space, invalidating the usual theory associated with such tests. However, these likelihood-ratio tests have been modified to be valid on the boundary. In particular, the null distribution of the likelihood-ratio test statistic is not the usual  $\chi_1^2$  but is rather a 50:50 mixture of a  $\chi_0^2$  (point mass at zero) and a  $\chi_1^2$ , denoted as  $\bar{\chi}_{01}^2$ . See [Gutierrez, Carter, and Drukker \(2001\)](#) for a full discussion. □

## References

- Andreß, H.-J., K. Golsch, and A. W. Schmidt. 2013. *Applied Panel Data Analysis for Economic and Social Surveys*. Berlin: Springer.
- Baltagi, B. H. 2013. *Econometric Analysis of Panel Data*. 5th ed. Chichester, UK: Wiley.
- Cameron, A. C., and P. K. Trivedi. 2010. *Microeconometrics Using Stata*. Rev. ed. College Station, TX: Stata Press.
- Center for Human Resource Research. 1989. *National Longitudinal Survey of Labor Market Experience, Young Women 14–24 years of age in 1968*. Columbus, OH: Ohio State University Press.
- Frees, E. W. 2004. *Longitudinal and Panel Data: Analysis and Applications in the Social Sciences*. Cambridge: Cambridge University Press.
- Greene, W. H. 2018. *Econometric Analysis*. 8th ed. New York: Pearson.
- Gutierrez, R. G., S. L. Carter, and D. M. Drukker. 2001. [sg160: On boundary-value likelihood-ratio tests](#). *Stata Technical Bulletin* 60: 15–18. Reprinted in *Stata Technical Bulletin Reprints*, vol. 10, pp. 269–273. College Station, TX: Stata Press.
- Hsiao, C. 2014. *Analysis of Panel Data*. 3rd ed. New York: Cambridge University Press.
- Sun, Y., and G. Dhaene. 2019. `xtspj`: A command for split-panel jackknife estimation. *Stata Journal* 19: 335–374.
- Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

## Also see

[XT] [xtset](#) — Declare data to be panel data