#### xtintreg - Random-effects interval-data regression model

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# Description

xtintreg fits a random-effects regression model in which the dependent variable may be measured as point data, interval data, left-censored data, or right-censored data. The dependent variable must be specified using two *depvars* that indicate how the dependent variable was measured. The user can request that a likelihood-ratio test comparing the panel interval regression model with the pooled model be conducted at estimation time.

# **Quick start**

Regression on x of an interval-measured dependent variable with lower endpoint y\_lower and upper endpoint y\_upper using xtset data

xtintreg y\_lower y\_upper x

Add indicators for levels of categorical variable a as covariates

xtintregy lowery upper x i.a

Perform likelihood-ratio test against pooled model

xtintreg y\_lower y\_upper x i.a, intreg

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## **Syntax**

xtintreg depvar<sub>lower</sub> depvar<sub>upper</sub> [indepvars] [if] [in] [weight] [, options]

Type of data		$depvar_{lower}$	<i>depvar</i> <sub>upper</sub>
point data	a = [a,a]	a	a
interval data	[a,b]	a	b
left-censored data	$(-\infty, b]$		b
right-censored data	$[a,+\infty)$	a	
missing			

The values in *depvar*<sub>lower</sub> and *depvar*<sub>upper</sub> should have the following form:

options	Description
/odel	
<u>nocons</u> tant	suppress constant term
<u>off</u> set( <i>varname</i> )	include varname in model with coefficient constrained to 1
<pre><u>constraints(constraints)</u></pre>	apply specified linear constraints
SE	
vce(vcetype)	vcetype may be oim, <u>boot</u> strap, or <u>jackknife</u>
Reporting	
<u>l</u> evel(#)	set confidence level; default is level(95)
lrmodel	perform the likelihood-ratio model test instead of the default Wald test
intreg	perform likelihood-ratio test against pooled model
<u>nocnsr</u> eport	do not display constraints
display_options	control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling
ntegration	
<pre>intmethod(intmethod)</pre>	integration method; <i>intmethod</i> may be <u>mv</u> aghermite (the default) or ghermite
<pre>intpoints(#)</pre>	use $\overline{\#}$ quadrature points; default is intpoints (12)
<i>I</i> aximization	
maximize_options	control the maximization process; see [R] Maximize
<u>col</u> linear	keep collinear variables
<u>coefl</u> egend	display legend instead of statistics

indepvars may contain factor variables; see [U] 11.4.3 Factor variables.

depvarlower, depvarupper, and indepvars may contain time-series operators; see [U] 11.4.4 Time-series varlists.

by, collect, and statsby are allowed; see [U] 11.1.10 Prefix commands.

iweights are allowed; see [U] 11.1.6 weight. Weights must be constant within panel.

collinear and coeflegend do not appear in the dialog box.

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

# Options

Model noconstant, offset(varname), constraints(constraints); see [R] Estimation options. SE vce(vcetype) specifies the type of standard error reported, which includes types that are derived from asymptotic theory (oim) and that use bootstrap or jackknife methods (bootstrap, jackknife); see [XT] vce\_options. Reporting level(#), lrmodel; see [R] Estimation options. intreg specifies that a likelihood-ratio test comparing the random-effects model with the pooled (intreg) model be included in the output. nocnsreport; see [R] Estimation options. *display\_options*: noci, nopvalues, noomitted, vsquish, noemptycells, baselevels, allbaselevels, nofvlabel, fvwrap(#), fvwrapon(style), cformat(% fmt), pformat(% fmt), sformat(% fmt), and nolstretch; see [R] Estimation options. [Integration] intmethod(*intmethod*), intpoints(#); see [R] Estimation options. Maximization maximize\_options: difficult, technique(algorithm\_spec), iterate(#), [no]log, trace, gradient, showstep, hessian, showtolerance, tolerance(#), ltolerance(#), nrtolerance(#), nonrtolerance, and from(*init\_specs*); see [R] Maximize. These options are seldom used.

The following options are available with xtintreg but are not shown in the dialog box:

collinear, coeflegend; see [R] Estimation options.

## **Remarks and examples**

xtintreg may be used to fit a random-effects interval regression model. Consider the linear regression model with panel-level random effects

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it}$$

for  $i = 1, \ldots, n$  panels, where  $t = 1, \ldots, n_i$ . The random effects,  $\nu_i$ , are i.i.d.,  $N(0, \sigma_{\nu}^2)$ , and  $\epsilon_{it}$  are i.i.d.,  $N(0, \sigma_{\epsilon}^2)$  independently of  $\nu_i$ . The observed data consist of the couples,  $(y_{1it}, y_{2it})$ , such that all that is known is that  $y_{1it} \leq y_{it} \leq y_{2it}$ , where  $y_{1it}$  is possibly  $-\infty$  and  $y_{2it}$  is possibly  $+\infty$ .

#### Example 1: Random-effects interval regression

We begin with the nlswork dataset described in [XT] **xt** and create two fictional dependent variables, where the wages are instead reported sometimes as ranges. The wages have been adjusted to 1988 dollars and have further been recoded such that some of the observations are known exactly, some are left-censored, some are right-censored, and some are known only in an interval.

We wish to fit a random-effects interval regression model of adjusted (log) wages. We specify the intreg option to test our random-effects model against our pooled estimator.

-	/www.stata-pre gitudinal Surv				rs old in 196	68)
. xtintreg ln (output omitted	_wage1 ln_wage !)	2 i.union a	age grade	not_smsa	south##c.yea	ar, intreg
Random-effect:	s interval reg	ression		Numb	er of obs	= 19,224
	-				Uncensored	1 = 4,810
					Left-censored	1 = 4,781
				R	ight-censored	1 = 4,848
				I	nterval-cens.	= 4,785
Group variable: idcode			Numb	er of groups	= 4,148	
Random effect:		an			per group:	,
					mir	1 = 1
					avg	g = 4.6
					max	x = 12
Integration m	ethod: mvagher	mite		Inte	gration pts.	= 12
				Wald	chi2(7)	= 2461.69
Log likelihoo	d = -23260.672	2		Prob	> chi2	= 0.0000
	Coefficient	Std. err.	z	P> z	[95% conf.	interval]
1.union	.1229681	.0092943	13.23	0.000	.1047516	.1411846
age	.0096333	.0019	5.07	0.000	.0059094	.0133572
grade	.0756045	.0023828	31.73	0.000	.0709343	.0802747
not_smsa	1481304	.011433	-12.96	0.000	1705387	1257221
1.south	3586443	.0977512	-3.67	0.000	5502331	1670555
year	.0029219	.0020353	1.44	0.151	0010671	.0069109
south#c.year						
1	.0032699	.0012076	2.71	0.007	.000903	.0056368
_cons	.2747391	.1141328	2.41	0.016	.0510429	.4984352
/sigma_u	.3044775	.0052644	57.84	0.000	.2941594	.3147956
/sigma_e	.3516248	.00307	114.54	0.000	.3456078	.3576418
rho	.4285095	.0101261			.4087613	.4484385
LR test of sig	gma_u=0: chiba	r2(01) = 26	583.77		Prob >= chiba	ar2 = 0.000

The results from an interval regression can be interpreted as we would those from a linear regression. Because the dependent variable is log transformed, the coefficients can be interpreted in terms of a percentage change. We see, for example, that on average, union members make 12.3% more than nonunion members.

The output also includes the overall and panel-level variance components (labeled sigma\_e and sigma\_u, respectively) together with  $\rho$  (labeled rho),

$$\rho = \frac{\sigma_{\nu}^2}{\sigma_{\epsilon}^2 + \sigma_{\nu}^2}$$

which is the proportion of the total variance contributed by the panel-level variance component.

When rho is zero, the panel-level variance component is unimportant, and the panel estimator is not different from the pooled estimator. A likelihood-ratio test of this is included at the bottom of the output. This test formally compares the pooled estimator (interval regression) with the panel estimator. In this case, we reject the null hypothesis that there are no panel-level effects.

#### Technical note

The random-effects model is calculated using quadrature, which is an approximation whose accuracy depends partially on the number of integration points used. We can use the quadchk command to see if changing the number of integration points affects the results. If the results change, the quadrature approximation is not accurate given the number of integration points. Try increasing the number of integration points using the intpoints() option and run quadchk again. Do not attempt to interpret the results of estimates when the coefficients reported by quadchk differ substantially. See [XT] quadchk for details and [XT] **xtprobit** for an example.

Because the xtintreg likelihood function is calculated by Gauss-Hermite quadrature, on large problems the computations can be slow. Computation time is roughly proportional to the number of points used for the quadrature.

## Stored results

```
xtintreg stores the following in e():
```

```
Scalars
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e(N)	number of observations
e(N_g)	number of groups
e(N_unc)	number of uncensored observations
e(N_lc)	number of left-censored observations
e(N_rc)	number of right-censored observations
e(N_int)	number of interval observations
e(k)	number of parameters
e(k_aux)	number of auxiliary parameters
e(k_eq)	number of equations in e(b)
e(k_eq_model)	number of equations in overall model test
e(k_dv)	number of dependent variables
e(df_m)	model degrees of freedom
e(11)	log likelihood
e(11_0)	log likelihood, constant-only model
e(ll_c)	log likelihood, comparison model
e(chi2)	$\chi^2$
e(chi2_c)	$\chi^2$ for comparison test
e(rho)	ho
e(sigma_u)	panel-level standard deviation
e(sigma_e)	standard deviation of $\epsilon_{it}$
e(n_quad)	number of quadrature points
e(g_min)	smallest group size
e(g_avg)	average group size
e(g_max)	largest group size
e(p)	<i>p</i> -value for model test
e(rank)	rank of e(V)
e(rank0)	rank of $e(V)$ for constant-only model
e(ic)	number of iterations
e(rc)	return code
e(converged)	1 if converged, 0 otherwise

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Macros	
e(cmd)	xtintreg
e(cmdline)	command as typed
e(depvar)	names of dependent variables
e(ivar)	variable denoting groups
e(wtype)	weight type
e(wexp)	weight expression
e(title)	title in estimation output
e(offset)	offset
e(chi2type)	Wald or LR; type of model $\chi^2$ test
e(chi2_ct)	Wald or LR; type of model $\chi^2$ test corresponding to e(chi2_c)
e(vce)	vcetype specified in vce()
e(intmethod)	integration method
e(distrib)	Gaussian; the distribution of the random effect
e(opt)	type of optimization
e(which)	max or min; whether optimizer is to perform maximization or minimization
e(ml_method)	type of ml method
e(user)	name of likelihood-evaluator program
e(technique)	maximization technique
e(properties)	b V
e(predict)	program used to implement predict
e(marginsok)	predictions allowed by margins
e(asbalanced)	factor variables fvset as asbalanced
e(asobserved)	factor variables fvset as asobserved
Matrices	
e(b)	coefficient vector
e(Cns)	constraints matrix
e(ilog)	iteration log
e(gradient)	gradient vector
e(V)	variance-covariance matrix of the estimators
Functions	
e(sample)	marks estimation sample
- (F	

In addition to the above, the following is stored in r():

Matrices r(table)

matrix containing the coefficients with their standard errors, test statistics, p-values, and confidence intervals

Note that results stored in r() are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

# Methods and formulas

Assuming a normal distribution,  $N(0, \sigma_{\nu}^2)$ , for the random effects  $\nu_i$ , we have the joint (unconditional of  $\nu_i$ ) density of the observed data for the *i*th panel

$$\begin{split} f\left\{(y_{1i1}, y_{2i1}), \dots, (y_{1in_i}, y_{2in_i}) | \mathbf{x}_{1i}, \dots, \mathbf{x}_{in_i}\right\} = \\ \int_{-\infty}^{\infty} \frac{e^{-\nu_i^2/2\sigma_\nu^2}}{\sqrt{2\pi}\sigma_\nu} \left\{ \prod_{t=1}^{n_i} F(y_{1it}, y_{2it}, \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i) \right\} d\nu_i \end{split}$$

where

$$F(y_{1it}, y_{2it}, \Delta_{it}) = \begin{cases} \left(\sqrt{2\pi}\sigma_{\epsilon}\right)^{-1} e^{-(y_{1it} - \Delta_{it})^2/(2\sigma_{\epsilon}^2)} & \text{if } (y_{1it}, y_{2it}) \in C \\ \Phi\left(\frac{y_{2it} - \Delta_{it}}{\sigma_{\epsilon}}\right) & \text{if } (y_{1it}, y_{2it}) \in L \\ 1 - \Phi\left(\frac{y_{1it} - \Delta_{it}}{\sigma_{\epsilon}}\right) & \text{if } (y_{1it}, y_{2it}) \in R \\ \Phi\left(\frac{y_{2it} - \Delta_{it}}{\sigma_{\epsilon}}\right) - \Phi\left(\frac{y_{1it} - \Delta_{it}}{\sigma_{\epsilon}}\right) & \text{if } (y_{1it}, y_{2it}) \in I \end{cases}$$

where C is the set of noncensored observations  $(y_{1it} = y_{2it} \text{ and both nonmissing})$ , L is the set of leftcensored observations  $(y_{1it} \text{ missing and } y_{2it} \text{ nonmissing})$ , R is the set of right-censored observations  $(y_{1it} \text{ nonmissing and } y_{2it} \text{ missing })$ , I is the set of interval observations  $(y_{1it} < y_{2it} \text{ and both nonmissing})$ , and  $\Phi()$  is the cumulative normal distribution.

The panel-level likelihood  $l_i$  is given by

$$\begin{split} l_i &= \int_{-\infty}^{\infty} \frac{e^{-\nu_i^2/2\sigma_\nu^2}}{\sqrt{2\pi}\sigma_\nu} \left\{ \prod_{t=1}^{n_i} F(y_{1it}, y_{2it}, \mathbf{x}_{it} \boldsymbol{\beta} + \nu_i) \right\} d\nu_i \\ &\equiv \int_{-\infty}^{\infty} g(y_{1it}, y_{2it}, x_{it}, \nu_i) d\nu_i \end{split}$$

This integral can be approximated with M-point Gauss-Hermite quadrature

$$\int_{-\infty}^{\infty}e^{-x^2}h(x)dx\approx\sum_{m=1}^{M}w_m^*h(a_m^*)$$

This is equivalent to

$$\int_{-\infty}^{\infty} f(x) dx \approx \sum_{m=1}^{M} w_m^* \exp\left\{(a_m^*)^2\right\} f(a_m^*)$$

where the  $w_m^*$  denote the quadrature weights and the  $a_m^*$  denote the quadrature abscissas. The log likelihood, L, is the sum of the logs of the panel-level likelihoods  $l_i$ .

The default approximation of the log likelihood is by adaptive Gauss-Hermite quadrature, which approximates the panel-level likelihood with

$$l_i \approx \sqrt{2} \hat{\sigma}_i \sum_{m=1}^M w_m^* \exp\left\{(a_m^*)^2\right\} g(y_{1it}, y_{2it}, x_{it}, \sqrt{2} \hat{\sigma}_i a_m^* + \hat{\mu}_i)$$

where  $\hat{\sigma}_i$  and  $\hat{\mu}_i$  are the adaptive parameters for panel *i*. Therefore, using the definition of  $g(y_{1it}, y_{2it}, x_{it}, \nu_i)$ , the total log likelihood is approximated by

$$L \approx \sum_{i=1}^{n} w_i \log \left[ \sqrt{2} \hat{\sigma}_i \sum_{m=1}^{M} w_m^* \exp\{(a_m^*)^2\} \frac{\exp\{-(\sqrt{2} \hat{\sigma}_i a_m^* + \hat{\mu}_i)^2 / 2\sigma_\nu^2\}}{\sqrt{2\pi}\sigma_\nu} \right]$$
$$\prod_{t=1}^{n_i} F(y_{1it}, y_{2it}, x_{it}\beta + \sqrt{2} \hat{\sigma}_i a_m^* + \hat{\mu}_i) \right]$$
(1)

where  $w_i$  is the user-specified weight for panel *i*; if no weights are specified,  $w_i = 1$ .

The default method of adaptive Gauss–Hermite quadrature is to calculate the posterior mean and variance and use those parameters for  $\hat{\mu}_i$  and  $\hat{\sigma}_i$  by following the method of Naylor and Smith (1982), further discussed in Skrondal and Rabe-Hesketh (2004). We start with  $\hat{\sigma}_{i,0} = 1$  and  $\hat{\mu}_{i,0} = 0$ , and the posterior means and variances are updated in the *k*th iteration. That is, at the *k*th iteration of the optimization for  $l_i$  we use

$$l_{i,k} \approx \sum_{m=1}^{M} \sqrt{2} \hat{\sigma}_{i,k-1} w_m^* \exp\{a_m^*)^2 \} g(y_{1it}, y_{2it}, x_{it}, \sqrt{2} \hat{\sigma}_{i,k-1} a_m^* + \hat{\mu}_{i,k-1})$$

Letting

$$\tau_{i,m,k-1} = \sqrt{2}\hat{\sigma}_{i,k-1}a_m^* + \hat{\mu}_{i,k-1}$$

$$\hat{\mu}_{i,k} = \sum_{m=1}^{M} (\tau_{i,m,k-1}) \frac{\sqrt{2} \hat{\sigma}_{i,k-1} w_m^* \exp\{(a_m^*)^2\} g(y_{1it}, y_{2it}, x_{it}, \tau_{i,m,k-1})}{l_{i,k}}$$

and

$$\hat{\sigma}_{i,k} = \sum_{m=1}^{M} (\tau_{i,m,k-1})^2 \frac{\sqrt{2} \hat{\sigma}_{i,k-1} w_m^* \exp\{(a_m^*)^2\} g(y_{1it}, y_{2it}, x_{it}, \tau_{i,m,k-1})}{l_{i,k}} - \left(\hat{\mu}_{i,k}\right)^2 \frac{1}{2} \frac{1}{2} \left( \frac{1}{2} \frac{1$$

and this is repeated until  $\hat{\mu}_{i,k}$  and  $\hat{\sigma}_{i,k}$  have converged for this iteration of the maximization algorithm. This adaptation is applied on every iteration until the log-likelihood change from the preceding iteration is less than a relative difference of 1e–6; after this, the quadrature parameters are fixed.

The log likelihood can also be calculated by nonadaptive Gauss-Hermite quadrature if the intmethod(ghermite) option is specified. For nonadaptive Gauss-Hermite quadrature, the following formula for the log likelihood is used in place of (1).

$$\begin{split} L &= \sum_{i=1}^{n} w_i \log f \left\{ (y_{1i1}, y_{2i1}), \dots, (y_{1in_i}, y_{2in_i}) | \mathbf{x}_{1i}, \dots, \mathbf{x}_{in_i} \right\} \\ &\approx \sum_{i=1}^{n} w_i \log \left\{ \frac{1}{\sqrt{\pi}} \sum_{m=1}^{M} w_m^* \prod_{t=1}^{n_i} F \left( y_{1it}, y_{2it}, \mathbf{x}_{it} \boldsymbol{\beta} + \sqrt{2} \sigma_{\nu} a_m^* \right) \right\} \end{split}$$

Both quadrature formulas require that the integrated function be well approximated by a polynomial of degree equal to the number of quadrature points. Panel size can affect whether

$$\prod_{t=1}^{n_i} F(y_{1it},y_{2it},\mathbf{x}_{it}\boldsymbol{\beta}+\nu_i)$$

is well approximated by a polynomial. As panel size and  $\rho$  increase, the quadrature approximation can become less accurate. For large  $\rho$ , the random-effects model can also become unidentified. Adaptive quadrature gives better results for correlated data and large panels than nonadaptive quadrature; however, we recommend that you use the quadchk command (see [XT] quadchk) to verify the quadrature approximation used in this command, whichever approximation you choose.

### References

- Naylor, J. C., and A. F. M. Smith. 1982. Applications of a method for the efficient computation of posterior distributions. Journal of the Royal Statistical Society, C ser., 31: 214–225. https://doi.org/10.2307/2347995.
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- Skrondal, A., and S. Rabe-Hesketh. 2004. Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models. Boca Raton, FL: Chapman and Hall/CRC.

## Also see

- [XT] **xtintreg postestimation** Postestimation tools for xtintreg
- [XT] quadchk Check sensitivity of quadrature approximation
- [XT] xteintreg Extended random-effects interval regression
- [XT] xtreg Linear models for panel data
- [XT] **xtset** Declare data to be panel data
- [XT] **xttobit** Random-effects tobit model
- [ME] meintreg Multilevel mixed-effects interval regression
- [R] intreg Interval regression
- [R] tobit Tobit regression
- [ST] stintreg Parametric models for interval-censored survival-time data
- [U] 20 Estimation and postestimation commands

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