Title

xtgee postestimation — Postestimation tools for xtgee

Description

The following postestimation command is of special interest for xtgee:

command	description	
estat wcorrelation	estimated matrix of the within-group correlations	_
East information about a star	t	_

For information about estat wcorrelation, see below.

The following standard postestimation commands are also available:

command	description
estat	VCE and estimation sample summary
estimates	cataloging estimation results
hausman	Hausman's specification test
lincom	point estimates, standard errors, testing, and inference for linear combinations of coefficients
margins	marginal means, predictive margins, marginal effects, and average marginal effects
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of coefficients
predict	predictions, residuals, influence statistics, and other diagnostic measures
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

See the corresponding entries in the Base Reference Manual for details.

Special-interest postestimation commands

estat wcorrelation displays the estimated matrix of the within-group correlations.

Syntax for predict

predict [type] newvar [if] [in] [, statistic nooffset]

statistic	description
Main	
mu	predicted value of <i>depvar</i> ; considers the offset() or exposure(); the default
<u>r</u> ate	predicted value of <i>depvar</i>
pr(<i>n</i>)	probability $Pr(y_j = n)$ for family(poisson) link(log)
pr(<i>a</i> , <i>b</i>)	probability $Pr(a \le y_j \le b)$ for family(poisson) link(log)
xb	linear prediction
stdp	standard error of the linear prediction
<u>sc</u> ore	first derivative of the log likelihood with respect to $\mathbf{x}_j \boldsymbol{\beta}$

These statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample.

Menu

Statistics > Postestimation > Predictions, residuals, etc.

Options for predict

Main

mu, the default, and rate calculate the predicted value of depvar. mu takes into account the offset()
or exposure() together with the denominator if the family is binomial; rate ignores those
adjustments. mu and rate are equivalent if you did not specify offset() or exposure() when
you fit the xtgee model and you did not specify family(binomial #) or family(binomial
varname), meaning the binomial family and a denominator not equal to one.

Thus mu and rate are the same for family(gaussian) link(identity).

mu and rate are not equivalent for family(binomial pop) link(logit). Then mu would predict the number of positive outcomes and rate would predict the probability of a positive outcome.

mu and rate are not equivalent for family(poisson) link(log) exposure(time). Then mu would predict the number of events given exposure time and rate would calculate the incidence rate—the number of events given an exposure time of 1.

- pr(n) calculates the probability $Pr(y_j = n)$ for family(poisson) link(log), where n is a nonnegative integer that may be specified as a number or a variable.
- pr(a,b) calculates the probability $Pr(a \le y_j \le b)$ for family(poisson) link(log), where a and b are nonnegative integers that may be specified as numbers or variables;

b missing $(b \ge .)$ means $+\infty$; pr (20,.) calculates $\Pr(y_j \ge 20)$; pr (20,*b*) calculates $\Pr(y_j \ge 20)$ in observations for which $b \ge .$ and calculates $\Pr(20 \le y_j \le b)$ elsewhere.

pr(.,b) produces a syntax error. A missing value in an observation of the variable *a* causes a missing value in that observation for pr(a,b).

xb calculates the linear prediction.

stdp calculates the standard error of the linear prediction.

score calculates the equation-level score, $u_j = \partial \ln L_j(\mathbf{x}_j \boldsymbol{\beta}) / \partial(\mathbf{x}_j \boldsymbol{\beta})$.

nooffset is relevant only if you specified offset(varname), exposure(varname), family(binomial #), or family(binomial varname) when you fit the model. It modifies the calculations made by predict so that they ignore the offset or exposure variable and the binomial denominator. Thus predict ..., mu nooffset produces the same results as predict ..., rate.

Syntax for estat wcorrelation

```
estat <u>wcor</u>relation [, <u>compact format(%fmt)</u>]
```

Menu

Statistics > Postestimation > Reports and statistics

Options for estat wcorrelation

. estat wcorrelation

compact specifies that only the parameters (alpha) of the estimated matrix of within-group correlations be displayed rather than the entire matrix.

format (% fmt) overrides the display format; see [D] format.

Remarks

Example 1

xtgee can estimate rich correlation structures. In example 2 of [XT] xtgee, we fit the model

```
. use http://www.stata-press.com/data/r11/nlswork2
(National Longitudinal Survey. Young Women 14-26 years of age in 1968)
. xtgee ln_w grade age c.age#c.age
(output omitted)
```

After estimation, estat wcorrelation reports the working correlation matrix R:

Estimat	Estimated within-idcode correlation matrix R:									
	c1	c2	c3	c4	c5	c6				
r1	1									
r2	.4851356	1								
r3	.4851356	.4851356	1							
r4	.4851356	.4851356	.4851356	1						
r5	.4851356	.4851356	.4851356	.4851356	1					
r6	.4851356	.4851356	.4851356	.4851356	.4851356	1				
r7	.4851356	.4851356	.4851356	.4851356	.4851356	.4851356				
r8	.4851356	.4851356	.4851356	.4851356	.4851356	.4851356				
r9	.4851356	.4851356	.4851356	.4851356	.4851356	.4851356				
	c7	c8	c9							
r7	1									
r8	.4851356	1								
r9	.4851356	.4851356	1							

The equal-correlation model corresponds to an exchangeable correlation structure, meaning that the correlation of observations within person is a constant. The working correlation estimated by xtgee is 0.4851. (xtreg, re, by comparison, reports 0.5140.) We constrained the model to have this simple correlation structure. What if we relaxed the constraint? To go to the other extreme, let's place no constraints on the matrix (other than its being symmetric). We do this by specifying correlation(unstructured), although we can abbreviate the option.

. xtgee ln_w g	grade age c.ag	nolog				
GEE population	n-averaged mod	lel		Number	of obs =	16085
Group and time	e vars:	idcode y	year	Number	of groups =	3913
Link:		ident	tity	Obs per	group: min =	1
Family:		Gauss	sian		avg =	4.1
Correlation:		unstructu	ired		max =	9
				Wald ch	= i2(3) =	2405.20
Scale paramete	er:	.1418	3513	Prob >	chi2 =	0.0000
ln_wage	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
grade	.0720684	.002151	33.50	0.000	.0678525	.0762843
age	.1008095	.0081471	12.37	0.000	.0848416	.1167775
c.age#c.age	0015104	.0001617	-9.34	0.000	0018272	0011936
0 0						
_cons	8645484	.1009488	-8.56	0.000	-1.062404	6666923
. estat wcorre	elation					
Estimated with	nin-idcode com	relation mat	trix R:			

	c1	c2	c3	c4	c5	c6
r1	1					
r2	.4354838	1				
r3	.4280248	.5597329	1			
r4	.3772342	.5012129	.5475113	1		
r5	.4031433	.5301403	.502668	.6216227	1	
r6	.3663686	.4519138	.4783186	.5685009	.7306005	1
r7	.2819915	.3605743	.3918118	.4012104	.4642561	.50219
r8	.3162028	.3445668	.4285424	.4389241	.4696792	.5222537
r9	.2148737	.3078491	.3337292	.3584013	.4865802	.4613128
	c7	c8	c9			
r7	1					
r8	.6475654	1				
r9	.5791417	.7386595	1			

This correlation matrix looks different from the previously constrained one and shows, in particular, that the serial correlation of the residuals diminishes as the lag increases, although residuals separated by small lags are more correlated than, say, AR(1) would imply.

4

Example 2

In example 1 of [XT] **xtprobit**, we showed a random-effects model of unionization using the union data described in [XT] **xt**. We performed the estimation using **xtprobit** but said that we could have used **xtgee** as well. Here we fit a population-averaged (equal correlation) model for comparison:

4

. use http://www.stata-press.com/data/r11/union (NLS Women 14-24 in 1968)								
. xtgee union	. xtgee union age grade i.not_smsa south##c.year, family(binomial) link(probit							
Iteration 1: 1	tolerance = .1	12544249						
Iteration 2: 1	tolerance = .(0034686						
Iteration 3: 1	tolerance = .(0017448						
Iteration 4: t	tolerance = 8.	.382e-06						
Iteration 5: 1	tolerance = 3	.997e-07						
GEE population	n-averaged mod	lel		Number	of obs =	= 26200		
Group variable	e:	id	code	Number	of groups =	= 4434		
Link:		pr	obit	Obs per	group: min =	= 1		
Family:		bino	mial		avg =	= 5.9		
Correlation:		exchange	exchangeable		max =			
				Wald ch		= 242.57		
Scale paramete	er:		1	Prob >	chi2 =	= 0.0000		
union	Coef.	Std. Err.	Z	P> z	L95% Conf	. Interval]		
age	.0089699	.0053208	1.69	0.092	0014586	.0193985		
grade	.0333174	.0062352	5.34	0.000	.0210966	.0455382		
1.not_smsa	0715717	.027543			1255551	0175884		
1.south	-1.017368	.207931	-4.89	0.000	-1.424905	6098308		
year	0062708	.0055314	-1.13	0.257	0171122	.0045706		
south#c.year								
1	.0086294	.00258	3.34	0.001	.0035727	.013686		
_cons	8670997	.294771	-2.94	0.003	-1.44484	2893592		

Let's look at the correlation structure and then relax it:

Estimat	Stimated within-idcode correlation matrix R:								
	c1	c2	c3	c4	c5	c6	c7		
r1 r2 r3 r4 r5 r6 r7 r8 r9 r10 r11	$\begin{array}{c} 1.0000\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ \end{array}$	$\begin{array}{c} 1.0000\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ 0.4615\\ \end{array}$	1.0000 0.4615 0.4615 0.4615 0.4615 0.4615 0.4615 0.4615 0.4615	1.0000 0.4615 0.4615 0.4615 0.4615 0.4615 0.4615 0.4615	1.0000 0.4615 0.4615 0.4615 0.4615 0.4615 0.4615	1.0000 0.4615 0.4615 0.4615 0.4615 0.4615	1.0000 0.4615 0.4615 0.4615 0.4615		
r12	0.4615 c8	0.4615 c9	0.4615 c10	0.4615 c11	0.4615 c12	0.4615	0.4615		
r8 r9 r10 r11 r12	1.0000 0.4615 0.4615 0.4615 0.4615	1.0000 0.4615 0.4615 0.4615	1.0000 0.4615 0.4615	1.0000 0.4615	1.0000				

. estat wcorrelation, format(%8.4f)

We estimate the fixed correlation between observations within person to be 0.4615. We have many data (an average of 5.9 observations on 4,434 women), so estimating the full correlation matrix is feasible. Let's do that and then examine the results:

> corr	(unstr)	nolog			v			-
GEE por	oulation	n-average	d model	Number o	fobs =	26200		
	and time	0		idcode	year	Number o:		4434
Link:					robit		group: min =	= 1
Family	:			-	omial	1	avg =	
Correla				unstruc	tured		max =	
						Wald chi	2(6) =	= 198.45
Scale p	paramete	er:			1	Prob > cl	hi2 =	0.0000
	union	Coe	ef. S	Std. Err.	Z	P> z	[95% Conf.	Interval]
	age	.0096	\$12	0053366	1.81	0.070	0007984	.0201208
	grade	.0352		0065621	5.38	0.000	.0224148	.0481377
1 not	t_smsa	093		0291971	-3.19	0.001	1502983	0358478
	.south	-1.028		.278802	-3.69	0.000	-1.574968	4820839
1	year	0088		.005719	-1.54	0.123	0200278	.0023904
	ycui		101	.000/15	1.04	0.120	.0200210	.0020004
south#c	vear							
500011#0	1	. 00898	324 .	0034865	2.58	0.010	.002149	.0158158
	_cons	7306	192	.316757	-2.31	0.021	-1.351451	109787
				(//				
. estat	t wcorre	elation, :	format((%8.4I)				
Estimat	ted with	nin-idcod	e corre	elation m	atrix R:			
		c1	c2	c3	c4	c5	c6	c7
r1	1.00	000						
r2	0.60	667 1.0	0000					
r3	0.6	151 0.0	6523	1.0000				
r4	0.5	268 0.9	5717	0.6101	1.0000			
r5	0.3	309 0.3	3669	0.4005	0.4783	1.0000		
r6	0.30	000 0.3	3706	0.4237	0.4562	0.6426	1.0000	
r7	0.29	995 0.3	3568	0.3851	0.4279	0.4931	0.6384	1.0000
r8	0.2	759 0.3	3021	0.3225	0.3751	0.4682	0.5597	0.7009
r9	0.29	989 0.3	2981	0.3021	0.3806	0.4605	0.5068	0.6090
r10	0.2	285 0.1	2597	0.2748	0.3637	0.3981	0.4909	0.5889
r11	0.23	325 0.3	2289	0.2696	0.3246	0.3551	0.4426	0.5103
r12	0.23	359 0.3	2351	0.2544	0.3134	0.3474	0.3822	0.4788
		c8	c9	c10	c11	c12		
r8	1.00	000					-	
r9	0.6	714 1.0	0000					

. xtgee union age grade i.not_smsa south##c.year, family(binomial) link(probit)

As before, we find that the correlation of residuals decreases as the lag increases, but more slowly than an AR(1) process.

1.0000

0.6428

1.0000

▷ Example 3

r10

r11

r12

0.5973

0.5625

0.4999

0.6325

0.5756

0.5412

1.0000

0.5738

0.5329

In this example, we examine injury incidents among 20 airlines in each of 4 years. The data are fictional, and, as a matter of fact, are really from a random-effects model.

6

. use http://www.stata-press.com/data/r11/airacc

. generate lnpm = ln(pmiles)

. xtgee i_cnt inprog, family(poisson) eform offset(lnpm) nolog

GEE population	n-averaged mod	del		Number o	f obs	=	80
Group variable	e:	air	line	Number o	f group	os =	20
Link:			log	Obs per	group:	min =	4
Family:		Poi	sson			avg =	4.0
Correlation:		exchange	able			max =	4
				Wald chi	2(1)	=	5.27
Scale paramete	er:		1	Prob > c	hi2	=	0.0217
	r						
i_cnt	IRR	Std. Err.	Z	P> z	[95%	Conf.	Interval]
inprog lnpm	.9059936 (offset)	.0389528	-2.30	0.022	.8327	7758	.9856487

```
. estat wcorrelation
```

Estimated within-airline correlation matrix R:

	c1	c2	c3	c4
r1 r2 r3 r4	1 .4606406 .4606406 .4606406	1 .4606406 .4606406	1	

Now there are not really enough data here to reliably estimate the correlation without any constraints of structure, but here is what happens if we try:

. xtgee i_cnt	inprog, fami	ly(poisson).	eform (offset(lnpm)	corr(u	unstr)	nolog
GEE population	n-averaged mo	del		Number o	f obs	=	80
Group and time	e vars:	airline	time	Number o	f group	s =	20
Link:			log	Obs per g	group:	min =	4
Family:		Po:	isson			avg =	4.0
Correlation:		unstruct	tured			max =	4
				Wald chi	2(1)	=	0.36
Scale paramete	er:		1	Prob > cl	hi2	=	0.5496
i_cnt	IRR	Std. Err.	z	P> z	[95%	Conf.	Interval]
inprog lnpm	.9791082 (offset)	.0345486	-0.6	0 0.550	.9136	826	1.049219

. estat wcorrelation

Estimated within-airline correlation matrix R:

	c1	c2	c3	c4
r1	1			
r2	.5700298	1		
r3	.716356	.4192126	1	
r4	.2383264	.3839863	.3521287	1

There is no sensible pattern to the correlations.

We created this dataset from a random-effects Poisson model. We reran our data-creation program and this time had it create 400 airlines rather than 20, still with 4 years of data each. Here are the equal-correlation model and estimated correlation structure

. use http://www.stata-press.com/data/r11/airacc2, clear

. xtgee i_cnt inprog, family(poisson) eform offset(lnpm) nolog

GEE population-averaged mod Group variable: Link: Family: Correlation: Scale parameter:		air	line log sson able 1		of group: group: hi2(1)		1600 400 4 1.0 4 111.80 0.0000
i_cnt	IRR	Std. Err.	z	P> z	[95%	Conf.	Interval]
inprog lnpm	.8915304 (offset)	.0096807	-10.57	0.000	.8727	7571	.9107076

. estat wcorrelation

8

Estimated within-airline correlation matrix R:

	c1	c2	c3	c4
r1 r2	1 .5291707	1		
r3	.5291707	.5291707	1	
r4	.5291707	.5291707	.5291707	1

The following estimation results assume unstructured correlation:

. xtgee i_cnt	inprog, fami	ly(poisson)	corr(unst	r) eform	offset	(lnpm)	nolog
GEE population-averaged model				Number o	f obs	=	1600
Group and time	e vars:	airline	time	Number o	f group	ps =	400
Link:			log	Obs per	group:	min =	4
Family:		Poi	sson			avg =	4.0
Correlation:		unstruct	ured			\max =	4
				Wald chi	2(1)	=	113.43
Scale parameter:			1	Prob > c	hi2	=	0.0000
i_cnt	IRR	Std. Err.	Z	P> z	[95%	Conf.	Interval]
inprog lnpm	.8914155 (offset)	.0096208	-10.65	0.000	.8727	7572	.9104728

. estat wcorrelation

Estimated within-airline correlation matrix R:

c1	c2	c3	c4
1			
.4733189	1		
.5240576	.5748868	1	
.5139748	.5048895	.5840707	1
	1 .4733189 .5240576	1 .4733189 1 .5240576 .5748868	1 .4733189 1 .5240576 .5748868 1

The equal-correlation model estimated a fixed correlation of 0.5292, and above we have correlations ranging between 0.4733 and 0.5841 with little pattern in their structure.

4

Methods and formulas

All postestimation commands listed above are implemented as ado-files.

Also see

[XT] xtgee — Fit population-averaged panel-data models by using GEE

[U] 20 Estimation and postestimation commands