xtreg postestimation — Postestimation tools for xtreg

Postestimation commands	predict	margins	xttest0
estat mundlak	Remarks and examples	Stored results	Methods and formulas
References	Also see		

Postestimation commands

The following postestimation commands are of special interest after xtreg:

Command	Description
xttest0	Breusch and Pagan LM test for random effects
estat mundlak	Mundlak specification test

The following standard postestimation commands are also available:

Command	Description
contrast	contrasts and ANOVA-style joint tests of parameters
* estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian infor- mation criteria (AIC, CAIC, AICc, and BIC, respectively)
estat summarize	summary statistics for the estimation sample
estat vce	variance-covariance matrix of the estimators (VCE)
estimates	cataloging estimation results
etable	table of estimation results
[†] forecast	dynamic forecasts and simulations
hausman	Hausman's specification test
lincom	point estimates, standard errors, testing, and inference for linear combinations of parameters
* lrtest	likelihood-ratio test
margins	marginal means, predictive margins, marginal effects, and average marginal effects
marginsplot	graph the results from margins (profile plots, interaction plots, etc.)
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of parameters
predict	linear predictions, residuals, error components
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
pwcompare	pairwise comparisons of parameters
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

*estat ic and lrtest are not appropriate after xtreg with the pa, re, or cre option.

[†]forecast is not appropriate with mi estimation results.

predict

Description for predict

predict creates a new variable containing predictions such as fitted values, standard errors, predicted values, linear predictions, and the equation-level score.

Menu for predict

Statistics > Postestimation

Syntax for predict

Fixed-effects (FE) model

predict [type] newvar [if] [in] [, FE_statistic]

Between-effects and GLS and ML random-effects (RE) model

predict [type] newvar [if] [in] [, RE/CRE_statistic]

Correlated random-effects (CRE) model

predict [type] newvar [if] [in] [, RE/CRE_statistic]

Population-averaged (PA) model

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

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FE_statistic	Description
Main	
xb	$\alpha + \mathbf{x}_{it}\boldsymbol{\beta}$, fitted values; the default
stdp	standard error of the fitted values
ue	$u_i + e_{it}$, the combined residual
* xbu	$\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + u_i$, prediction including panel effect
* u	u_i , the fixed error component
* xbd	$\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + d_{absorbvars}$, prediction including effects of absorbed variables
* d	$d_{\rm absorbvars}$, effects of absorbed variables
* е	e_{it} , the overall error component

Unstarred statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample. Starred statistics are calculated only for the estimation sample, even when if e(sample) is not specified.

<i>RE/CRE_statistic</i>	Description		
Main			
xb	$\alpha + \mathbf{x}_{it}\boldsymbol{\beta}$ or $\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + \overline{\mathbf{x}}_i\boldsymbol{\gamma}$ for CRE, fitted values; the default		
stdp	standard error of the fitted values		
ue	$u_i + e_{it}$, the combined residual		
* xbu	$\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + u_i \text{ or } \alpha + \mathbf{x}_{it}\boldsymbol{\beta} + \overline{\mathbf{x}}_i \boldsymbol{\gamma} + u_i \text{ for CRE, prediction including panel effect}$		
* u	u_i , the random-error component		
* е	e_{it} , the overall error component		

Unstarred statistics are available both in and out of sample; type predict ... if e(sample) ... if wanted only for the estimation sample. Starred statistics are calculated only for the estimation sample, even when if e(sample) is not specified.

PA_statistic	Description	
Main		
mu	predicted value of <i>depvar</i> ; considers the offset()	
rate	predicted value of <i>depvar</i>	
xb	linear prediction	
stdp	standard error of the linear prediction	
score	first derivative of the log likelihood with respect to $\mathbf{x}_{it} \boldsymbol{\beta}$	

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

Options for predict

Main

xb calculates the linear prediction. This is the default for all except the population-averaged model. The linear prediction equals $\alpha + \mathbf{x}_{it}\beta$ for the fixed-, between-, and random-effects models; and equals $\alpha + \mathbf{x}_{it}\beta + \overline{\mathbf{x}}_i\gamma$ for the correlated random-effects model. Panel means are recalculated when predicting out of sample in the correlated random-effects model.

stdp calculates the standard error of the linear prediction. For the fixed-effects model, this excludes the variance due to uncertainty about the estimate of u_i .

- mu and rate both calculate the predicted value of *depvar*. mu takes into account the offset(), and rate ignores those adjustments. mu and rate are equivalent if you did not specify offset(). mu is the default for the population-averaged model.
- ue calculates the prediction of $u_i + e_{it}$.
- xbu calculates the linear prediction including the fixed or random component. This prediction equals $\alpha + \mathbf{x}_{it}\beta + u_i$ for the fixed-, between-, and random-effects models; and equals $\alpha + \mathbf{x}_{it}\beta + \overline{\mathbf{x}}_i\gamma + u_i$ for the correlated random-effects model.
- u calculates the prediction of u_i , the estimated fixed or random effect.
- xbd calculates the prediction of $\alpha + \mathbf{x}_{it} \boldsymbol{\beta} + d_{\text{absorbvars}}$, the prediction including the absorbed variables' effects.
- d calculates the prediction of $d_{\rm absorbvars}$, the absorbed variables' effects.
- e calculates the prediction of e_{it} .
- score calculates the equation-level score, $u_{it} = \partial \ln L(\mathbf{x}_{it}\beta) / \partial(\mathbf{x}_{it}\beta)$.
- nooffset is relevant only if you specified offset (*varname*) for xtreg, pa. It modifies the calculations made by predict so that they ignore the offset variable; the linear prediction is treated as $\mathbf{x}_{it}\beta$ rather than $\mathbf{x}_{it}\beta$ + offset_{it}.

margins

Description for margins

margins estimates margins of response for fitted values, probabilities, and linear predictions.

Menu for margins

Statistics > Postestimation

Syntax for margins

margins [marginlist] [, options]
margins [marginlist], predict(statistic ...) [predict(statistic ...) [options]

Fixed-effects (FE) model

FE_statistic	Description
xb	$\alpha + \mathbf{x}_{it} \boldsymbol{\beta}$, fitted values; the default
stdp	not allowed with margins
ue	not allowed with margins
xbu	not allowed with margins
u	not allowed with margins
xbd	not allowed with margins
d	not allowed with margins
e	not allowed with margins

Between-effects, GLS and ML random-effects (RE), and correlated random-effects (CRE) model

<i>RE_statistic</i>	Description
xb	$\alpha + \mathbf{x}_{it}\boldsymbol{\beta}$ or $\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + \overline{\mathbf{x}}_i\boldsymbol{\gamma}$ for CRE, fitted values; the default
stdp	not allowed with margins
ue	not allowed with margins
xbu	not allowed with margins
u	not allowed with margins
е	not allowed with margins

Population-averaged (PA) model

Description
probability of <i>depvar</i> ; considers the offset()
probability of <i>depvar</i>
linear prediction
not allowed with margins
not allowed with margins

Statistics not allowed with margins are functions of stochastic quantities other than e(b).

For the full syntax, see [R] margins.

xttest0

Description for xttest0

xttest0, for use after xtreg, re, presents the Breusch and Pagan (1980) Lagrange multiplier test for random effects, a test that $Var(\nu_i) = 0$.

Menu for xttest0

Statistics > Longitudinal/panel data > Linear models > Lagrange multiplier test for random effects

Syntax for xttest0

xttest0

collect is allowed; see [U] 11.1.10 Prefix commands.

estat mundlak

Description for estat mundlak

estat mundlak performs a Mundlak specification test, a test that ν_i is uncorrelated with the regressors in \mathbf{x}_{it} . estat mundlak is for use after xtreg with the re, cre, and fe options but not with the absorb() option or the vce(hc2) option.

Menu for estat

Statistics > Postestimation

Syntax for estat mundlak

estat mundlak [, options]

options	Description
* reps(#)	perform # bootstrap replications; default is reps(50)
* rseed(#)	set random-number seed to #

*reps() and rseed() allowed only after xtreg, vce(bootstrap).

collect is allowed; see [U] 11.1.10 Prefix commands.

Options for estat mundlak

reps(#) specifies the number of bootstrap replications to perform when computing the *p*-value for the Mundlak test. This option is allowed only after xtreg, vce(bootstrap).

rseed(#) sets the random-number seed. This option is allowed only after xtreg, vce(bootstrap).

Remarks and examples

Example 1: Lagrange multiplier test for random effects

Continuing with our random-effects model from example 4 in xtreg, we can see that xttest0 will report a test of $\nu_i = 0$. In case we have any doubts, we could type

```
. use https://www.stata-press.com/data/r19/nlswork
(National Longitudinal Survey of Young Women, 14-24 years old in 1968)
. xtreg ln_w grade age c.age#c.age ttl_exp c.ttl_exp#c.ttl_exp
> tenure c.tenure#c.tenure 2.race not_smsa south, re theta
 (output omitted)
. xttest0
Breusch and Pagan Lagrangian multiplier test for random effects
        ln wage[idcode,t] = Xb + u[idcode] + e[idcode,t]
        Estimated results:
                                 Var
                                         SD = sqrt(Var)
                 ln_wage
                             .2283326
                                            .4778416
                             .0845002
                                            .2906892
                       е
                             .0665151
                                            .2579053
                       11
       Test: Var(u) = 0
                             chibar2(01) = 14779.98
                          Prob > chibar2 = 0.0000
```

Example 2: Hausman specification test

(output omitted)

More importantly, after xtreg, re estimation, hausman will perform the Hausman specification test. If our model is correctly specified, and if ν_i is uncorrelated with \mathbf{x}_{it} , the (subset of) coefficients that are estimated by the fixed-effects estimator and the same coefficients that are estimated here should not statistically differ:

```
. xtreg ln_w grade age c.age#c.age ttl_exp c.ttl_exp#c.ttl_exp
> tenure c.tenure#c.tenure 2.race not_smsa south, re
(output omitted)
. estimates store random_effects
. xtreg ln_w grade age c.age#c.age ttl_exp c.ttl_exp#c.ttl_exp
> tenure c.tenure#c.tenure 2.race not_smsa south, fe
```

1

	-						
	Coeff:	icients ——					
	(b)	(B)	(b-B)	<pre>sqrt(diag(V_b-</pre>	-V_B))		
	•	random_eff~s	Difference	Std. err.			
age	.0359987	.0368059	0008073	.0013177			
c.age#c.age	000723	0007133	-9.68e-06	.0000184			
ttl_exp	.0334668	.0290208	.0044459	.001711			
c.ttl_exp#							
c.ttl_exp	.0002163	.0003049	0000886	.000053			
tenure	.0357539	.0392519	003498	003498 .0005797			
c.tenure#							
c.tenure	0019701	0020035	.0000334	.0000373			
not_smsa	0890108	1308252	.0418144 .0062745				
south	0606309	0868922	.0262613 .0081345				
	b	= Consistent un	der HO and Ha:	obtained from	xtreg.		
В =	B = Inconsistent under Ha, efficient under HO; obtained from xtreg .						
Test of HO: Difference in coefficients not systematic							
chi2(8) =	(b-B)'[(V_b-V_	_B)^(-1)](b-B)					
Prob > chi2 = 0.0000							

We can reject the hypothesis that the coefficients are the same. Before turning to what this means, note that hausman listed the coefficients estimated by the two models. It did not, however, list grade and 2.race. hausman did not make a mistake; in the Hausman test, we compare only the coefficients estimated by both techniques.

This means that we have an unpleasant choice: we can admit that our model is misspecified—that we have not parameterized it correctly—or we can hold that our specification is correct, in which case the observed differences must be due to the zero correlation of ν_i and the \mathbf{x}_{it} assumption.

4

Technical note

. hausman . random effects

We can also mechanically explore the underpinnings of the test's dissatisfaction. In the comparison table from hausman, it is the coefficients on not_smsa and south that exhibit the largest differences. In equation (1') of [XT] **xtreg**, we showed how to decompose a model into within and between effects. Let's do that with these two variables, assuming that changes in the average have one effect, whereas transitional changes have another:

. egen avgnsma	sa = mean(not_	smsa), by(i	.d)			
. generate dev (8 missing val	/nsma = not_sm Lues generated	sa -avgnsms)	a			
. egen avgsout	th = mean(sout	h), by(id)				
. generate dev (8 missing val	vsouth = south Lues generated	- avgsouth)	1			
. xtreg ln_w g > c.tenure 2.1	grade age c.ag race avgnsm de	e#c.age ttl vnsm avgsou	exp c.t1 1 devsou	tl_exp#c.	ttl_exp tenur	e c.tenure#
Random-effects Group variable	s GLS regressi e: idcode	on		Number Number	of obs = of groups =	28,091 4,697
R-squared:				Obs per	group:	
Within =	= 0.1723			000 poi	min =	1
Between =	= 0.4809				avg =	6.0
Overall =	= 0.3737				max =	15
				Wald ch	.i2(12) =	9319.56
<pre>corr(u_i, X) =</pre>	= 0 (assumed)			Prob >	chi2 =	0.0000
ln_wage	Coefficient	Std. err.	z	P> z	[95% conf.	interval]
grade	.0631716	.0017903	35.29	0.000	.0596627	.0666805
age	.0375196	.0031186	12.03	0.000	.0314072	.043632
c.age#c.age	0007248	.00005	-14.50	0.000	0008228	0006269
ttl_exp	.0286543	.0024207	11.84	0.000	.0239098	.0333989
c.ttl_exp#	0003000	0001162	0 77	0.006	0000045	0005400
c.tti_exp	.0003222	.0001162	2.11	0.000	.0000945	.0005499
tenure	.0394423	.001754	22.49	0.000	.0360044	.0428801
c.tenure#	- 0020081	0001192	-16 85	0 000	- 0022417	- 0017746
010011110	10020001		10100	01000		
race						
Black	0545936	.0102101	-5.35	0.000	074605	0345821
avgnsmsa	1833237	.0109339	-16.77	0.000	2047537	1618937
devnsma	088/596	.0095071	-9.34	0.000	10/3931	0/0126
avgsouth	- 0508539	01090709	-10.24	0.000	- 081000	- 038/707
_cons	.2682987	.0495778	5.41	0.000	.171128	.3654694
sigma_u sigma_e rho	.2579182 .29068923 .44047745	(fraction	of varia	nce due t	o u_i)	

We will leave the reinterpretation of this model to you, except that if we were really going to sell this model, we would have to explain why the between and within effects are different. Focusing on residence in a non-SMSA, we might tell a story about rural people being paid less and continuing to get paid less when they move to the SMSA. Given our panel data, we could create variables to measure this (an indicator for moved from non-SMSA to SMSA) and to measure the effects. In our assessment of this model, we should think about women in the cities moving to the country and their relative productivity in a bucolic setting.

In any case, the Hausman test now is

- . estimates store new_random_effects
- . xtreg ln_w grade age c.age#c.age ttl_exp c.ttl_exp#c.ttl_exp
- > tenure c.tenure#c.tenure 2.race avgnsm devnsm avgsou devsou, fe
 (output omitted)
- . hausman . new random effects

Coefficients					
	(b)	(B)	(b-B)	<pre>sqrt(diag(V_b-V_B))</pre>	
	•	new_random~s	Difference	Std. err.	
age	.0359987	.0375196	0015209	.0013198	
c.age#c.age	000723	0007248	1.84e-06	.0000184	
ttl_exp	.0334668	.0286543	.0048124	.0017127	
c.ttl_exp#					
c.ttl_exp	.0002163	.0003222	0001059	.0000531	
tenure	.0357539	.0394423	0036884	.0005839	
c.tenure#					
c.tenure	0019701	0020081	.000038	.0000377	
devnsma	0890108	0887596	0002512	.000683	
devsouth	0606309	0598538	0007771	.0007618	
	b	= Consistent un	der HO and Ha:	obtained from xtreg .	
B = Inconsistent under Ha, efficient under HO; obtained from xtreg .					
Test of MO: Difference in coefficients not sustantic					

We have mechanically succeeded in greatly reducing the χ^2 , but not by enough. The major differences now are in the age, experience, and tenure effects. We already knew this problem existed because of the ever-increasing effect of experience. More careful parameterization work rather than simply including squares needs to be done.

Example 3: Mundlak specification test

Suppose now that the errors in our random-effects model are serially correlated within idcode. For most panel-data structures, this is probably a more realistic assumption than assuming i.i.d. errors. We can no longer rely on the Hausman specification test when the errors are correlated. However, we can still conduct a cluster-robust specification test by using estat mundlak.

We first refit the random-effects model with cluster-robust standard errors and then use estat mundlak to perform the specification test.

```
. xtreg ln_w grade age c.age#c.age ttl_exp c.ttl_exp#c.ttl_exp tenure
> c.tenure#c.tenure 2.race not_smsa south, re vce(cluster idcode)
  (output omitted)
. estat mundlak
Mundlak specification test
HO: Covariates are uncorrelated with unobserved panel-level effects
    chi2(8) = 123.10
Prob > chi2 = 0.0000
Notes: Fixed effects and correlated random effects are
    consistent under HO and Ha.
    Random effects are efficient under HO.
```

With a Wald test statistic of 123.10 and a *p*-value of 0.0000, we reject the null hypothesis that ν_i is uncorrelated with the regressors in \mathbf{x}_{it} . This result implies that the random-effects model as stated is misspecified and that either the model needs to be reparameterized or estimation by correlated random effects or fixed effects should be considered.

Stored results

xttest0 stores the following in r():

Scalars

r(lm)	Lagrange multiplier statistic
r(df)	degrees of freedom
r(p)	<i>p</i> -value

estat mundlak stores the following in r():

```
Scalars
    r(chi2_mundlak)
                           Mundlak test \chi^2 statistic
                           Mundlak test degrees of freedom
    r(df_mundlak)
                           Mundlak test p-value
    r(p_mundlak)
                           number of complete replications
    r(N_reps)
                           number of clusters
    r(N_clust)
Macros
    r(rngstate)
                           random-number state
                           name of cluster variable
    r(clustvar)
```

Methods and formulas

Methods and formulas are presented under the following headings:

Predictions for fixed-effects model with absorbed variables xttest0 estat mundlak 4

Predictions for fixed-effects model with absorbed variables

The following uses the notation introduced in Methods and formulas in [XT] xtreg.

Suppose we fit the model

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

where $\eta_{it} = \mathbf{d}_{1(it)} \boldsymbol{\gamma}_1 + \mathbf{d}_{2(it)} \boldsymbol{\gamma}_2 + \cdots + \mathbf{d}_{h(it)} \boldsymbol{\gamma}_h$ and $\mathbf{d}_{k(it)}$ is an indicator vector for absorbed variable k in panel i at time t. By convention, we define the first absorb variable (k = 1) as the panel-ID variable and write $\eta_{it} = \nu_i + \sum_{k=2}^{h} \mathbf{d}_{k(it)} \boldsymbol{\gamma}_k = \nu_i + \Delta_{it}$. Let $\boldsymbol{\eta}$ be the $1 \times N$ vector with the values of η_{it} in the sample. Define vectors Δ and $\boldsymbol{\nu}$ similarly.

We are interested in making predictions for the panel effects ν (the u option), the absorbed variables' effects Δ (the d option), and the residuals ϵ (the e option). These postestimation predictions use alternating projection methods to avoid the computational burden of estimating the γ 's. Two alternating projection method algorithms are available: Halperin and Cimmino. For a description of these two algorithms, see *Methods and formulas* in [XT] **xtreg**.

Estimates for ν , Δ , and the residuals can be extracted from $\hat{\upsilon} = \mathbf{y} - \mathbf{X}\hat{\beta}$, where $\hat{\beta}$ is the estimated regression coefficient vector. Here is the procedure. First, separate the absorbed variables into two sets: $\iota_1 = \{1\}$, the panel effect, and $\iota_2 = \{2, \ldots, h\}$, the remaining absorbed variables. Let project $(\hat{\upsilon}, \iota_i)$ denote the projection of vector $\hat{\upsilon}$ over the variables in set ι_i , using either the Halperin or Cimmino algorithm, and let \mathbf{p} -error $(\hat{\upsilon}, \iota_i)$ denote the corresponding projection error. Second, initialize the values of the algorithm to $\tilde{\boldsymbol{\epsilon}}^{(1)} = \hat{\upsilon}$, $\tilde{\boldsymbol{\nu}}^{(1)} = \mathbf{0}$, and $\tilde{\boldsymbol{\Delta}}^{(1)} = \mathbf{0}$. Third and finally, iterate until convergence using the following formulas:

$$\begin{split} & \widetilde{\boldsymbol{\nu}}^{(j+1)} = \widetilde{\boldsymbol{\nu}}^{(j)} + \operatorname{project}(\widetilde{\boldsymbol{\epsilon}}^{(j)}, \iota_1) \\ & \widetilde{\boldsymbol{\epsilon}}^{(j+1)} = \operatorname{p_error}\{\operatorname{p_error}(\widetilde{\boldsymbol{\epsilon}}^{(j)}, \iota_1), \iota_2\} \\ & \widetilde{\boldsymbol{\Delta}}^{(j+1)} = \widetilde{\boldsymbol{\Delta}}^{(j)} + \operatorname{project}\{\operatorname{p_error}(\widetilde{\boldsymbol{\epsilon}}^{(j)}, \iota_1), \iota_2\} \end{split}$$

Convergence is declared at j = j when the elements of $\operatorname{project}(\tilde{\epsilon}^{(j)}, \iota_1)$ and $\operatorname{project}(\tilde{\epsilon}^{(j)}, \iota_2)$ are negligible. At convergence, $\tilde{\epsilon}^{(j)}$ contains the estimated residuals, $\tilde{\nu}^{(j)}$ the estimated panel effects, and $\widetilde{\Delta}^{(j)}$ the estimated absorbed variables' effects.

xttest0

xttest0 reports the Lagrange multiplier test for random effects developed by Breusch and Pagan (1980) and as modified by Baltagi and Li (1990). The model

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

is fit via OLS, and then the quantity

$$\lambda_{\rm LM} = \frac{(n\overline{T})^2}{2} \bigg\{ \frac{A_1^2}{(\sum_i T_i^2) - n\overline{T}} \bigg\}$$

is calculated, where

$$A_1 = 1 - \frac{\sum_{i=1}^{n} (\sum_{t=1}^{T_i} v_{it})^2}{\sum_i \sum_t v_{it}^2}$$

The Baltagi and Li modification allows for unbalanced data and reduces to the standard formula

$$\lambda_{\mathrm{LM}} = \begin{cases} \frac{nT}{2(T-1)} \bigg\{ \frac{\sum_i (\sum_t v_{it})^2}{\sum_i \sum_t v_{it}^2} - 1 \bigg\}^2, & \hat{\sigma}_u^2 \ge 0\\ 0 & , & \hat{\sigma}_u^2 < 0 \end{cases}$$

when $T_i = T$ (balanced data). Under the null hypothesis, λ_{LM} is distributed as a 50:50 mixture of a point mass at zero and $\chi^2(1)$.

estat mundlak

estat mundlak performs a Mundlak specification test to help decide between estimation by random effects or estimation by correlated random effects or fixed effects. The test consists of first fitting a correlated random-effects model, using the same covariates and the same sample as the previously fitted xtreg model, and then testing whether the coefficients of the panel means are all jointly equal to 0. See Mundlak (1978), Wooldridge (2019), and xtreg, cre in [XT] xtreg for more details on correlated random-effects models and the Mundlak specification test. estat mundlak is available after xtreg, re; xtreg, fe; and xtreg, cre.

estat mundlak uses the same VCE specified in the estimation step to fit the underlying correlated random-effects model. So, for example, if the vce(cluster *clustvar*) option was specified in the estimation step, estat mundlak will fit the correlated random-effects model using the same level of clustering for the standard errors. If the vce(bootstrap) option was specified in the estimation step, estat mundlak computes a bootstrapped *p*-value for the Mundlak test following the procedure for Wald-type bootstrap tests in Hansen (2022, 294). You can set the number of bootstrap replications used in this computation with the reps() option.

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Also see

- [XT] xtreg Linear models for panel data
- [U] 20 Estimation and postestimation commands

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