**Description**

`xthtaylor` fits a random-effects model for panel data in which some of the covariates are correlated with the unobserved individual-level random effects. The command implements the Hausman–Taylor estimator by default, but the Amemiya–MaCurdy estimator is available for balanced panels.

**Quick start**

Hausman–Taylor model of $y$ as a function of time-varying exogenous variable $x_1$, time-invariant binary variable $a$, and time-varying endogenous variable $x_2$ using `xtset` data

```
xthtaylor y x1 x2 a, endog(x2)
```

As above, and verify that $a$ is the only time-invariant variable in the model

```
xthtaylor y x1 x2 a, endog(x2) constant(a)
```

Add time-invariant $x_3$ as an endogenous covariate, but do not verify that $a$ and $x_3$ are the only time-invariant variables

```
xthtaylor y x1 x2 a x3, endog(x2 x3)
```

As above, but use Amemiya–MaCurdy estimator for balanced panels

```
xthtaylor y x1 x2 a x3, endog(x2 x3) am
```

**Menu**

Statistics > Longitudinal/panel data > Endogenous covariates > Hausman-Taylor regression (RE)
Syntax

```
xthtaylor  depvar indepvars  [if]  [in]  [weight],  endog(varlist)  [options]
```

**options**

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
</table>

**Model**

- **noconstant** suppress constant term
- *endog(varlist)* explanatory variables in `indepvars` to be treated as endogenous
- `constant(varlist_t)` independent variables that are constant within panel
- `varying(varlist_t)` independent variables that are time varying within panel
- `amacurdy` fit model based on Amemiya and MaCurdy estimator

**SE/Robust**

- `vce(vcetype)` `vcetype` may be conventional, robust, `cluster clustvar`, bootstrap, or jackknife

**Reporting**

- `level(#)` set confidence level; default is `level(95)`
- `small` report small-sample statistics

*`endog(varlist)` is required.*

A panel variable must be specified. For `xthtaylor`, `amacurdy`, a time variable must also be specified. Use `xtset`; see [XT] `xtset`.

`depvar`, `indepvars`, and all `varlists` may contain time-series operators; see [U] 11.4.4 Time-series varlists.

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

`iweights` and `fweights` are allowed unless the `amacurdy` option is specified. Weights must be constant within panel; see [U] 11.1.6 weight.

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

**Options**

- **noconstant**: see [R] Estimation options.

  `endog(varlist)` specifies that a subset of explanatory variables in `indepvars` be treated as endogenous variables, that is, the explanatory variables that are assumed to be correlated with the unobserved random effect. `endog()` is required.

  `constant(varlist_t)` specifies the subset of variables in `indepvars` that are time invariant, that is, constant within panel. By using this option, you assert not only that the variables specified in `varlist_t` are time invariant but also that all other variables in `indepvars` are time varying. If this assertion is false, `xthtaylor` does not perform the estimation and will issue an error message. `xthtaylor` automatically detects which variables are time invariant and which are not. However, users may want to check their understanding of the data and specify which variables are time invariant and which are not.

  `varying(varlist_t)` specifies the subset of variables in `indepvars` that are time varying. By using this option, you assert not only that the variables specified in `varlist_t` are time varying but also that all other variables in `indepvars` are time invariant. If this assertion is false, `xthtaylor` does not perform the estimation and will issue an error message. `xthtaylor` automatically detects which variables are time varying and which are not. However, users may want to check their understanding of the data and specify which variables are time varying and which are not.
amacurdy specifies that the Amemiya–MaCurdy estimator be used. This estimator uses extra instruments to gain efficiency at the cost of additional assumptions on the data-generating process. This option may be specified only for samples containing balanced panels, and weights may not be specified. The panels must also have a common initial period.

\[ \text{vce(vcetype)} \] specifies the type of standard error reported, which includes types that are derived from asymptotic theory (conventional), that are robust to some kinds of misspecification (robust), that allow for intragroup correlation (cluster clustvar), and that use bootstrap or jackknife methods (bootstrap, jackknife); see [XT] \textit{vce options}.

\text{vce(}\textit{conventional)}\text{, the default, uses the conventionally derived variance estimator for this Hausman–Taylor model.}

Specifying \text{vce(robust)} is equivalent to specifying \text{vce(cluster panelvar)}; see \textit{xtpoisson}, \textit{re} and the robust VCE estimator in \textit{Methods and formulas} of [XT] \textit{xtpoisson}.

\[ \text{level(#)} \]; see [R] \textit{Estimation options}.

\text{small} specifies that the \( p \)-values from the Wald tests in the output and all subsequent Wald tests obtained via \textit{test} use \( t \) and \( F \) distributions instead of the large-sample normal and \( \chi^2 \) distributions. By default, the \( p \)-values are obtained using the normal and \( \chi^2 \) distributions.

Remarks and examples \hspace{1cm} stata.com

If you have not read [XT] \textit{xt}, please do so.

Consider a random-effects model of the form

\[ y_{it} = X_{1it} \beta_1 + X_{2it} \beta_2 + Z_{1i} \delta_1 + Z_{2i} \delta_2 + \mu_i + \epsilon_{it} \]

where

- \( X_{1it} \) is a \( 1 \times k_1 \) vector of observations on exogenous, time-varying variables assumed to be uncorrelated with \( \mu_i \) and \( \epsilon_{it} \);
- \( X_{2it} \) is a \( 1 \times k_2 \) vector of observations on endogenous, time-varying variables assumed to be (possibly) correlated with \( \mu_i \) but orthogonal to \( \epsilon_{it} \);
- \( Z_{1i} \) is a \( 1 \times g_1 \) vector of observations on exogenous, time-invariant variables assumed to be uncorrelated with \( \mu_i \) and \( \epsilon_{it} \);
- \( Z_{2i} \) is a \( 1 \times g_2 \) vector of observations on endogenous, time-invariant variables assumed to be (possibly) correlated \( \mu_i \) but orthogonal to \( \epsilon_{it} \);
- \( \mu_i \) is the unobserved, panel-level random effect that is assumed to have zero mean and finite variance \( \sigma^2_\mu \) and to be independent and identically distributed (i.i.d.) over the panels;
- \( \epsilon_{it} \) is the idiosyncratic error that is assumed to have zero mean and finite variance \( \sigma^2_\epsilon \) and to be i.i.d. over all the observations in the data;
- \( \beta_1, \beta_2, \delta_1, \text{ and } \delta_2 \) are \( k_1 \times 1, k_2 \times 1, g_1 \times 1, \text{ and } g_2 \times 1 \) coefficient vectors, respectively; and
- \( \epsilon \) = 1, \ldots, \text{ where } n \text{ is the number of panels in the sample and, for each } i, t = 1, \ldots, T_i. \]
Because \( X_{2it} \) and \( Z_{2i} \) may be correlated with \( \mu_i \), the simple random-effects estimators—xtreg, \( \text{re} \) and xtreg, mle—are generally not consistent for the parameters in this model. Because the within estimator, xtreg, fe, removes the \( \mu_i \) by mean-differencing the data before estimating \( \beta_1 \) and \( \beta_2 \), it is consistent for these parameters. However, in the process of removing the \( \mu_i \), the within estimator also eliminates the \( Z_{1i} \) and the \( Z_{2i} \). Thus it cannot estimate \( \delta_1 \) nor \( \delta_2 \). The Hausman–Taylor and Amemiya–MaCurdy estimators implemented in xthtaylor are designed to resolve this problem.

The within estimator consistently estimates \( \beta_1 \) and \( \beta_2 \). Using these estimates, we can obtain the within residuals, called \( \hat{d}_i \). Intermediate, albeit consistent, estimates of \( \delta_1 \) and \( \delta_2 \)—called \( \hat{\delta}_{11V} \) and \( \hat{\delta}_{21V} \), respectively—are obtained by regressing the within residuals on \( Z_{1i} \) and \( Z_{2i} \), using \( X_{1it} \) and \( Z_{1i} \) as instruments. The order condition for identification requires that the number of variables in \( X_{1it}, k_1 \), be at least as large as the number of elements in \( Z_{2i}, g_2 \) and that there be sufficient correlation between the instruments and \( Z_{2i} \) to avoid a weak-instrument problem.

The within estimates of \( \beta_1 \) and \( \beta_2 \) and the intermediate estimates \( \hat{\delta}_{11V} \) and \( \hat{\delta}_{21V} \) can be used to obtain sets of within and overall residuals. These two sets of residuals can be used to estimate the variance components (see Methods and formulas for details).

The estimated variance components can then be used to perform a GLS transform on each of the variables. For what follows, define the general notation \( \tilde{w}_{it} \) to represent the GLS transform of the variable \( w_{it} \), \( \bar{w}_i \) to represent the within-panel mean of \( w_{it} \), and \( \tilde{w}_{it} \) to represent the within transform of \( w_{it} \). With this notational convention, the Hausman–Taylor (1981) estimator of the coefficients of interest can be obtained by the instrumental-variables regression

\[
\tilde{y}_{it} = \tilde{X}_{1it}\beta_1 + \tilde{X}_{2it}\beta_2 + \tilde{Z}_{1i}\delta_1 + \tilde{Z}_{2i}\delta_2 + \tilde{\mu}_i + \tilde{\epsilon}_{it}
\]

using \( \tilde{X}_{1it}, \tilde{X}_{2it}, \tilde{X}_{1i}, \tilde{X}_{2i}, \) and \( \tilde{Z}_{1i} \) as instruments.

For the instruments to be valid, this estimator requires that \( \tilde{X}_{1i} \) and \( \tilde{Z}_{1i} \) be uncorrelated with the random-effect \( \tilde{\mu}_i \). More precisely, the instruments are valid when

\[
\lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \tilde{X}_{1i}\mu_i = 0
\]

and

\[
\lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \tilde{Z}_{1i}\mu_i = 0
\]

Amemiya and MaCurdy (1986) place stricter requirements on the instruments that vary within panels to obtain a more efficient estimator. Specifically, Amemiya and MaCurdy (1986) assume that \( X_{1it} \) is orthogonal to \( \mu_i \) in every period; that is, \( \lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} X_{1it}\mu_i = 0 \) for \( t = 1, \ldots, T \). With this restriction, they derive the Amemiya–MaCurdy estimator as the instrumental-variables regression of (1) using instruments \( \tilde{X}_{1it}, \tilde{X}_{2it}, X_{1it}, \) and \( Z_{1i} \). The order condition for the Amemiya–MaCurdy estimator is now \( Tk_1 > g_2 \). xthtaylor uses the Amemiya–MaCurdy estimator when the amacurdy option is specified.

Although the estimators implemented in xthtaylor and xtivreg (see [XT] xtivreg) use the method of instrumental variables, each command is designed for different problems. The estimators implemented in xtivreg assume that a subset of the explanatory variables in the model are correlated with the idiosyncratic error \( \epsilon_{it} \). In contrast, the Hausman–Taylor and Amemiya–MaCurdy estimators that are implemented in xthtaylor assume that some of the explanatory variables are correlated with the individual-level random effects, \( u_i \), but that none of the explanatory variables are correlated with the idiosyncratic error, \( \epsilon_{it} \).
Example 1

This example replicates the results of Baltagi and Khanti-Akom (1990, table II, column HT) using 595 observations on individuals over 1976–1982 that were extracted from the Panel Study of Income Dynamics (PSID). In the model, the log-transformed wage \( \ln wage \) is assumed to be a function of how long the person has worked for a firm, \( \text{wks} \); binary variables indicating whether a person lives in a large metropolitan area or in the south, \( \text{smsa} \) and \( \text{south} \); marital status is \( \text{ms} \); years of education, \( \text{ed} \); a quadratic of work experience, \( \text{exp} \) and \( \text{exp2} \); occupation, \( \text{occ} \); a binary variable indicating employment in a manufacture industry, \( \text{ind} \); a binary variable indicating that wages are set by a union contract, \( \text{union} \); a binary variable indicating gender, \( \text{fem} \); and a binary variable indicating whether the individual is African American, \( \text{blk} \).

We suspect that the time-varying variables \( \text{exp} \), \( \text{exp2} \), \( \text{wks} \), \( \text{ms} \), and \( \text{union} \) are all correlated with the unobserved individual random effect. We can inspect these variables to see if they exhibit sufficient within-panel variation to serve as their own instruments.

\[
\begin{array}{l}
\text{. use https://www.stata-press.com/data/r16/psidextract} \\
\text{. xtsum exp exp2 wks ms union} \\
\end{array}
\]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Observations</th>
</tr>
</thead>
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<td>exp</td>
<td>19.85378</td>
<td>10.96637</td>
<td>1</td>
<td>51</td>
<td>N = 4165</td>
</tr>
<tr>
<td></td>
<td>10.79018</td>
<td>4</td>
<td>48</td>
<td>n = 595</td>
<td></td>
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<tr>
<td></td>
<td>2.00024</td>
<td>16.85378</td>
<td>22.85378</td>
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<td></td>
</tr>
<tr>
<td>exp2</td>
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<td>496.9962</td>
<td>1</td>
<td>2601</td>
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</tr>
<tr>
<td></td>
<td>489.0495</td>
<td>20</td>
<td>2308</td>
<td>n = 595</td>
<td></td>
</tr>
<tr>
<td></td>
<td>90.44581</td>
<td>231.405</td>
<td>807.405</td>
<td>T = 7</td>
<td></td>
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<tr>
<td>wks</td>
<td>46.81152</td>
<td>5.129098</td>
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<td>52</td>
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</tr>
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<td></td>
<td>3.284016</td>
<td>31.57143</td>
<td>51.57143</td>
<td>n = 595</td>
<td></td>
</tr>
<tr>
<td></td>
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<td>12.2401</td>
<td>63.66867</td>
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<td></td>
</tr>
<tr>
<td>ms</td>
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<td>1</td>
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<tr>
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<td>.3686109</td>
<td>0</td>
<td>1</td>
<td>n = 595</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.1245274</td>
<td>-.0427371</td>
<td>1.671549</td>
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<td></td>
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<tr>
<td>union</td>
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<td>.4812023</td>
<td>0</td>
<td>1</td>
<td>N = 4165</td>
</tr>
<tr>
<td></td>
<td>.4543848</td>
<td>0</td>
<td>1</td>
<td>n = 595</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.1593351</td>
<td>-.4931573</td>
<td>1.221128</td>
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<td></td>
</tr>
</tbody>
</table>

We are also going to assume that the exogenous variables \( \text{occ} \), \( \text{south} \), \( \text{smsa} \), \( \text{ind} \), \( \text{fem} \), and \( \text{blk} \) are instruments for the endogenous, time-invariant variable \( \text{ed} \). The output below indicates that although \( \text{fem} \) appears to be a weak instrument, the remaining instruments are probably sufficiently correlated to identify the coefficient on \( \text{ed} \). (See Baltagi and Khanti-Akom [1990] for more discussion.)

\[
\begin{array}{l}
\text{. correlate fem blk occ south smsa ind ed} \\
\end{array}
\]

<table>
<thead>
<tr>
<th></th>
<th>fem</th>
<th>blk</th>
<th>occ</th>
<th>south</th>
<th>smsa</th>
<th>ind</th>
<th>ed</th>
</tr>
</thead>
<tbody>
<tr>
<td>fem</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>blk</td>
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<td></td>
</tr>
<tr>
<td>occ</td>
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<td>0.0837</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>south</td>
<td>0.0516</td>
<td>0.1218</td>
<td>0.0413</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>smsa</td>
<td>0.1044</td>
<td>0.1154</td>
<td>-0.2018</td>
<td>-0.1350</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ind</td>
<td>-0.1778</td>
<td>-0.0475</td>
<td>0.2260</td>
<td>-0.0769</td>
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<td>1.0000</td>
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</tr>
<tr>
<td>ed</td>
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<td>-0.1196</td>
<td>-0.6194</td>
<td>-0.1216</td>
<td>0.1843</td>
<td>-0.2365</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

We will assume that the correlations are strong enough and proceed with the estimation. The output below gives the Hausman–Taylor estimates for this model.
The estimated $\sigma_\mu$ and $\sigma_\epsilon$ are 0.9418 and 0.1518, respectively, indicating that a large fraction of the total error variance is attributed to $\mu_i$. The $z$ statistics indicate that several the coefficients may not be significantly different from zero. Whereas the coefficients on the time-invariant variables fem and blk have relatively large standard errors, the standard error for the coefficient on ed is relatively small.

Baltagi and Khanti-Akom (1990) also present evidence that the efficiency gains of the Amemiya–MaCurdy estimator over the Hausman–Taylor estimator are small for these data. This point is especially important given the additional restrictions that the estimator places on the data-generating process. The output below replicates the Baltagi and Khanti-Akom (1990) results from column AM of table II.
. xthtaylor lwage occ south smsa ind exp exp2 wks ms union fem blk ed, > endog(exp exp2 wks ms union ed) amacurdy

Amemiya-MaCurdy estimation

Number of obs = 4,165
Group variable: id
Number of groups = 595
Time variable: t
Obs per group:

min = 7
avg = 7
max = 7

Random effects u_i ~ i.i.d.
Wald chi2(12) = 6879.20
Prob > chi2 = 0.0000

| lwage | Coef.  | Std. Err. | z     | P>|z| | [95% Conf. Interval] |
|-------|--------|-----------|-------|------|---------------------|
| TVexogenous |       |           |       |      |                     |
| occ   | -.0208498 | .0137653  | -1.51 | 0.130 | -.0478292           | .0061297 |
| south | .0072818  | .0319365  | 0.23  | 0.820 | -.0553126           | .0698761 |
| smsa  | -.0419507 | .0189471  | -2.21 | 0.027 | -.0790864           | -.0048149 |
| ind   | .0136289  | .015229   | 0.89  | 0.371 | -.0162194           | .0434771 |
| TVendogenous |       |           |       |      |                     |
| exp   | .1129704  | .0024688  | 45.76 | 0.000 | .1081316            | .1178093 |
| exp2  | -.0004214 | .0000546  | -7.72 | 0.000 | -.0005283           | -.0003145 |
| wks   | .0008381  | .0005995  | 1.40  | 0.162 | -.0003368           | .0002013 |
| ms    | -.0300894 | .0189674  | -1.59 | 0.113 | -.0672649           | .0070861 |
| union | .0324752  | .0148939  | 2.18  | 0.029 | .0032837            | .0616667 |
| Tl exogenous |       |           |       |      |                     |
| fem   | -.132008  | .1266039  | -1.04 | 0.297 | -.380147            | .1161311 |
| blk   | -.2859004 | .1554857  | -1.84 | 0.066 | -.5906468           | .0188459 |
| Tl endogenous |       |           |       |      |                     |
| ed    | .1372049  | .0205695  | 6.67  | 0.000 | .0968894            | .1775205 |
| _cons | 2.927338  | .2751274  | 10.64 | 0.000 | 2.388098            | 3.466578 |

sigma_u .94180304
sigma_e .15180273
rho .97467788 (fraction of variance due to u_i)

Note: TV refers to time varying; TI refers to time invariant.

Technical note

We mentioned earlier that insufficient correlation between an endogenous variable and the instruments can give rise to a weak-instrument problem. Suppose that we simulate data for a model of the form

\[ y = 3 + 3x_{1a} + 3x_{1b} + 3x_2 + 3z_1 + 3z_2 + u_i + e_{it} \]

and purposely construct the instruments so that they exhibit little correlation with the endogenous variable \( z_2 \).
use https://www.stata-press.com/data/r16/xhtaylor1
correlate ui z1 z2 x1a x1b x2 eit
(obs=10,000)

<table>
<thead>
<tr>
<th></th>
<th>ui</th>
<th>z1</th>
<th>z2</th>
<th>x1a</th>
<th>x1b</th>
<th>x2</th>
<th>eit</th>
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<tbody>
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<td>ui</td>
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<td></td>
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<tr>
<td>z1</td>
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<tr>
<td>z2</td>
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<td>1.0000</td>
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</tr>
<tr>
<td>x1a</td>
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<td>0.0065</td>
<td>-0.0034</td>
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</tr>
<tr>
<td>x1b</td>
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<td>0.0079</td>
<td>0.0038</td>
<td>-0.0030</td>
<td>1.0000</td>
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<tr>
<td>x2</td>
<td>0.8765</td>
<td>0.0191</td>
<td>0.7671</td>
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<td>0.0037</td>
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<tr>
<td>eit</td>
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<td>0.0123</td>
<td>-0.0100</td>
<td>-0.0138</td>
<td>0.0092</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

In the output below, weak instruments have serious consequences on the estimates produced by xhtaylor. The estimate of the coefficient on \( z_2 \) is three times larger than its true value, and its standard error is rather large. Without sufficient correlation between the endogenous variable and its instruments in a given sample, there is insufficient information for identifying the parameter. Also, given the results of Stock, Wright, and Yogo (2002), weak instruments will cause serious size distortions in any tests performed.

In the output below, weak instruments have serious consequences on the estimates produced by xhtaylor. The estimate of the coefficient on \( z_2 \) is three times larger than its true value, and its standard error is rather large. Without sufficient correlation between the endogenous variable and its instruments in a given sample, there is insufficient information for identifying the parameter. Also, given the results of Stock, Wright, and Yogo (2002), weak instruments will cause serious size distortions in any tests performed.

Example 2

Now let’s consider why we might want to specify the constant(`varlist\_i`) option. For this example, we will use simulated data. In the output below, we fit a model over the full sample. Note the placement in the output of the coefficient on the exogenous variable \( x_{1c} \).
. use https://www.stata-press.com/data/r16/xthtaylor2
. xthtaylor yit x1a x1b x1c x2 z1 z2, endog(x2 z2)

Hausman-Taylor estimation
Group variable: id

<table>
<thead>
<tr>
<th>Obs per group:</th>
</tr>
</thead>
<tbody>
<tr>
<td>min = 10</td>
</tr>
<tr>
<td>avg = 10</td>
</tr>
<tr>
<td>max = 10</td>
</tr>
</tbody>
</table>

Random effects u_i ~ i.i.d.
Wald chi2(6) = 10341.63
Prob > chi2 = 0.0000

| yit     | Coef.  | Std. Err. | z      | P>|z| | [95% Conf. Interval] |
|---------|--------|-----------|--------|------|-----------------------|
| TVexogenous |       |           |        |      |                       |
| x1a     | 3.023647 | .0570274 | 53.02  | 0.000| 2.911875 3.135418     |
| x1b     | 2.966666 | .0572659 | 51.81  | 0.000| 2.854427 3.078905     |
| x1c     | .2355318 | .123502  | 1.91   | 0.057| -.0065276 .4775912   |
| TVendogenous |     |           |        |      |                       |
| x2      | 14.17476 | 3.128385 | 4.53   | 0.000| 8.043234 20.30628     |
| TIexogenous |      |           |        |      |                       |
| z1      | 1.741709 | .4280022 | 4.07   | 0.000| .9028398 2.580578     |
| TIendogenous |    |           |        |      |                       |
| z2      | 7.983849 | .6970903 | 11.45  | 0.000| 6.617577 9.350121     |
| _cons   | 2.146038 | .3794179 | 5.66   | 0.000| 1.402393 2.889684     |
| sigma_u | 5.6787791 |         |        |      |                       |
| sigma_e | 3.1806188 |         |        |      |                       |
| rho     | .76120931 |         |        |      | (fraction of variance due to u_i) |

Note: TV refers to time varying; TI refers to time invariant.

Now suppose that we want to fit the model using only the first eight periods. Below, x1c now appears under the TIexogenous heading rather than the TVexogenous heading because x1c is time invariant in the subsample defined by t<9.
. xthtaylor yit xia xib xic x2 z1 z2 if t<9, endog(x2 z2)

Hausman–Taylor estimation
Number of obs = 8,000
Group variable: id
Number of groups = 1,000
Obs per group:
  min = 8
  avg = 8
  max = 8

Random effects u_i ~ i.i.d.
Wald chi2(6) = 15354.87
Prob > chi2 = 0.0000

|        | Coef.   | Std. Err. | z     | P> |z| | [95% Conf. Interval] |
|--------|---------|-----------|-------|----|---|---------------------|
| yit    |         |           |       |    |   |                     |
| TVexogenous |        |           |       |    |   |                     |
| x1a    | 3.051966| .0367026  | 83.15 | 0.000 | 2.98003 | 3.123901 |
| x1b    | 2.967822| .0368144  | 80.62 | 0.000 | 2.895667 | 3.039977 |
| TVendogenous |        |           |       |    |   |                     |
| x2     | .7361217| 3.199764  | 0.23  | 0.818 | -5.5353 | 7.007543 |
| TIexogenous |        |           |       |    |   |                     |
| x1c    | 3.215907| .5657191  | 5.68  | 0.000 | 2.107118 | 4.324696 |
| z1     | 3.347644| .5819756  | 5.75  | 0.000 | 2.206992 | 4.488295 |
| TIendogenous |        |           |       |    |   |                     |
| z2     | 2.010578| 1.143982  | 1.76  | 0.079 | -.231586 | 4.252742 |
| _cons  | 3.257004| .5295828  | 6.15  | 0.000 | 2.219041 | 4.294967 |
| sigma_u| 15.445594|           |       |    |   |                     |
| sigma_e| 3.175083|           |       |    |   |                     |
| rho    | .95945606| (fraction of variance due to u_i) |       |    |   |                     |

Note: TV refers to time varying; TI refers to time invariant.

To prevent a variable from becoming time invariant, you can use either constant(varlist_ti) or varying(varlist_tv). constant(varlist_ti) specifies the subset of variables in varlist that are time invariant and requires the remaining variables in varlist to be time varying. If you specify constant(varlist_ti) and any of the variables contained in varlist_ti are time varying, or if any of the variables not contained in varlist_ti are time invariant, xthtaylor will not perform the estimation and will issue an error message.

. xthtaylor yit xia xib xic x2 z1 z2 if t<9, endog(x2 z2) constant(z1 z2)
xic not included in constant().
r(198);
Stored results

_xhtaylor_ stores the following in _e():_

**Scalars**
- `e(N)` number of observations
- `e(N_g)` number of groups
- `e(df_m)` model degrees of freedom
- `e(df_r)` residual degrees of freedom (small only)
- `e(g_min)` smallest group size
- `e(g_avg)` average group size
- `e(g_max)` largest group size
- `e(Tcon)` 1 if panels balanced, 0 otherwise
- `e(N_clust)` number of clusters
- `e(sigma_u)` panel-level standard deviation
- `e(sigma_e)` standard deviation of \( \epsilon_{it} \)
- `e(chi2)` \( \chi^2 \)
- `e(rho)` \( \rho \)
- `e(F)` model \( F \) (small only)
- `e(Tbar)` harmonic mean of group sizes
- `e(rank)` rank of `e(V)`

**Macros**
- `e(cmd)` `xhtaylor`
- `e(cmdline)` command as typed
- `e(depvar)` name of dependent variable
- `e(i)` variable denoting groups
- `e(t)` variable denoting time within groups, amakurdy only
- `e(TVexogenous)` exogenous time-varying variables
- `e(TIexogenous)` exogenous time-invariant variables
- `e(TVendogenous)` endogenous time-varying variables
- `e(TIendogenous)` endogenous time-invariant variables
- `e(wtype)` weight type
- `e(wexp)` weight expression
- `e(title)` Hausman-Taylor or Amemiya-MacCurdy
- `e(clustvar)` name of cluster variable
- `e(chi2type)` Wald; type of model \( \chi^2 \) test
- `e(vce)` `vcetype` specified in `vce()`
- `e(vctype)` title used to label Std. Err.
- `e(properties)` `b V`
- `e(predict)` program used to implement predict

**Matrices**
- `e(b)` coefficient vector
- `e(V)` variance–covariance matrix of the estimators
- `e(V_modelbased)` model-based variance

**Functions**
- `e(sample)` marks estimation sample

**Methods and formulas**

Consider an error-components model of the form

\[
y_{it} = X_{1it}\beta_1 + X_{2it}\beta_2 + Z_{1i}\delta_1 + Z_{2i}\delta_2 + \mu_i + \epsilon_{it} \tag{2}
\]

for \( i = 1, \ldots, n \) and, for each \( i, t = 1, \ldots, T_i \), of which \( T_i \) periods are observed; \( n \) is the number of panels in the sample. The covariates in \( X \) are time varying, and the covariates in \( Z \) are time invariant. Both \( X \) and \( Z \) are decomposed into two parts. The covariates in \( X_1 \) and \( Z_1 \) are assumed to be uncorrelated with \( \mu_i \) and \( \epsilon_{it} \), whereas the covariates in \( X_2 \) and \( Z_2 \) are allowed to be correlated with \( \mu_i \) but not with \( \epsilon_{it} \). Hausman and Taylor (1981) suggest an instrumental-variable estimator for this model.
For some variable $w$, the within transformation of $w$ is defined as

$$\tilde{w}_{it} = w_{it} - \overline{w}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} w_{it}$$

Because the within estimator removes $Z$, the within transformation reduces the model to

$$\tilde{y}_{it} = \tilde{X}_{1it} \beta_1 + \tilde{X}_{2it} \beta_2 + \tilde{\epsilon}_{it}$$

The within estimators $\hat{\beta}_{1w}$ and $\hat{\beta}_{2w}$ are consistent for $\beta_1$ and $\beta_2$, but they may not be efficient. Also, note that the within estimator cannot estimate $\delta_1$ and $\delta_2$.

From the within estimator, we can be obtain an estimate of the idiosyncratic error component, $\sigma^2_\epsilon$, as

$$\hat{\sigma}^2_\epsilon = \frac{RSS}{N - n}$$

where RSS is the residual sum of squares from the within regression and $N$ is the total number of observations in the sample.

Using the results of the within estimation, we can define

$$\tilde{d}_{it} = \tilde{y}_{it} - \tilde{X}_{1it} \hat{\beta}_{1w} - \tilde{X}_{2it} \hat{\beta}_{2w}$$

where $\tilde{y}_{it}$, $\tilde{X}_{1it}$, and $\tilde{X}_{2it}$ contain the panel level means of these variables in all observations.

Regressing $\tilde{d}_{it}$ on $Z_1$ and $Z_2$, using $X_1$ and $Z_1$ as instruments, provides intermediate, consistent estimates of $\delta_1$ and $\delta_2$, which we will call $\hat{\delta}_{11V}$ and $\hat{\delta}_{21V}$.

Using the within estimates, $\hat{\delta}_{11V}$, and $\hat{\delta}_{21V}$, we can obtain an estimate of the variance of the random effect, $\sigma^2_\mu$. First, let

$$\tilde{c}_{it} = \left( y_{it} - X_{1it} \hat{\beta}_{1w} - X_{2it} \hat{\beta}_{2w} - Z_{1it} \hat{\delta}_{11V} - Z_{2it} \hat{\delta}_{21V} \right)$$

Then define

$$s^2 = \frac{1}{N} \sum_{i=1}^{n} \sum_{t=1}^{T_i} \left( \frac{1}{T_i} \sum_{t=1}^{T_i} \tilde{c}_{it} \right)^2$$

Hausman and Taylor (1981) showed that, for balanced panels,

$$\text{plim}_{n \to \infty} s^2 = T \sigma^2_\mu + \sigma^2_\epsilon$$

For unbalanced panels,

$$\text{plim}_{n \to \infty} s^2 = \bar{T} \sigma^2_\mu + \sigma^2_\epsilon$$

where

$$\bar{T} = \frac{n}{\sum_{i=1}^{n} \frac{1}{T_i}}$$

After we plug in $\hat{\sigma}^2_\epsilon$, our consistent estimate for $\sigma^2_\epsilon$, a little algebra suggests the estimate

$$\hat{\sigma}^2_\mu = \left( s^2 - \hat{\sigma}^2_\epsilon \right) (\bar{T})^{-1}$$
Define $\hat{\theta}_i$ as

$$\hat{\theta}_i = 1 - \left( \frac{\hat{\sigma}_e^2}{\hat{\sigma}_e^2 + T_i \hat{\sigma}_\mu^2} \right)^{\frac{1}{2}}$$

With $\hat{\theta}_i$ in hand, we can perform the standard random-effects GLS transform on each of the variables. The transform is given by

$$w_{it}^* = w_{it} - \hat{\theta}_i \bar{w}_i,$$

where $\bar{w}_i$ is the within-panel mean.

We can then obtain the Hausman–Taylor estimates of the coefficients in (2) and the conventional VCE by fitting an instrumental-variables regression of the GLS-transformed $y_{it}^*$ on $X_{it}^*$ and $Z_{it}^*$, with instruments $\tilde{X}_{it}$, $\bar{X}_{1it}$, and $Z_{1i}$.

We can obtain Amemiya–MaCurdy estimates of the coefficients in (2) and the conventional VCE by fitting an instrumental-variables regression of the GLS-transformed $y_{it}^*$ on $X_{it}^*$ and $Z_{it}^*$, using $\tilde{X}_{it}$, $\bar{X}_{1it}$, and $Z_{1i}$ as instruments, where $\bar{X}_{1it} = X_{1i1}, X_{1i2}, \ldots, X_{1iT_i}$. The order condition for the Amemiya–MaCurdy estimator is $Tk > g_2$, and this estimator is available only for balanced panels.

References


Also see

[XT] xhtaylor postestimation — Postestimation tools for xhtaylor

[XT] xtivreg — Instrumental variables and two-stage least squares for panel-data models

[XT] xtreg — Fixed-, between-, and random-effects and population-averaged linear models

[XT] xtset — Declare data to be panel data

[U] 20 Estimation and postestimation commands