

Bias-corrected estimation of linear dynamic panel data models

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```
ssc install xtdpdbc
net install xtdpdbc, from(http://www.kripfganz.de/stata/)
```

Estimation of linear dynamic panel data models

- In the presence of unobserved group-specific heterogeneity, the traditional “fixed effects” (FE) / “random effects” (RE) estimators for linear panel data models with a lagged dependent variable are biased when the time horizon is short (Nickell, 1981).
- Existing solutions include generalized method of moments (GMM) estimators (e.g. `xtdpdgmm`; Kripfganz, 2019) and quasi-maximum likelihood (QML) estimators (e.g. `xtdpdqml`; Kripfganz, 2016).
 - GMM estimators can flexibly accommodate predetermined or endogenous regressors by utilizing appropriate instrumental variables.
 - QML estimators can be much more efficient when all regressors are strictly exogenous, but they require additional assumptions on the initial observations.

Bias-corrected estimation of dynamic panel models

- We present a new easy-to-use bias-corrected (BC) estimator with attractive finite-sample properties (Breitung, Kripfganz, and Hayakawa, 2021): [xtdpdbc](#)
 - Since the analytical form of the bias is known, the BC estimator can correct it directly at the source by adjusting the respective moment conditions.
 - The small variance of FE/RE estimators is retained.
 - Higher-order autoregressive models can be accommodated.
 - Both FE and RE versions are available.
 - Our BC estimator is a method of moments estimator with known asymptotic distribution. Consequently, standard errors can be readily computed.
 - Standard errors can be adjusted to be robust to cross-sectional dependence.

Bias-corrected estimation of dynamic panel models

- The FE version of our BC estimator is equivalent to the Dhaene and Jochmans (2016) adjusted profile likelihood estimator. When there is only a single lag of the dependent variable, it is also equivalent to the iterative BC estimator of Bun and Carree (2005).
- In addition to the mentioned advantages, our BC estimator does not require a preliminary consistent estimator, as is needed for the bias approximation of Kiviet (1995) (`xtlsdvc`; Bruno, 2005).

Linear dynamic panel data model

$$y_{it} = \sum_{j=1}^p \lambda_j y_{i,t-j} + \mathbf{x}'_{it} \boldsymbol{\beta} + \underbrace{\alpha_i + u_{it}}_{=e_{it}}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T$$

- Basic model assumptions:

- (Higher-order) autoregressive model with p lags of the dependent variable and only minimal regularity conditions on the initial observations
- Strictly exogenous regressors \mathbf{x}_{it} with respect to the idiosyncratic error term: $E[\mathbf{x}_{it} u_{is}] = \mathbf{0}$ for all t and s
- Unobserved group-specific “fixed effects”, $E[\mathbf{x}_{it} \alpha_i] \neq \mathbf{0}$, or “random effects”, $E[\mathbf{x}_{it} \alpha_i] = \mathbf{0}$
- Seriously uncorrelated idiosyncratic errors, $E[u_{it} u_{is}] = 0$ for all t and s , but possibly heteroskedastic, $E[u_{it}^2] = \sigma_i^2$

Bias-corrected method of moments estimator

- For simplicity, let $p = 1$ and define $\theta = (\lambda_1, \beta')'$.
- The **just-identified FE-BC estimator** solves

$$\hat{\theta} = \arg \min_{\theta} \left(\sum_{i=1}^N \mathbf{m}_i(\theta) \right)' \left(\sum_{i=1}^N \mathbf{m}_i(\theta) \right)$$

with moment functions

$$\mathbf{m}_i(\theta) = \frac{1}{T} \sum_{t=1}^T \left[\begin{pmatrix} y_{i,t-1} - \bar{y}_{-1,i} \\ \mathbf{x}_{it} - \bar{\mathbf{x}}_i \end{pmatrix} - \begin{pmatrix} \frac{T}{T-1} b(\lambda_1) (e_{it} - \bar{e}_i) \\ \mathbf{0} \end{pmatrix} \right] e_{it}$$

where $\bar{x}_i = \frac{1}{T} \sum_{t=1}^T \mathbf{x}_{it}$ and $b(\lambda_1) = -\frac{1}{T^2} \sum_{t=0}^{T-2} \sum_{s=0}^t \lambda_1^s$, such that $E[\mathbf{m}_i(\theta)] = \mathbf{0}$.

- See Breitung, Kripfganz, and Hayakawa (2021) for details.

Bias-corrected method of moments estimator

- The overidentified RE-BC estimator solves

$$\hat{\theta}^{(j)} = \arg \min_{\theta} \left(\sum_{i=1}^N \mathbf{m}_i(\theta) \right)' \mathbf{W} \left(\sum_{i=1}^N \mathbf{m}_i(\theta) \right)$$

with moment functions

$$\mathbf{m}_i(\theta) = \frac{1}{T} \sum_{t=1}^T \underbrace{\begin{pmatrix} y_{i,t-1} - \bar{y}_{-1,i} \\ \mathbf{x}_{it} - \bar{x}_i \\ \mathbf{x}_{it} \end{pmatrix}}_{=\mathbf{z}_{it}} - \begin{pmatrix} \frac{T}{T-1} b(\lambda_1)(e_{it} - \bar{e}_i) \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix} e_{it}$$

and weighting matrix $\mathbf{W} = \left(\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \mathbf{z}_{it} \mathbf{z}'_{it} \right)^{-1}$ for the 1-step estimator $\hat{\theta}^{(1)}$, or $\mathbf{W} = \left(\frac{1}{N} \sum_{i=1}^N \mathbf{m}_i(\hat{\theta}^{(1)}) \mathbf{m}_i(\hat{\theta}^{(1)})' \right)^{-1}$ for the 2-step estimator $\hat{\theta}^{(2)}$.

Bias-corrected fixed-effects estimator

```
. webuse abdata  
. xtdpdbc n w k, fe vce(robust)
```

Bias-corrected estimation
Iteration 0: f(b) = .00268095
Iteration 1: f(b) = 9.158e-06
Iteration 2: f(b) = 1.024e-08
Iteration 3: f(b) = 1.829e-14

Group variable: id Number of obs = 891
Time variable: year Number of groups = 140

Fixed-effects model Obs per group: min = 6
 avg = 6.364286
 max = 8

(Std. err. adjusted for clustering on id)

	Robust					
n	Coefficient	std. err.	z	P> z	[95% conf. interval]	
<hr/>						
n						
L1.	.7795513	.1171015	6.66	0.000	.5500366	1.009066
w	-.4609536	.1117199	-4.13	0.000	-.6799206	-.2419865
k	.2429143	.0580169	4.19	0.000	.1292033	.3566253
_cons	1.750505	.4455191	3.93	0.000	.8773034	2.623706
<hr/>						

```
. estimates store fe
```

Bias-corrected random-effects estimator

```
. xtdpdcbc n w k, re vce(robust)
```

Bias-corrected estimation

Step 1:

(iteration log partly omitted)
Iteration 3: f(b) = .00483265

Step 2:

(iteration log partly omitted)
Iteration 4: f(b) = .07006667

Group variable: id	Number of obs	=	891
Time variable: year	Number of groups	=	140

Random-effects model	Obs per group:	min =	6
	avg =	6.364286	
	max =	8	

(Std. err. adjusted for clustering on id)

	Robust					
n	Coefficient	std. err.	z	P> z	[95% conf. interval]	
<hr/>						
n						
L1.	.6424014	.0559358	11.48	0.000	.5327693	.7520336
w	-.3010359	.0775378	-3.88	0.000	-.4530073	-.1490646
k	.3075345	.047089	6.53	0.000	.2152418	.3998271
_cons	1.427429	.2735669	5.22	0.000	.8912479	1.963611

Postestimation specification tests

- Hansen (1982) overidentification test (RE versus FE):

```
. estat overid
```

```
Hansen test of the overidentifying restrictions          chi2(2)      =      9.8093
H0: overidentifying restrictions are valid          Prob > chi2 =      0.0074
```

- Generalized Hausman (1978) test (RE versus FE):

```
. estat hausman fe
```

```
Generalized Hausman test          chi2(2)      =      9.0373
H0: coefficients do not systematically differ          Prob > chi2 =      0.0109
```

- Arellano and Bond (1991) serial-correlation test:

```
. estat serial
```

```
Arellano-Bond test for autocorrelation of the first-differenced residuals
H0: no autocorrelation of order 1:    z =     -2.6032  Prob > |z| =      0.0092
H0: no autocorrelation of order 2:    z =     -0.5955  Prob > |z| =      0.5515
```

Higher-order autoregressive model and time effects

```
. xtdpdcbc n w k, fe vce(robust) lags(2) teffects nolog
```

Bias-corrected estimation

Group variable: id	Number of obs	=	751
Time variable: year	Number of groups	=	140
Fixed-effects model	Obs per group:	min =	5
		avg =	5.364286
		max =	7

(Std. err. adjusted for clustering on id)

n	Robust					
	Coefficient	std. err.	z	P> z	[95% conf. interval]	
<hr/>						
n						
L1.	.8497413	.1276216	6.66	0.000	.5996076	1.099875
L2.	-.1058313	.1069847	-0.99	0.323	-.3155175	.1038548
w	-.4105421	.1694169	-2.42	0.015	-.742593	-.0784911
k	.2569002	.0590054	4.35	0.000	.1412516	.3725487
<hr/>						
year						
1979	.0001341	.0090099	0.01	0.988	-.0175249	.0177932
1980	-.0310339	.010839	-2.86	0.004	-.0522781	-.0097898
1981	-.07454	.01572	-4.74	0.000	-.1053507	-.0437294
1982	-.0341935	.0160473	-2.13	0.033	-.0656455	-.0027414
1983	.009513	.0192666	0.49	0.621	-.0282489	.0472749
1984	.0338537	.0309918	1.09	0.275	-.0268891	.0945966
<hr/>						
_cons	1.65538	.5712723	2.90	0.004	.5357066	2.775053

Time effects and postestimation specification tests

```
. estimates store fe

. xtdpdpc n w k, re vce(robust) lags(2) teffects nolog eigtolerance(0.1)
(output omitted)

. estat overid
note: degrees of freedom adjusted for time effects in unbalanced panels

Hansen test of the overidentifying restrictions      chi2(2)      =   13.2684
HO: overidentifying restrictions are valid          Prob > chi2 =   0.0013

. estat hausman fe
note: degrees of freedom might be incorrect -- use option df()

Generalized Hausman test                          chi2(6)      =   19.2573
HO: coefficients do not systematically differ    Prob > chi2 =   0.0038

. estat hausman fe, df(2)

Generalized Hausman test                          chi2(2)      =   19.2573
HO: coefficients do not systematically differ    Prob > chi2 =   0.0001
```

- In unbalanced panels, the degrees of freedom need to be adjusted because the additional moment conditions for the time effects used by the RE-BC estimator are irrelevant for the tested hypothesis. This is only detected automatically if time effects are specified with the `teffects` option.

Technical comment on multiple solutions

- Due to the nonlinearity of the bias-corrected moment function, there are multiple solutions and the numerical algorithm occasionally converges to an incorrect solution. The command automatically re-initializes the optimization with alternative initial parameter values until a correct solution is found (Breitung, Kripfganz, and Hayakawa, 2021).

```
. set seed 20220908
. xtdpdbc n w k, fe vce(robust) from(0.99 0 0 0, copy)
```

```
Bias-corrected estimation
Iteration 0:  f(b) =  .02226985
Iteration 1:  f(b) =  .01587185
Iteration 2:  f(b) =  .0006813
Iteration 3:  f(b) =  7.378e-06
Iteration 4:  f(b) =  9.699e-09
Iteration 5:  f(b) =  3.249e-14
incorrect solution -- reinitialize
Iteration 0:  f(b) =  7.0030413
Iteration 1:  f(b) =  .00300671
Iteration 2:  f(b) =  .00001076
Iteration 3:  f(b) =  1.375e-08
Iteration 4:  f(b) =  3.285e-14

(output omitted)
```

Summary

- **xtdpdbc** provides an easy-to-use implementation of a bias-corrected method of moments estimator for linear dynamic panel data models with fixed or random effects:
 - Attractive finite-sample properties
 - Higher-order autoregressive models supported
 - Analytical standard errors available
 - Time-invariant regressors can be included under the random-effects assumption
 - Specification tests for random effects versus fixed effects readily available

```
ssc install xtdpdbc
net install xtdpdbc, from(http://www.kripfganz.de/stata/)  
  
help xtdpdbc
help xtdpdbc postestimation
```

References

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