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Estimating long-run effects and the exponent of cross-sectional dependence: An update to xtdcce2

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Abstract. In this article, I describe several updates to `xtdcce2` (Ditzen, 2018, *Stata Journal* 18: 585–617). First, I explain how to estimate long-run effects in models with cross-sectional dependence. I review three methods to estimate the long-run effects and discuss their implementation into Stata using `xtdcce2`. Two of the estimation methods build on Chudik et al. (2016, *Advances in Econometrics: Vol. 36—Essays in Honor of Aman Ullah*, 85–135): the cross-sectionally augmented distributed lag and the cross-sectionally augmented autoregressive distributed lag estimator. As a third alternative, I review an error-correction model in the presence of cross-sectional dependence. Second, I explain how to estimate the exponent of cross-sectional dependence using `xtcse2` following Bailey, Kapetanios, and Pesaran (2016, *Journal of Applied Econometrics* 31: 929–960; 2019, *Sankhyā* 81: 46–102).

Keywords: st0536_1, xtdcce2, xtcse2, xtcd2, parameter heterogeneity, dynamic panels, cross-section dependence, common-correlated effects, pooled mean-group estimator, mean-group estimator, error-correction model, ardl, long-run coefficients

1 Introduction

Estimation of long-run relationships is important in empirical applications of economic models, particularly macroeconomic models. Long-run relationships describe how one or more variables react to changes in the steady state. An example would be the relationships between macroeconomic variables, such as gross domestic product (GDP) and inflation. Another would be the effects of investments, exchange rates, educational progress, or technological progress on economic growth.

With pure time-series data, the autoregressive distributed lag (ARDL) model is widely used to estimate long-run relationships. ARDL models estimate the short-run coefficients and then back out the long-run coefficients. They were implemented by the community-contributed `ardl` command in Stata (Kripfganz and Schneider 2018). A related model is the error-correction model (ECM). The model consists of two terms; one term captures the short-run deviations from equilibrium, and the other captures the long-run movements (Engle and Granger 1987). Both models can be applied to panel data (Pesaran and Smith 1995; Pesaran, Shin, and Smith 1999). Panel-data models add an extra layer of dimension compared with time-series models. Time-series models cover one panel unit, and slope heterogeneity across units is not an issue. Panel models include many panel units, and long- or short-run coefficients can vary across those. A popular method is the pooled mean-group (PMG) estimator, which assumes heterogeneous short-run and homogeneous long-run effects in a panel ECM (Pesaran, Shin, and Smith 1999). Blackburne and Frank (2007) implemented this method into Stata with the community-contributed command `xtpmg`.

The estimation of unit-specific coefficients requires datasets with many observations across time periods and cross-sectional units. Such datasets often exhibit cross-sectional dependence (CD). It implies that cross-sectional units depend on each other, for instance, by sharing a common factor. If this dependence is ignored, estimation results can be biased and inconsistent. Therefore, the extent of CD needs to be understood, and the estimation method chosen accordingly. The literature proposes two methods to identify CD. The first is to estimate the strength of the dependence (Bailey, Kapetanios, and Pesaran 2016), and the other is to test for CD (Pesaran 2015). The community-contributed command `xtcd2` (Ditzen 2018) tests for CD. This article introduces the first method, the estimation of the exponent of CD using `xtcse2`.

After one establishes the existence of strong CD, it can be approximated or controlled for by either principal components (Bai and Ng 2002; Bai 2009) or adding cross-sectional averages (Pesaran 2006). For a comparison, see Westerlund and Urbain (2015). Because of its simplicity, the approach using cross-sectional averages is very popular and started its own literature; Everaert and De Groote (2016), Chudik, Pesaran, and Tosetti (2011), and Chudik and Pesaran (2015a) provide overviews. The estimation method, called the common-correlated effects (CCE) estimator, applies to static (Pesaran 2006) and dynamic panel models (Chudik and Pesaran 2015b and Karabiyik, Reese, and Westerlund 2017), as well as pooled- (Juodis, Karabiyik, and Westerlund 2021) and mean-group estimators (Chudik and Pesaran 2019). The idea of the estimator is to add cross-sectional averages of the independent and dependent variables that approximate the CD. This estimator was implemented into Stata in the static version by the community-contributed command `xtmg` (Eberhardt 2012) and in the dynamic version by `xtdcce2` (Ditzen 2018).

Neither of the commands was able to estimate long-run relationships directly. In this article, I introduce an extended version of `xtdcce2` that allows the estimation of the long-run coefficients.[1] The estimation methods are based on Chudik et al. (2016) and an augmented ECM.

The remainder of the article is structured as follows. The next section introduces the panel model, CD, and CCE estimator. Then, I discuss three different methods to estimate the long-run coefficients, first from a theoretical perspective and then from an applied perspective. I give examples on how to fit the models using `xtdcce2`. The article closes with a conclusion.

1. The estimation of long-run coefficients is possible with `xtdcce2` version 1.33 and later. This article refers to version 2.0 or later. See the author's webpage (http://www.jan.ditzen.net) for updates.

2 Panel model and CCE estimators

For this section, assume a dynamic ARDL(1,1) panel model with heterogeneous coefficients in the form of[2]

$$
\begin{aligned}
y_{i,t} &= \mu_i + \lambda_i y_{i,t-1} + \beta_{0,i} x_{i,t} + \beta_{1,i} x_{i,t-1} + u_{i,t} \qquad (1)\\
u_{i,t} &= \sum_{l=1}^{m} \varrho_{y,i,l} f_{t,l} + e_{i,t}\\
x_{i,t} &= \sum_{l=1}^{m} \varrho_{x,i,l} f_{t,l} + \xi_{i,t}\\
\text{with } i &= 1,\dots,N \quad \text{and} \quad t = 1,\dots,T_i
\end{aligned}
$$

where $y_{i,t}$ is the dependent variable and $x_{i,t}$ an observed independent variable that includes m unobserved common factors $f_{t,l}$. The estimation of the long-run effect of x on y is the main point of interest. $e_{i,t}$ is a cross-section unit-specific independent and identically distributed error term. The factor loadings $\varrho_{x,i,l}$ and $\varrho_{y,i,l}$ are heterogeneous across units, and μ_i is a unit-specific fixed effect. The heterogeneous coefficients are randomly distributed around a common mean, such that $\beta_i = \beta + v_i$, and $\lambda_i = \lambda + a_i$, where v_i and a_i are random deviations with mean zero, independent of the error term and the common factors. λ_i lies strictly inside the unit circle to ensure a nonexplosive series.

2.1 Estimating and testing for CD

The strength of the factors can be measured by a constant $0 \le \alpha \le 1$, the so-called exponent of CD. Depending on its limiting behavior, Chudik, Pesaran, and Tosetti (2011) propose four types of CD: weak ($\alpha = 0$), semiweak ($0 < \alpha < 0.5$), semistrong ($0.5 \le \alpha < 1$), and strong ($\alpha = 1$) CD. (Semi)weak CD can be thought of as the following: even if the number of cross-sectional units increases to infinity, the sum of the effect of the common factors remains constant. In the case of strong CD, the sum of the effect of the common factors becomes stronger with an increase in the number of cross-sectional units.

Bailey, Kapetanios, and Pesaran (2016) propose a method for the estimation of the exponent of a variable under semistrong and strong CD. They derive a bias-adjusted estimator for α and its standard error based on auxiliary regressions using principal components and cross-sectional averages. In the case of estimating the exponent of CD in residuals, Bailey, Kapetanios, and Pesaran (2019) propose to use significant pairwise correlations of the residuals after multiple tests. A closed-form solution for standard errors is not available, and confidence intervals are constructed using a simple bootstrap. The community-contributed command `xtcse2` estimates the exponent of a variable and residual.

2. A more in-depth discussion of the model and the assumptions is provided in Chudik, Pesaran, and Tosetti (2011), Chudik and Pesaran (2015a), and Ditzen (2018).

Another possibility to determine the strength of CD is to test for (semi)weak CD (Pesaran 2015). Thus, the so-called CD test indirectly tests for $\alpha < 0.5$. The test statistic is the sum across all pairwise correlations and under the null asymptotically standard normal distributed. For a further theoretical discussion of the CD test, see Pesaran (2015). The CD test is implemented in Stata by the community-contributed command `xtcd2` (Ditzen 2018).

2.2 Common correlated effects estimator

Given the model in (1), leaving the factor structure unaccounted for leads to an omitted-variable bias, and ordinary least squares becomes inconsistent (Everaert and De Groote 2016). Pesaran (2006) and Chudik and Pesaran (2015b) propose an estimator to estimate (1) consistently by approximating the common factors with cross-sectional averages. In a dynamic model, the floor of $\sqrt[3]{T}$ lags of the cross-sectional averages is added. The estimated equation becomes

$$y_{i,t} = \mu_i + \lambda_i y_{i,t-1} + \beta_{0,i} x_{i,t} + \beta_{1,i} x_{i,t-1} + \sum_{l=0}^{p_T} \gamma'_{i,l} \overline{\mathbf{z}}_{t-l} + e_{i,t} \tag{2}$$

where $\overline{\mathbf{z}}_t = (\overline{y}_t, \overline{x}_t)' = (1/N \sum_{i=1}^N y_{i,t}, 1/N \sum_{i=1}^N x_{i,t})'$ are the cross-sectional averages of the dependent and independent variables. $\boldsymbol{\gamma}_{i,l} = (\gamma_{y,i,l}, \gamma_{x,i,l})'$ are the estimated coefficients of the cross-sectional averages and are generally treated as nuisance parameters. The model can be fit by either a mean-group estimator (Pesaran and Smith 1995; Pesaran 2006; Chudik and Pesaran 2019) or a pooled estimator (Pesaran 2006; Juodis, Karabiyik, and Westerlund 2021).[3] This estimator is known as the common-correlated effects mean-group (CCE-MG) estimator or CCE pooled estimator. The CCE-MG estimator is implemented in Stata by `xtmg` (Eberhardt 2012) and both estimators by `xtdcce2` (Ditzen 2018).

3 Estimating long-run relationships

Dynamic models allow the estimation of long-run relationships. They measure the effect of an explanatory variable on the steady state value of the dependent variable. Following the notation from (1) and assuming that the model is in its steady state with $y_t^* = y_{t-1}^* = y^*$ and $x_t^* = x_{t-1}^* = x^*$, we denote the long-run effect of variable x as

$$\theta_i = \frac{\beta_{0,i} + \beta_{1,i}}{1 - \lambda_i} \tag{3}$$

The long-run effect in (3) can be estimated by an ARDL, distributed lag (DL), and ECM approach. All three can be augmented by cross-sectional averages to approximate CD.

3. The assumption of heterogeneous slopes can be tested; see Pesaran and Yamagata (2008), and Blomquist and Westerlund (2013), and, in Stata, Bersvendsen and Ditzen (2020).

3.1 CS-ECM

The cross-sectionally augmented error-correction approach (CS-ECM) follows on the lines of Lee, Pesaran, and Smith (1997) and Pesaran, Shin, and Smith (1999). Equation (2) is transformed into an ECM:[4]

$$\Delta y_{i,t} = \mu_i - \phi_i \left(y_{i,t-1} - \theta_{1,i} x_{i,t}\right) - \beta_{1,i} \Delta x_{i,t} + \sum_{l=0}^{p_T} \boldsymbol{\gamma}_{i,l}' \overline{\mathbf{z}}_{t-l} + e_{i,t} \tag{4}$$

Δ is the first-difference operator, θ_i is defined as in (3),

$$\phi_i = (1 - \lambda_i)$$

is the error-correction speed of the adjustment parameter, and $(y_{i,t-1} - \theta_{1,i} x_{i,t})$ is the error-correction term. A long-run relationship exists if $\phi_i \neq 0$ (Pesaran, Shin, and Smith 1999). $\beta_{0,i}$ captures the immediate or short-run effect of $x_{i,t}$ on $y_{i,t}$. The long-run or equilibrium effect is captured by θ_i. The long-run effect measures how the equilibrium changes, and ϕ_i represents how fast the adjustment occurs.

In the case without CD and homogeneous long-run coefficients ($\theta_i = \theta \quad \forall \quad i$), the model can be fit by the PMG estimator (Pesaran, Shin, and Smith 1999).

3.2 CS-ARDL

An alternative to the CS-ECM is the cross-sectionally augmented ARDL (CS-ARDL) approach (Chudik et al. 2016). First, the short-run coefficients are estimated, and then the long-run coefficients are calculated. The advantage of this approach is that a full set of estimates for the long- and short-run coefficients is obtained. An ARDL model can be rewritten as an ECM, and therefore the long-run estimates from the CS-ECM and CS-ARDL approaches are numerically equivalent.

Equation (1) can be generalized to an ARDL(p_y, p_x) model:

$$y_{i,t} = \mu_i + \sum_{l=1}^{p_y} \lambda_{l,i} y_{i,t-l} + \sum_{l=0}^{p_x} \beta_{l,i} x_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\gamma}_{i,l}' \overline{\mathbf{z}}_{t-l} + e_{i,t}$$

The individual long-run coefficients are calculated as

$$\widehat{\theta}_{\text{CS-ARDL},i} = \frac{\sum_{l=0}^{p_x} \widehat{\beta}_{l,i}}{1 - \sum_{l=1}^{p_y} \widehat{\lambda}_{l,i}}$$

The coefficients can be directly estimated by the mean-group or pooled estimator. The mean-group variance estimator can be applied (Chudik et al. 2016) if the mean-group estimator is used.

4. The ECM can be expressed in terms of regressors in time $t-1$ instead of time t. In this case, (4) would be $\Delta y_{i,t} = \mu_i - \phi_i(y_{i,t-1} - \theta_{1,i} x_{i,t-1}) + \beta_{0,i} \Delta x_{i,t} + \sum_{l=0}^{p_T} \boldsymbol{\gamma}_{i,l}' \overline{\mathbf{z}}_{t-l} + e_{i,t}$. This is only a different parameterization, and long-run estimates will remain the same. For a more detailed discussion, see the help file of the community-contributed `ardl` command (Kripfganz and Schneider 2018).

3.3 CS-DL

Under the assumption that λ_i lies in the unit circle, the general representation of an ARDL(p_y, p_x) model can be written in DL form:[5]

$$y_{i,t} = \mu_i + \theta_{1,i} x_{i,t} + \delta_i(L)\Delta x_{i,t} + \widetilde{u}_{i,t} \tag{5}$$

Chudik et al. (2016) show that (5) can be directly estimated by the CCE estimator, named the cross-sectionally augmented DL (CS-DL) approach. The regression is augmented with the differences of the explanatory variables (x), their lags, and the cross-sectional averages. Following Pesaran (2006), the estimation is consistent even if the errors are serially correlated.

For a general ARDL(p_y, p_x) model with added cross-sectional averages to take out strong CD, the CS-DL estimator is based on the equation

$$\begin{aligned} y_{i,t} = \mu_i + \theta_{1,i} x_{i,t} &+ \sum_{l=0}^{p_x - 1} \delta_{i,l} \Delta x_{i,t-l} \\ &+ \sum_{l=0}^{p_{\overline{y}}} \gamma_{y,i,l} \overline{y}_{t-l} + \sum_{l=0}^{p_{\overline{x}}} \gamma_{x,i,l} \overline{x}_{t-l} + e_{i,t} \end{aligned}$$

where $\overline{y}_{t-l}$ and $\overline{x}_{t-l}$ are the cross-sectional averages and $p_{\overline{x}} = \lfloor T^{1/3} \rfloor$ and $p_{\overline{y}} = 0$.

4 Updates to the xtdcce2 command

4.1 Syntax

The updated syntax is described below. New and updated options compared with the version explained in Ditzen (2018) are described in section 4.2.

```
xtdcce2 depvar [indepvars] [(varlist2 = varlist_iv)] [if] [in] ,
   {crosssectional(varlist_cr) | nocrosssectional} [pooled(varlist_p)
   cr_lags(integers) ivreg2options(options1) e_ivreg2 ivslow noisily
   pooledconstant reportconstant noconstant trend pooledtrend
   [jackknife | recursive] nocd fullsample showindividual pooledvce(type)
   fast lr(varlist_lr) lr_options(options2) exponent xtcse2options(options3)
   blockdiaguse nodimcheck useinvsym useqr noomitted showomitted]
```

5. The other parameters are defined as $\delta_i(L) = -\sum_{l=0}^{\infty} \{\lambda_i^{l+1} (1-\lambda_i)^{-1} \beta_{1,i}\} L^l, \theta_{0,i} = (1-\lambda_i L)^{-1} \mu_i$, $\widetilde{u}_{i,t} = (1-\lambda_i L)^{-1} u_{i,t}$, and L is the lag operator.

4.2 New and updated options

In the following, the updated or new options are explained. For a full explanation, see Ditzen (2018, 2019) and the help file for `xtdcce2`.

`crosssectional(`*varlist*`)` defines the variables that are included in z_t and added as cross-sectional averages ($\overline{z}_{t-l}$) to the equation. Variables in `crosssectional()` may be included in `pooled()`, `exogenous_vars()`, `endogenous_vars()`, and `lr()`. Variables in `crosssectional()` are partialed out, and the coefficients are not estimated and reported.

> `crosssectional(_all)` adds all variables as cross-sectional averages. No cross-sectional averages are added if `crosssectional(_none)` is used, which is equivalent to `nocrosssectional`.
>
> `crosssectional()` is required but can be substituted by `nocrosssectional`.

`nocrosssectional` suppresses adding cross-sectional averages. Results will be equivalent to the Pesaran and Smith (1995) mean-group estimator or, if `lr(`*varlist*`)` is specified, to the Pesaran, Shin, and Smith (1999) PMG estimator. `nocrosssectional` cannot be specified with `crosssectional()`.

`cr_lags(`*integers*`)` specifies the number of lags of the cross-sectional averages. If not defined but `crosssectional()` contains a *varlist*, then only contemporaneous cross-sectional averages are added but no lags. `cr_lags(0)` is the equivalent. The number of lags can be different for different variables, where the order is the same as defined in `crosssectional()`. For example, if `crosssectional(y x)` and only contemporaneous cross-sectional averages of `y` but 2 lags of `x` are added, then `cr_lags(0 2)`.

`fast` omits calculation of unit-specific standard errors.

`lr(`*varlist_lr*`)` specifies the variables to be included in the long-run cointegration vector. The first variable or variables are the error-correction speed of the adjustment term. The default is to use the PMG model. In this case, each estimated coefficient is divided by the negative of the long-run cointegration coefficient (the first variable). If the option `lr_options(ardl)` is used, then the long-run coefficients are estimated as the sum over the coefficients relating to a variable divided by the sum of the coefficients of the dependent variable.

`lr_options(`*options2*`)` specifies options for the long-run estimation. *options2* may be the following:

> `ardl` estimates the CS-ARDL estimator.
>
> `nodivide`, where coefficients are not divided by the error-correction speed of the adjustment vector.
>
> `xtpmgnames`, where coefficients' names in `e(b)` and `e(V)` match the name convention from `xtpmg`.

`exponent` uses `xtcse2` to estimate the exponent of the CD of the residuals. A value above 0.5 indicates strong CD.

`xtcse2options(`*options3*`)` passes options to `xtcse2`.

`blockdiaguse` uses the `mata blockdiag` option rather than an alternative algorithm. `mata blockdiag` is slower but might produce more stable results.

`nodimcheck` does not check for dimension. Before fitting a model, `xtdcce2` automatically checks whether the time dimension within each panel is long enough to run an MG regression. Panel units with an insufficient number are automatically dropped.

`useinvsym` calculates the generalized inverse via `mata invsym`.

`useqr` calculates the generalized inverse via QR decomposition. The default is `mata cholinv`. QR decomposition was the default for rank-deficient matrices for `xtdcce2` preversion 1.35.

`noomitted` suppresses checks for collinearity.

`showomitted` displays a cross-sectional unit—variable breakdown of omitted coefficients.

4.2.1 New stored results

The new version stores the following two additional results:

Matrices

`e(alpha)`	estimates of the exponent of cross-section dependence
`e(alphaSE)`	estimates of the standard-error exponent of cross-section dependence

5 The xtcse2 command

5.1 Syntax

`xtcse2` [*varlist*] [*if*] [, `pca(`*integer*`)` `standardize` `nocenter` `nocd` `residual` `reps(`*integer*`)` `size(`*real*`)` `tuning(`*real*`)` `lags(`*integer*`)`]

5.2 Options

`pca(`*integer*`)` sets the number of principal components for the calculation of *cn*. The default is to use the first four components.

`standardize` standardizes variables.

`nocenter` specifies to not center variables (that is, the cross-sectional mean is zero).

`nocd` suppresses the test for weak CD using `xtcd2`.

`residual` estimates the exponent of CD in residuals, following Bailey, Kapetanios, and Pesaran (2019).

`reps(`*integer*`)` sets the number of repetitions for bootstrap for calculation of the standard error and confidence interval for the exponent in residuals. The default is `reps(0)`.

`size(`*real*`)` sets the size of the test. The default is `size(0.1)` (10%).

`tuning(`*real*`)` specifies the tuning parameter for estimation of the exponent in residuals. The default is `tuning(0.5)`.

`lags(`*integer*`)` specifies the number of lags (or training periods) for calculation of recursive residuals when estimating the exponent after a regression with weakly exogenous regressors.

5.3 Stored results

`xtcse2` stores the following in `r()`:

Matrices

`r(alpha)`	matrix of estimated αs
`r(alphaSE)`	matrix with standard errors of αs
`r(alphas)`	matrix with estimated $\widetilde{\alpha}$, $\widehat{\alpha}$, and α
`r(N_g)`	matrix with number of cross-sectional units
`r(T)`	matrix with number of time periods
`r(CD)`	matrix with values of CD test statistic (if requested)
`r(CDp)`	matrix of p-values of CD test statistic (if requested)

6 Empirical examples

6.1 Estimating and testing for CD

Blackburne and Frank (2007) explain the use of `xtpmg` by estimating the long-run consumption function from Lee, Pesaran, and Smith (1997) and Pesaran, Shin, and Smith (1999):[6]

$$c_{i,t} = \theta_{0t} + \theta_{1t} y_{i,t} + \theta_{2t} \pi_{i,t} + \mu_i + \epsilon_{i,t} \tag{6}$$

$c_{i,t}$ is the log of consumption per capita, $y_{i,t}$ is the log of real per capita income, and $\pi_{i,t}$ is the inflation rate.

6. The following example uses `jasa2.dta`, which is available with the `xtpmg` command.

Before fitting the model, one must evaluate whether the variables inhibit CD. `xtcse2` is used to estimate the exponent of and test for CD for the variables $c_{i,t}$ (`c`), $y_{i,t}$ (`y`), and $\pi_{i,t}$ (`pi`):

```
. use jasa2
. xtcse2 c pi y
Cross-Sectional Dependence Exponent Estimation and Test
Panel Variable (i): id
Time Variable (t): year
Estimation of Cross-Sectional Exponent (alpha)
```

variable	alpha	Std. Err.	[95% Conf.	Interval]
c	1.004833	.0544669	.8980796	1.111586
pi	1.004841	1.763292	-2.451148	4.460831
y	1.004833	.0466978	.913307	1.096359

```
0.5 <= alpha < 1 implies strong cross-sectional dependence.
Pesaran (2015) test for weak cross-sectional dependence.
H0: errors are weakly cross-sectional dependent.
```

variable	CD	p-value	N_g	T
c	89.656	0.000	24	33
pi	96.751	0.000	24	33
y	89.659	0.000	24	33

The CD test rejects the null of weak CD for all variables, and the estimated exponent of CD is well above 0.5. This is evidence that an estimation method accounting for CD is necessary. All remaining examples are dynamic models. Following Chudik and Pesaran (2015b), the contemporaneous levels of the dependent and independent variables and the floor of $T^{1/3}$ lags of the cross-sectional averages will be added to approximate strong CD. After each regression, the residuals are tested for strong CD using the CD test, and the exponent of CD is estimated.

6.2 CS-ECM

The ECM representation of (6) is

$$\Delta c_{i,t} = \mu_i - \phi_i(c_{i,t-1} - \theta_{1,i} y_{i,t} - \theta_{2,i}\pi_{i,t}) - \beta_{1,i}\Delta y_{i,t} - \beta_{2,i}\Delta\pi_{i,t} + \epsilon_{i,t} \tag{7}$$

Blackburne and Frank (2007) and Ditzen (2018) fit a PMG model without and with contemporaneous cross-sectional averages using `xtpmg` and `xtdcce2`, respectively. This exercise focuses on the CS-ECM model, and all coefficients are assumed to be heterogeneous. Following Chudik and Pesaran (2015b), $p = \lfloor T^{1/3} \rfloor = \lfloor 29^{1/3} \rfloor = 3$ lags of the cross-sectional averages are added to be estimated (7):[7]

7. $\lfloor . \rfloor$ denotes the floor of a number.

```
. xtdcce2 d.c d.y d.pi if year >= 1962,
> lr(L.c y pi) crosssectional(_all) cr_lags(3) exponent
(Dynamic) Common Correlated Effects Estimator - Mean Group (CS-ECM)

Panel Variable (i): id                            Number of obs     =        695
Time Variable (t): year                           Number of groups  =         24

Degrees of freedom per group:                     Obs per group:
 without cross-sectional avg. min   = 22                        min =         28
                              max   = 23                        avg =         29
 with cross-sectional avg.    min   = 10                        max =         29
                              max   = 11
Number of                                         F(432, 263)       =       2.90
 cross-sectional lags               = 3           Prob > F          =       0.00
 variables in mean group regression = 120         R-squared         =       0.17
 variables partialled out           = 312         R-squared (MG)    =       0.83
                                                  Root MSE          =       0.01
                                                  CD Statistic      =       0.27
                                                     p-value        =     0.7899

               D.c      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

 Short Run Est.

   Mean Group:
               D.y   .0088767   .0511634    0.17   0.862     -.0914017    .109155
              D.pi   .0146379   .0412939    0.35   0.723     -.0662966   .0955725

 Adjust. Term

   Mean Group:
               L.c  -.6112082    .056361  -10.84   0.000     -.7216738  -.5007426

 Long Run Est.

   Mean Group:
                pi  -.5976237    .275682   -2.17   0.030      -1.13795   -.057297
                 y   .7872628   .0995928    7.90   0.000      .5920646    .982461

Mean Group Variables: D.y D.pi pi y
Cross Sectional Averaged Variables: pi y c
Long Run Variables:  pi y
Cointegration variable(s): L.c
Heterogenous constant partialled out.
Estimation of Cross-Sectional Exponent (alpha)

          variable      alpha   Std. Err.     [95% Conf. Interval]

         residuals   .5844011   .0243676      .5366414    .6321607

0.5 <= alpha < 1 implies strong cross sectional dependence.
SE and CI bootstrapped with 100 repetitions.
```

The mean-group estimate of the partial adjustment coefficients is $\widehat{\phi} = -0.611$ (`L.c`), the long-run effect of income on consumption is $\widehat{\theta}_1 = 0.787$ (`y`), and the long-run effect of inflation on consumption is $\widehat{\theta}_2 = -0.598$ (`pi`). The results imply that 61.1% of the disequilibrium is adjusted every period. An increase in income increases consumption in the long run, while an increase in prices hampers consumption in the long run.

There are some notable differences between `xtpmg` and `xtdcce2`. `xtpmg` calculates the long-run coefficients using maximum likelihood. `xtdcce2` internally estimates (leaving out any cross-sectional averages)

$$\Delta c_{i,t} = \mu_i - \phi_i c_{i,t-1} + \kappa_{1,i} y_{i,t} + \kappa_{2,i} \pi_{i,t} - \beta_{1,i} \Delta y_{i,t} - \beta_{2,i} \Delta \pi_{i,t} + \epsilon_{i,t}$$

using ordinary least squares with $\kappa_{1,i} = -\theta_{1,i}\phi_i$ and $\kappa_{2,i} = -\theta_{2,i}\phi_i$. The long-run coefficients and the mean-group coefficients are estimated in three steps, and the variances are calculated using the delta method. First, the cross-section–specific coefficients μ_i, ϕ_i, $\kappa_{1,i}$, $\kappa_{2,i}$, $\beta_{1,i}$, and $\beta_{2,i}$ are estimated. Then, the cross-section–specific long-run coefficients are calculated. Lastly, the mean-group coefficients are calculated as the unweighed average over the unit-specific long-run coefficients. As an example, the average long-run unit-specific coefficient for $\widehat{\theta}_{1,i}$ is derived as $\widehat{\theta}_{1,i} = -\widehat{\kappa}_{1,i}/\widehat{\phi}_i$. Then, the mean-group estimator is $\widehat{\widehat{\theta}}_1 = 1/N \sum_{i=1}^{N} \widehat{\theta}_{1,i} = 1/N \sum_{i=1}^{N} (-\widehat{\kappa}_{1,i}/\widehat{\phi}_i)$.

The PMG estimator assumes homogeneous long-run and heterogeneous short-run coefficients. `xtdcce2` is built to handle both coefficients to be heterogeneous or homogeneous. If the long-run coefficients are homogeneous but the short-run coefficients are heterogeneous, then the mean-group estimate of the error speed of the correction term is used to calculate the long-run coefficient. They then become $\theta_1^p = -\kappa_1^p/\phi_{\text{MG}}$.

The option `exponent` is used to calculate the exponent of the CD using `xtcse2`. Standard errors and confidence intervals can be obtained by a simple bootstrap in which the cross-sectional units are drawn with replacement. `xtdcce2` automatically runs a bootstrap with 100 repetitions. Further options to `xtcse2` can be passed by the option `xtcse2option()`. In the example above, the p-value of the CD test is 0.79, and the test cannot reject the null hypothesis of (semi)weak CD. Bailey, Kapetanios, and Pesaran (2019, S92) state that the estimated exponent of CD should be close to 0.5 if the residuals are weakly CD. The estimated exponent of CD is 0.584 and close to the threshold of 0.5.

6.3 CS-ARDL

The ECM in (7) can be transferred into an ARDL(1,1,1) model:

$$c_{i,t} = \mu_i + \lambda_i c_{i,t-1} + \beta_{10,i} y_{i,t} + \beta_{11,i} y_{i,t-1} + \beta_{20,i} \pi_{i,t} + \beta_{20,i} \pi_{i,t-1} + \epsilon_{i,t}$$

Using `xtdcce2`, we add all short-run variables to the `lr()` option and invoke the ARDL routine by using `lr_options(ardl)`:[8]

```
. xtdcce2 c if year >= 1962,
> lr(L.c L(0/1).y pi L.pi) lr_options(ardl)
> crosssectional(_all) cr_lags(3)
(Dynamic) Common Correlated Effects Estimator -  (CS-ARDL)

Panel Variable (i): id                           Number of obs     =        695
Time Variable (t): year                          Number of groups  =         24

Degrees of freedom per group:                    Obs per group:
 without cross-sectional avg. min   = 22                      min =         28
                              max   = 23                      avg =         29
 with cross-sectional avg.    min   = 10                      max =         29
                              max   = 11
Number of                                        F(432, 263)       =       3.27
 cross-sectional lags             = 3            Prob > F          =       0.00
 variables in mean group regression = 120        R-squared         =       0.16
 variables partialled out         = 312          R-squared (MG)    =       1.00
                                                 Root MSE          =       0.01
                                                 CD Statistic      =       0.27
                                                    p-value        =     0.7899

-------------------------------------------------------------------------------
               c |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------------------------------------------------------------
 Short Run Est.  |
-------------------------------------------------------------------------------
   Mean Group:   |
             L.c |   .3887918    .056361     6.90   0.000      .2783262   .4992574
              pi |  -.1113299   .0760736    -1.46   0.143     -.2604314   .0377716
               y |    .486285   .0598417     8.13   0.000      .3689975   .6035726
             L.y |  -.0088767   .0511634    -0.17   0.862      -.109155   .0914017
            L.pi |  -.0146379   .0412939    -0.35   0.723     -.0955725   .0662966
-------------------------------------------------------------------------------
 Adjust. Term    |
-------------------------------------------------------------------------------
   Mean Group:   |
            lr_c |  -.6112082    .056361   -10.84   0.000     -.7216738  -.5007426
-------------------------------------------------------------------------------
 Long Run Est.   |
-------------------------------------------------------------------------------
   Mean Group:   |
           lr_pi |  -.5976237    .275682    -2.17   0.030      -1.13795   -.057297
            lr_y |   .7872628   .0995928     7.90   0.000      .5920646    .982461
-------------------------------------------------------------------------------
Mean Group Variables: L.c pi y L.y L.pi lr_pi lr_y
Cross Sectional Averaged Variables: pi y c
Long Run Variables:  lr_pi lr_y
Adjustment variable(s): lr_c (L.c)
Heterogenous constant partialled out.
```

As expected, the regression results are the same as above for the CS-ECM model. In the output, the long-run coefficient estimates have the prefix `lr_`, and the adjustment parameter (ϕ) is displayed in a separate section. If the long-run coefficients are pooled,

8. There is no need to specify the long-run variables separately because `xtdcce2` automatically detects the common base of variables if time-series operators are used. If lags are created as variables via `generate lx = L.x`, then the variables with the same base that form a long-run coefficient need to be enclosed in parentheses, for example, `lr((y ly) (x lx))`.

xtdcce2 uses the delta method to calculate the variance–covariance matrix of the long-run coefficients.

For the remaining examples, the results in Chudik et al. (2013) will be replicated. The authors estimate the long-run effect of public debt on output growth with the following equation:

$$\Delta y_{i,t} = \mu_i + \sum_{l=1}^{p} \lambda_{i,l} \Delta y_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}'_{i,l} \mathbf{x}_{i,t-l} + \sum_{l=0}^{3} \boldsymbol{\gamma}'_{i,l} \overline{\mathbf{z}}_{t-l} + e_{i,t} \tag{8}$$

$y_{i,t}$ is the logarithm of real GDP, and $\Delta y_{i,t}$ is its growth rate. $\mathbf{x}_{i,t} = (\Delta d_{i,t}, \pi_{i,t})'$, $d_{i,t}$ is the log of debt to GDP ratio, π is the log of the inflation rate, and p is the number of lags. The cross-sectional averages are $\overline{\mathbf{z}}_t = (\overline{\mathbf{x}}_t, \overline{\Delta y_t})'$. The variables in the example dataset are dy for $\Delta y_{i,t}$, dgd for $\Delta d_{i,t}$, and dp for the inflation rate $\pi_{i,t}$.

The degree of CD is checked with

```
. use cmpr, clear
. xtset ccode year
Panel variable: ccode (strongly balanced)
 Time variable: year, 1965 to 2010
         Delta: 1 unit
. generate double y=ln(gdp)
(34 missing values generated)
. generate double dy=d.y
(74 missing values generated)
. generate double p=ln(cpi)
(1 missing value generated)
. generate double dp=d.p
(41 missing values generated)
. generate double gd=ln(gdebt)
(105 missing values generated)
. generate double dgd = d.gd
(145 missing values generated)
. xtcse2 y p gd, standardize
  (output omitted)
```

All variables are strongly CD with $\widehat{\alpha}_y = 1$, $\widehat{\alpha}_{\texttt{dp}} = 0.94$, and $\widehat{\alpha}_{\texttt{dgd}} = 0.92$. The CD test statistic yields the same conclusion: all variables contain strong CD.

Next we can turn to fit the ARDL model. As before, three lags of the cross-sectional averages are added to take out any strong CD. To replicate the results of the ARDL(1,1,1) model from Chudik et al. (2013, table 17), we add the first lag of the dependent and the base and the first lag of the dependent variables:

```
. xtdcce2 dy, lr(L.dy L.dp dp L.dgd dgd)
> lr_options(ardl) crosssectional(dy dp dgd) cr_lags(3)
> fullsample
(Dynamic) Common Correlated Effects Estimator -  (CS-ARDL)
Panel Variable (i): ccode                          Number of obs     =      1599
Time Variable (t): year                            Number of groups  =        40
Degrees of freedom per group:                      Obs per group (T) =        40
 without cross-sectional averages   = 33.975
 with cross-sectional averages      = 21.975
Number of                                          F(720, 879)       =      0.79
 cross-sectional lags               = 3            Prob > F          =      1.00
 variables in mean group regression = 200          R-squared         =      0.61
 variables partialled out           = 520          R-squared (MG)    =      0.44
                                                   Root MSE          =      0.03
                                                   CD Statistic      =      0.57
                                                      p-value        =    0.5690

---------------------------------------------------------------------------------
             dy |     Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
 Short Run Est. |
----------------+----------------------------------------------------------------
   Mean Group:  |
           L.dy |  .0475615   .0393516    1.21   0.227    -.0295662   .1246891
             dp | -.1036032   .0402887   -2.57   0.010    -.1825676  -.0246389
            dgd | -.0745686   .0122305   -6.10   0.000    -.0985399  -.0505974
           L.dp |  -.019946   .0462871   -0.43   0.667    -.1106671    .070775
          L.dgd | -.0132481   .0156115   -0.85   0.396    -.0438461   .0173498
----------------+----------------------------------------------------------------
 Adjust. Term   |
----------------+----------------------------------------------------------------
   Mean Group:  |
          lr_dy | -.9524385   .0393516  -24.20   0.000    -1.029566  -.8753109
----------------+----------------------------------------------------------------
 Long Run Est.  |
----------------+----------------------------------------------------------------
   Mean Group:  |
         lr_dgd | -.0873993   .0164431   -5.32   0.000    -.1196272  -.0551713
          lr_dp | -.1639757   .0378599   -4.33   0.000    -.2381797  -.0897717
---------------------------------------------------------------------------------
Mean Group Variables: L.dy dp dgd L.dp L.dgd lr_dgd lr_dp
Cross Sectional Averaged Variables: dy dp dgd
Long Run Variables:  lr_dgd lr_dp
Adjustment variable(s): lr_dy (L.dy)
Heterogenous constant partialled out.
```

The long-run coefficients for the logarithm of debt to GDP ratio and inflation are both significant and negative. A decrease in the debt burden and inflation will increase GDP growth. A 1% decrease of the debt to GDP growth is associated with an increase of the GDP growth rate of 0.16%. A 1% decrease in the inflation rate leads to an increase of the GDP growth rate of 0.087%. The partial adjustment to the long-run equilibrium appears to be very quick; 95% of the gap is closed within one year.

For the ARDL(3,3,3), the three lags of the explanatory variables and the dependent variable are added. To improve readability, we enclose the different bases in parentheses:

```
. xtdcce2 dy, cr_lags(3) fullsample
> lr((L(1/3).dy) (L(0/3).dp) (L(0/3).dgd))
> lr_options(ardl) crosssectional(dy dp dgd)
(Dynamic) Common Correlated Effects Estimator -  (CS-ARDL)

Panel Variable (i): ccode                        Number of obs     =       1562
Time Variable (t): year                          Number of groups  =         40

Degrees of freedom per group:                    Obs per group (T) =         39
 without cross-sectional averages   = 27.05
 with cross-sectional averages      = 15.05
Number of                                        F(960, 602)       =       0.96
 cross-sectional lags               = 3          Prob > F          =       0.71
 variables in mean group regression = 440        R-squared         =       0.39
 variables partialled out           = 520        R-squared (MG)    =       0.51
                                                 Root MSE          =       0.02
                                                 CD Statistic      =      -0.51
                                                    p-value        =     0.6108

------------------------------------------------------------------------------
             dy|     Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
Short Run Est. |
---------------+--------------------------------------------------------------
   Mean Group: |
           L.dy|  .0123738   .0349377     0.35   0.723    -.0561029    .0808506
          L2.dy| -.1395645   .0948427    -1.47   0.141    -.3254529    .0463238
          L3.dy|  -.082903   .1072901    -0.77   0.440    -.2931877    .1273817
             dp|  -.070708   .0503039    -1.41   0.160    -.1693018    .0278858
            dgd|  -.085307   .0137595    -6.20   0.000    -.1122752   -.0583388
           L.dp| -.0312712   .0513435    -0.61   0.542    -.1319025    .0693601
          L2.dp|  .0982105   .1017365     0.97   0.334    -.1011893    .2976103
          L3.dp| -.0424631   .0581692    -0.73   0.465    -.1564726    .0715464
          L.dgd| -.0270311   .0204753    -1.32   0.187    -.0671619    .0130997
         L2.dgd| -.0114103    .012726    -0.90   0.370    -.0363528    .0135322
         L3.dgd|  .0283551   .0177666     1.60   0.110    -.0064667    .0631769
---------------+--------------------------------------------------------------
Adjust. Term   |
---------------+--------------------------------------------------------------
   Mean Group: |
          lr_dy| -1.210094   .2005902    -6.03   0.000    -1.603243   -.8169442
---------------+--------------------------------------------------------------
Long Run Est.  |
---------------+--------------------------------------------------------------
   Mean Group: |
         lr_dgd| -.1198362   .0402251    -2.98   0.003     -.198676   -.0409965
          lr_dp| -.0795245   .0586992    -1.35   0.175    -.1945727    .0355238
------------------------------------------------------------------------------
Mean Group Variables: L.dy L2.dy L3.dy dp dgd L.dp L2.dp L3.dp L.dgd L2.dgd
> L3.dgd lr_dgd lr_dp
Cross Sectional Averaged Variables: dy dp dgd
Long Run Variables:  lr_dgd lr_dp
Adjustment variable(s): lr_dy (L.dy L2.dy L3.dy)
Heterogenous constant partialled out.
```

6.4 CS-DL

Besides the ARDL model, Chudik et al. (2013) fit a CS-DL model. Equation (8) in CS-DL form is

$$\Delta y_{i,t} = \mu_i + \boldsymbol{\theta}_i' \mathbf{x}_{i,t} + \sum_{l=0}^{p-1} \boldsymbol{\beta}_{i,l}' \Delta \mathbf{x}_{i,t-l} + \gamma_{y,i} \Delta \overline{y}_t + \sum_{l=0}^{3} \boldsymbol{\gamma}_{x,i,l}' \overline{\mathbf{x}}_{t-l} + e_{i,t}$$

The results from Chudik et al. (2013, table 18) with 1 lag ($p = 1$) in the form of an ARDL(1,1,1) model can be replicated as follows:

```
. xtdcce2 dy dp dgd d.(dp dgd),
> crosssectional(dy dp dgd) cr_lags(0 3 3) fullsample
(Dynamic) Common Correlated Effects Estimator - Mean Group

Panel Variable (i): ccode                          Number of obs     =      1601
Time Variable (t): year                            Number of groups  =        40

Degrees of freedom per group:                      Obs per group (T) =        40
 without cross-sectional averages   = 35.025
 with cross-sectional averages      = 26.025
Number of                                          F(560, 1041)      =      0.90
 cross-sectional lags               0 to 3         Prob > F          =      0.93
 variables in mean group regression = 160          R-squared         =      0.67
 variables partialled out           = 400          R-squared (MG)    =      0.40
                                                   Root MSE          =      0.03
                                                   CD Statistic      =      1.11
                                                      p-value        =    0.2667

------------------------------------------------------------------------------
          dy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 Mean Group: |
          dp | -.0889337    .0256445   -3.47   0.001     -.1391959  -.0386715
         dgd | -.0865123       .0143   -6.05   0.000     -.1145398  -.0584849
        D.dp |  .0053277    .0413627    0.13   0.898     -.0757417   .0863971
       D.dgd |  .0068065    .0148306    0.46   0.646      -.022261   .0358739
------------------------------------------------------------------------------
Mean Group Variables: dp dgd D.dp D.dgd
Cross Sectional Averaged Variables: dy(0) dp(3) dgd(3)
Heterogenous constant partialled out.
```

The first differences as part of the vector $\Delta \mathbf{x}_{i,t}$ are added as `d.(dp dgd)`. The `fullsample` option is used to make use of the entire sample. The long-run coefficients are -0.0889 (`dp`) and -0.0865 (`dgd`). While the coefficient on the inflation rate is almost identical to the CS-ARDL model, the coefficient on the debt to GDP is about half the absolute size. An advantage (or disadvantage) of the CS-DL model is that no partial-adjustment coefficient is estimated, because the long-run coefficients are directly estimated.

An ARDL(3,3,3) model is fit using three rather than one lag for the differences, and `L(0/2).d.(dp dgd)` replaces `d.(dp dgd)`:

```
. xtdcce2 dy dp dgd L(0/2).d.(dp dgd),
> crosssectional(dy dp dgd) cr_lags(0 3 3) fullsample
(Dynamic) Common Correlated Effects Estimator - Mean Group
Panel Variable (i): ccode                        Number of obs     =      1571
Time Variable (t): year                          Number of groups  =        40
Degrees of freedom per group:                    Obs per group (T) =        39
 without cross-sectional averages   = 30.275
 with cross-sectional averages      = 21.275
Number of                                        F(720, 851)       =      1.12
 cross-sectional lags               0 to 3       Prob > F          =      0.06
 variables in mean group regression = 320        R-squared         =      0.51
 variables partialled out           = 400        R-squared (MG)    =      0.47
                                                 Root MSE          =      0.03
                                                 CD Statistic      =      0.73
                                                    p-value        =    0.4680

               dy       Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

 Mean Group:
               dp   -.0855842   .0400845   -2.14   0.033     -.1641483    -.00702
              dgd   -.0816583   .0196252   -4.16   0.000     -.1201231  -.0431936
             D.dp    .0183584   .0478696    0.38   0.701     -.0754643    .112181
            LD.dp    .0015586   .0373619    0.04   0.967     -.0716695   .0747866
           L2D.dp    .0034012   .0294771    0.12   0.908     -.0543729   .0611752
            D.dgd    .0045224   .0144741    0.31   0.755     -.0238463   .0328912
           LD.dgd   -.0129675   .0134553   -0.96   0.335     -.0393395   .0134045
          L2D.dgd   -.0095151   .0090813   -1.05   0.295     -.0273142    .008284

Mean Group Variables: dp dgd D.dp LD.dp L2D.dp D.dgd LD.dgd L2D.dgd
Cross Sectional Averaged Variables: dy(0) dp(3) dgd(3)
Heterogenous constant partialled out.
```

The first two variables (`dp` and `dgd`) represent the long-run coefficients.

7 Conclusion

In this article, I explained how to test for CD and estimate the exponent of CD using the community-contributed command `xtcse2`. I then reviewed three different methods to estimate long-run coefficients in dynamic panels with many observations over time and cross-sectional units with CD. I used an extended version of `xtdcce2` (Ditzen 2018) that allows for the estimation of long-run coefficients using the CS-DL, CS-ARDL, and CS-ECM estimators. Examples on how to apply `xtdcce2` were given and options were explained.

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9 Programs and supplemental materials

To install a snapshot of the corresponding software files as they existed at the time of publication of this article, type

```
. net sj 21-3
. net install st0536_1      (to install program files, if available)
. net get st0536_1          (to install ancillary files, if available)
```

10 References

Bai, J. 2009. Panel data models with interactive fixed effects. *Econometrica* 77: 1229–1279. https://doi.org/10.3982/ECTA6135.

Bai, J., and S. Ng. 2002. Determining the number of factors in approximate factor models. *Econometrica* 70: 191–221. https://doi.org/10.1111/1468-0262.00273.

Bailey, N., G. Kapetanios, and M. H. Pesaran. 2016. Exponent of cross-sectional dependence: Estimation and inference. *Journal of Applied Econometrics* 31: 929–960. https://doi.org/10.1002/jae.2476.

———. 2019. Exponent of cross-sectional dependence for residuals. *Sankhyā* 81: 46–102. https://doi.org/10.1007/s13571-019-00196-9.

Bersvendsen, T., and J. Ditzen. 2020. xthst: Testing for slope homogeneity in Stata. CEERP Working Paper No. 11. https://ceerp.hw.ac.uk/RePEc/hwc/wpaper/011.pdf.

Blackburne, E. F., III, and M. W. Frank. 2007. Estimation of nonstationary heterogeneous panels. *Stata Journal* 7: 197–208. https://doi.org/10.1177/1536867X0700700204.

Blomquist, J., and J. Westerlund. 2013. Testing slope homogeneity in large panels with serial correlation. *Economics Letters* 121: 374–378. https://doi.org/10.1016/j.econlet.2013.09.012.

Chudik, A., K. Mohaddes, M. H. Pesaran, and M. Raissi. 2013. Debt, inflation and growth: Robust estimation of long-run effects in dynamic panel data models. Federal Reserve Bank of Dallas, Globalization and Monetary Policy Institute Working Paper

No. 162. https://www.dallasfed.org/~/media/documents/institute/wpapers/2013/0162.pdf.

———. 2016. Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors. In *Advances in Econometrics: Vol. 36—Essays in Honor of Aman Ullah*, ed. G. González-Rivera, R. C. Hill, and T.-H. Lee, 85–135. Bingley, UK: Emerald. https://doi.org/10.1108/S0731-905320160000036013.

Chudik, A., and M. H. Pesaran. 2015a. Large panel data models with cross-sectional dependence: A survey. In *The Oxford Handbook Of Panel Data*, ed. B. H. Baltagi, 3–45. Oxford: Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199940042.013.0001.

———. 2015b. Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics* 188: 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007.

———. 2019. Mean group estimation in presence of weakly cross-correlated estimators. *Economics Letters* 175: 101–105. https://doi.org/10.1016/j.econlet.2018.12.036.

Chudik, A., M. H. Pesaran, and E. Tosetti. 2011. Weak and strong cross-section dependence and estimation of large panels. *Econometrics Journal* 14: C45–C90. https://doi.org/10.1111/j.1368-423X.2010.00330.x.

Ditzen, J. 2018. Estimating dynamic common-correlated effects in Stata. *Stata Journal* 18: 585–617. https://doi.org/10.1177/1536867X1801800306.

———. 2019. Estimating long run effects in models with cross-sectional dependence using xtdcce2. CEERP Working Paper No. 7. https://ceerp.hw.ac.uk/RePEc/hwc/wpaper/007.pdf.

Eberhardt, M. 2012. Estimating panel time-series models with heterogeneous slopes. *Stata Journal* 12: 61–71. https://doi.org/10.1177/1536867X1201200105.

Engle, R. F., and C. W. J. Granger. 1987. Co-integration and error correction: Representation, estimation, and testing. *Econometrica* 55: 251–276. https://doi.org/10.2307/1913236.

Everaert, G., and T. De Groote. 2016. Common correlated effects estimation of dynamic panels with cross-sectional dependence. *Econometric Reviews* 35: 428–463. https://doi.org/10.1080/07474938.2014.966635.

Juodis, A., H. Karabiyik, and J. Westerlund. 2021. On the robustness of the pooled CCE estimator. *Journal of Econometrics* 220: 325–348. https://doi.org/10.1016/j.jeconom.2020.06.002.

Karabiyik, H., S. Reese, and J. Westerlund. 2017. On the role of the rank condition in CCE estimation of factor-augmented panel regressions. *Journal of Econometrics* 197: 60–64. https://doi.org/10.1016/j.jeconom.2016.10.006.

Kripfganz, S., and D. C. Schneider. 2018. ardl: Estimating autoregressive distributed lag and equilibrium correction models. Presented September 6–7, 2018, at the Stata Conference 2018, London. https://www.stata.com/meeting/uk18/slides/uk18_Kripfganz.pdf.

Lee, K., M. H. Pesaran, and R. Smith. 1997. Growth and convergence in a multi-country empirical stochastic Solow model. *Journal of Applied Econometrics* 12: 357–392. https://doi.org/10.1002/(SICI)1099-1255(199707)12:4<357::AID-JAE441>3.0.CO;2-T.

Pesaran, M. H. 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74: 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x.

———. 2015. Testing weak cross-sectional dependence in large panels. *Econometric Reviews* 34: 1089–1117. https://doi.org/10.1080/07474938.2014.956623.

Pesaran, M. H., Y. Shin, and R. P. Smith. 1999. Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association* 94: 621–634. https://doi.org/10.2307/2670182.

Pesaran, M. H., and R. Smith. 1995. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* 68: 79–113. https://doi.org/10.1016/0304-4076(94)01644-F.

Pesaran, M. H., and T. Yamagata. 2008. Testing slope homogeneity in large panels. *Journal of Econometrics* 142: 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010.

Westerlund, J., and J.-P. Urbain. 2015. Cross-sectional averages versus principal components. *Journal of Econometrics* 185: 372–377. https://doi.org/10.1016/j.jeconom.2014.09.014.

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