Federal Reserve Bank of Dallas

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Alexander Chudik and Benjamin Hoham

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xtcipsunb: The CIPS Panel Unit Root Test for Unbalanced Panel Data[*]

Alexander Chudik[†] and Benjamin Hoham[‡]

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Abstract

We develop and demonstrate the command xtcipsunb, which implements the cross-sectionally augmented panel unit root test (CIPS) from Pesaran (2007) and Pesaran, Smith, and Yamagata (2013) for unbalanced panels. Several modifications relative to the existing Stata implementations of CIPS test are necessitated by the unbalanced panel data setting, including computing critical values through simulations for a given panel composition. We provide users the ability to specify a minimum number of cross-section units for the computation of cross-section averages, a minimum number of time periods for the computations of individual t-statistics in the CIPS test, as well as two options for the computation of cross-section averages. Monte Carlo experiments demonstrate our modifications are necessary to avoid potentially severe size distortions of the CIPS test in the case of unbalanced panels. An empirical application using annual country-industry macroeconomic data illustrates the use of xtcipsunb command.

JEL Codes: C12

Keywords: xtcipsunb, panel time series, time series, unit-root testing, cross-section dependence, unbalanced panels

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[†]Alexander Chudik, Federal Reserve Bank of Dallas, alexander.chudik@gmail.com.

[‡]Benjamin Hoham, Federal Reserve Bank of Dallas, benjamin.hoham.econ@gmail.com.

1 Introduction

The cross-sectionally augmented panel unit root test (CIPS) of Pesaran (2007) and extended by Pesaran, Smith, and Yamagata (2013) is an indispensable unit root test for panel data applications. However, most economic applications feature unbalanced panel data, and the implementation of the CIPS test in the case of unbalanced panels is not trivial. First, critical values need to be simulated for each unbalanced panel dataset. Second, in contrast to balanced panels, where rescaling any of the individual cross-section units does not affect the CIPS test outcomes, this is no longer necessarily the case for unbalanced panels. When the data availability on cross-section units changes over time and the latent factors are proxied by cross-section averages of available cross-section units at a given point in time, then the entry and/or exit of cross-section units from the panel can influence the CIPS test outcomes and distort the size of CIPS test.

Given the popularity of the CIPS test in empirical work, it is surprising that existing Stata packages do not address these important implementation considerations. To our knowledge, there are three other commands that implement the CIPS test: `xtcips`, `xtcsb`, and `pescadf` (Lewandowski (2006), Burdisso and Sangiácomo (2016)). Commands `xtcips` and `xtcsb` are not compatible with unbalanced panels, requiring the user to provide a balanced subset of the data to avoid an error. Command `pescadf` allows for unbalanced panels, but it does not satisfactorily deal with the two problems outlined above. `pescadf` relies on large-T approximations of critical values in the case of unbalanced datasets. Such approximations can be inaccurate for panels where the time dimension is not very large. Moreover, `pescadf` does not offer users any options on the construction of cross-section averages.

This paper fills this gap by introducing the `xtcipsunb` command that implements different versions of CIPS tests for unbalanced panels. We allow for general panel data composition, including panels with gaps. Our command simulates critical values for the given panel data composition. To mitigate potential size distortions from entry and exit of cross-section units, we also implement an option to compute latent factor proxies by cumulating cross-section averages of first-differenced variables, as opposed to cross-section averages of levels. These two options are identical in the case of balanced panels, but they could result in different CIPS tests outcomes in the case of unbalanced panels. Our Monte Carlo evidence provides strong support for averaging first differences. In addition, we provide several other helpful implementation options for users to choose from. We allow users to set the minimum number of cross-section units for the computation of cross-section averages, and the minimum number of time periods for the computation of individual t-statistics in the CIPS test. We also allow users to select between the truncated and not truncated versions of CIPS tests as originally proposed by Pesaran, Smith, and Yamagata (2013). Our simulations suggest both have good size, but the truncated version achieves a better power.

We compare CIPS tests implemented by `xtcipsunb` and `pescadf` commands by means of Monte Carlo experiments as well as with an empirical illustration taken from Eberhardt, Helmers, and Strauss (2013). Our MC experiments show that our approach avoids size distortions that may arise using the `pescadf` command on unbalanced panel data. Replicating results from Eberhardt, Helmers, and Strauss (2013) illustrates the empirical relevance of these considerations while providing an illustration of the use of our package.

2 The CIPS Test

2.1 The Balanced Case

We begin we a brief description of the CIPS test for balanced panels featuring N individuals, indexed by $i = 1, 2, ..., N$, over T time periods, indexed by $t = 1, 2, ..., T$. The CIPS test, as extended in Pesaran et al. (2013), considers the following cross-sectionally augmented Dickey Fuller regression for each cross-section unit

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + \mathbf{d}_i' \overline{\mathbf{x}}_{t-1} + \sum_{j=1}^{p} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p} \beta_{ij} \Delta \overline{y}_{t-j} + \sum_{j=0}^{p} \gamma_{ij}' \Delta \overline{\mathbf{x}}_{t-j} + \epsilon_{it}, \tag{1}$$

where $\mathbf{x}_{it}$ is a vector of covariates, $\overline{\mathbf{x}}_t = N^{-1} \sum_{i=1}^{N} \mathbf{x}_{it}$, and $\overline{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$. In the case $p = 0$, the first sum is omitted. Additional deterministic terms, such as a linear time trend, may also be added to (1).

For each b_i, denote the corresponding standard t-statistic as $t_i(N, T)$. The CIPS test is then given by the average of the individual t-statistics,

$$CIPS_{NT} = N^{-1} \sum_{i=1}^{N} t_i(N, T).$$

Alternatively, extreme values of the individual t-statistics can be truncated,

$$t_i^*(N,T) = \begin{cases} t_i(N,T), & -K_1 < t_i(N,T) < K_2, \\ -K_1, & t_i(N,T) \leq -K_1, \\ K_2, & t_i(N,T) \geq K_2, \end{cases}$$

resulting in the truncated CIPS test statistic

$$CIPS_{NT}^* = N^{-1} \sum_{i=1}^{N} t_i^*(N, T).$$

The choice of truncation constants K_1 and K_2 is discussed in Pesaran, Smith, and Yamagata (2013). Either of the above formulations of the CIPS test statistic can then be used to test the unit root null hypothesis

$$H_0 : b_i = 0 \text{ for all } i,$$

against the alternative

$$\begin{aligned} H_1 : b_i &< 0 \text{ for } i = 1, 2, \ldots, N_1, \\ b_i &= 0 \text{ for } i = N_1 + 1, N_1 + 2, \ldots, N. \end{aligned}$$

The CIPS test statistics follow a nonstandard distribution, thus critical values must be obtained through simulation. The critical values for select combinations of N, T, the number of covariates, and the choice of deterministic terms are reported in Pesaran (2007) and Pesaran, Smith, and Yamagata (2013).

2.2 Considerations for Unbalanced Panels

Unbalanced panels present extra challenges in computing the CIPS statistic. Particular cross-section units or time periods may have sample sizes smaller than desired. We adjust for this by letting the user to specify if some observations should be omitted from estimations. To be precise, let s_{it} be the binary 0/1 indicator variable indicating if observations are available for the cross-section unit i and the time period t. Such indicator captures the panel composition. In addition, define $N_t = \sum_{i=1}^{N} s_{it}$ as the number of cross-section units with observations for a time period t, and $T_i = \sum_{t=1}^{T} s_{it}$ as the number of time periods available for unit i. Our code allows the user to specify the required minimum number of cross-section units for a each time period, denoted as $\underline{N}$, and the required minimum number of time periods for the estimation of the regression (1), denoted as $\underline{T}$.[1] We take the following steps:

1) Calculate N_t and T_i for the current sample.

2) Omit any cross section units such that $T_i < \underline{T}$

3) Omit any time periods such that $N_t < \underline{N}$

4) Repeat steps 1) — 3) until convergence, unless no subsample satisfying the requirements can be found.

We denote the vectors corresponding to N_t and T_i in the final subsample as $\tilde{N}_t$ and $\tilde{T}_i$, and the corresponding binary indicator variable for selected observations as $\tilde{s}_{it}$.

The entry and exit of units in an unbalanced panel also complicates the use of cross-section averages as proxies for latent factors. The most straightforward approach to constructing cross-section averages is to average observations available at the given point in time,

$$\overline{y}_t = \tilde{N}_t^{-1} \sum_{i=1}^{N} \tilde{s}_{it} y_{it}, \tag{2}$$

and similarly for $\overline{\mathbf{x}}_t$. However, this approach may distort the size of the CIPS test. For example, entry or exit of individuals can distort the cross-section average without any change in the underlying latent factor that it proxies. This could plausibly occur in firm or country level data with large variability in size. To mitigate the effects of entry and exit, one can use the cumulative sum of averaged first differences,

$$\overline{y}_t = \begin{cases} \sum_{\ell=2}^{t} \left(\tilde{N}_\ell^{\,-1} \sum_{i=1}^{N} \tilde{s}_{i\ell} \tilde{s}_{i,\ell-1} \Delta y_{i\ell} \right) & \text{, for } t > 1, \\ 0 & \text{, for } t = 1, \end{cases} \tag{3}$$

1. N is defined by the option minNt in the program, while T is defined by the option minTi in the program.

where $\Delta y_{it} = y_{it} - y_{i,t-1}$ is the first-difference of y_{it}, and the product $\tilde{s}_{it}\tilde{s}_{i,t-1}$ indicates the availability of Δy_{it}.[2] (3) mitigates the pitfalls that (2) can cause and is our default choice.

While standardized tables can be made from simulations of the balanced panel case, as in Pesaran, Smith, and Yamagata (2013), the critical values of the CIPS statistic depend on $\tilde{s}_{it}$. We simulate these critical values by default in our program, using the same procedure to generate simulated data as in Pesaran, Smith, and Yamagata (2013).

3 The `xtcipsunb` Command

The `xtcipsunb` command uses mata functions from the `moremata` package by Jann (2005). Installation of the `moremata` package is required.

3.1 Syntax

`xtcipsunb` *depvar* [*indepvars*] [*if*] [*in*]

[, `lagorder(#)` `minnt(#)` `minti(#)` `trend` `nosimulation` `levels_average` `n_draws(#)` `nogaps` `nocsaverages` `notruncation`]

The `xtcipsunb` command supports balanced and unbalanced panel data, and requires the dataset to be `xtset`. Variable inputs are also compatible with time series operators.

3.2 Options

`lagorder(#)` Number of lags, p, in (1). The default is `lagorder(0)`, which sets $p = 0$ and uses no lagged differences in the regression.

`minnt(#)` Sets the required minimum number of cross-section units for the calculation of cross-sectional averages. The default is 5. Setting this value to zero will return an error.

`minti(#)` Sets the required minimum number of time periods for estimating regression (1). The default is the number of unknown coefficients of (1) plus one, resulting in at least on degree of freedom for the least square estimation of (1).

`trend` Includes a linear trend term in the regression. There is no linear trend by default.

`nosimulation` Allows the user to skip simulation of critical values by using the critical values reported in Pesaran et al. (2013) of an approximate balanced panel. This option can be used to skip on the computationally demanding simulation of critical

2. Arbitrarily setting $\overline{y}_1 = 0$ in (3) is inconsequential due to the included constant term in regression (1).

values. By default simulation will be used.

`levels_average` By default the program creates cross-section averages defined by (3), to avoid level effects from panel units distorting the CIPS test. This option gives the user the choice of using the direct cross-section averages of levels defined by (2) instead.

`n_draws(#)` The number of draws used in simulating critical values. Larger numbers are recommended (at least 2,000). The default is 2,000.

`nogaps` This option drops cross-section units that contain gaps, either from the raw data or from trimming the data according the minimum panel and time observation settings above. If there is a gap across all units, an error is returned. The default option is to retain units with gaps in the data.

`nocsaverages` This option allows the user to remove cross-section averages from the regressions and simulations. The omission of cross-section averages results in IPS test.

`notruncation` By default the command replaces extreme t-statistics values with constants $-K_1$ or K_2, as proposed in Pesaran et al. (2013). `notruncation` gives users the option to use original t-statistics values.

3.3 Stored Results

`xtcipsunb` stores the following results to `e()`.

Scalars			
`e(cips)`	CIPS test statistic	`e(obs)`	total available observations
`e(used_obs)`	total used observations	`e(total_N)`	number of units
`e(Tbar)`	average obs. per unit	`e(Ttilde_bar)`	average obs. used per unit
`e(Tmin)`	minimum obs. per unit	`e(Tmax)`	maximum obs. per unit
`e(Ttildemin)`	minimum obs. used per unit	`e(Ttildemax)`	maximum obs. used per unit
`e(cv1)`	1% critical value	`e(cv5)`	5% critical value
`e(cv10)`	10% critical value	`e(pvalue)`	p-value of the test. Not reported without simulations
`e(k1)`	lower truncation constant K_1, reported if applicable	`e(k2)`	upper truncation constant K_2, reported if applicable
Macros			
`e(timevar)`	time period identifier	`e(panelvar)`	cross section identifier
`e(cmd)`	name of estimation command	`e(depvar)`	name of dependent variable
Matrices			
`e(b)`	average regression coefficients	`e(t)`	t-statistics for each unit
`e(Nt)`	counts units observed per time period	`e(NtTilde)`	counts units used per time period
`e(Ti)`	counts time periods per unit	`e(TiTilde)`	counts time periods used per group
`e(unused_N)`	indicates if a unit is trimmed	`e(unused_T)`	indicates if a time period is trimmed
`e(simulated_t)`	test statistics for each simulated draw. Not reported without simulation		

4 Monte Carlo

We provide evidence on the small sample performance of the CIPS tests implemented in the `xtcipsunb` and `pescadf` commands. Subsection 4.1 outlines the data generating process. Subsection 4.2 outlines the six versions of CIPS tests employed in this study. Subsection 4.3 presents the simulation findings. We find both truncated and not truncated versions of CIPS tests from the `xtcipsunb` command achieve good empirical size, but the former achieves a better power. In our experiments, proxying latent factors with cross-section averages of variables in levels leads to significant size distortions of the CIPS tests. Such distortions are fully overcome by cumulating cross-sectional averages of first differences, in place of directly averaging of variables in levels. This confirms that our default choice of using the truncated version of the CIPS test with cross-section averages given by (3) is a good choice for practitioners. In addition, the CIPS tests implemented in the `pescadf` package show large size distortions in our experiments.

4.1 Data Generating Process (DGP)

As before, let s_{it} be the observation availability indicator variable taking the value of 1 when y_{it} is observed for unit i at time t, and zero otherwise. We generate s_{it} to allow for uneven start dates, uneven end dates, as well as gaps in the panel data. s_{it} is generated at the beginning of simulations, for each choice of panel dimensions (N, T), and kept fixed across Monte Carlo replications.

Generating s_{it}

The start dates of the first $\pi_1 = 50\%$ of cross-section units are drawn randomly from the uniform distribution in the first quarter of the observation window. End dates of these units are the last period, T. The start dates of the next $\pi_2 = 25\%$ of cross-section units are at $t = 1$ and their end dates are drawn randomly from the uniform distribution in the third quarter of the observation window. The remaining $1 - \pi_1 - \pi_2 = 25\%$ of the cross-section units start at $t = 1$ and end at $t = T$. In addition to uneven start and end dates, there is a small probability of gaps in the data, drawn from a Bernoulli distribution with a success probability of 0.02. In summary, we generate

$$s_{it} = \begin{cases} 1 \times g_{it}, & \text{for } s_i^{start} \leq t \leq s_i^{end} \\ 0, & \text{otherwise} \end{cases},$$

where $g_{it} \sim Bernoulli(0.98)$, $s_i^{start} \sim IIDU\{1, 2, ..., T/4\}$ for $i = 1, 2, ..., \pi_1 N$, and $s_i^{start} = 1$ otherwise, $s_i^{end} \sim IIDU\{0.5T_{\max}, 0.5T + 1, ..., 0.75T\}$ for $i = \pi_1 N + 1, \pi_1 N + 2, ..., (\pi_1 + \pi_2) N$ and $s_i^{end} = T$ otherwise.

We consider $T = \{10, 20, 30\}$ and $N = \{50, 100, 500\}$. Table 1 provides a basic summary of data availability.

Table 1: Summary information on the unbalanced panel data in Monte Carlo experiments

N	T	T_{ave}	Total number of observations
50	10	7.88	394
50	20	15.98	799
50	30	23.98	1,199
100	10	8.08	808
100	20	16.03	1,603
100	30	25.17	2,517
500	10	8.12	4,058
500	20	16.02	8,008
500	30	23.94	11,968

NOTE: T is the number of periods in the observation window and the largest time dimension. $T_{ave} = N^{-1}\sum_{i=1}^{N} T_i$ is the average time dimension, where $T_i = \sum_{t=1}^{T} s_{it}$ is the number of observations for cross section unit i. The last column is the total number of observations in the panel on y_{it}.

Generating y_{it}

The observed data is given by $y_{it} = y_{it}^*$ when $s_{it} = 1$. y_{it} is not observed when $s_{it} = 0$. The latent process y_{it}^* is generated according to:

$$y_{it}^* = (1 - \phi_i)\,\omega_i + \phi_i y_{i,t-1}^* + u_{it}, \tag{4}$$

for $t = 1, 2, ..., T$ and $i = 1, 2, ..., N$. We have two experiments, based on $\phi_i = 0.5$ or 1. Initial values are generated as $y_{i0} \sim N(\omega_i, 1)$. We allow for a dependence of the initial values on s_{it} by setting $\omega_i = T_i^3$, where $T_i = \sum_{t=1}^{T} s_{it}$. Errors are generated according to

$$u_{it} = \gamma_i f_t + \varepsilon_{it}. \tag{5}$$

where ε_{it} are AR(1) idiosyncratic errors,

$$\varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + e_{it}, \tag{6}$$

for $t = 1, 2, ..., T$ and $i = 1, 2, ..., N$, where $\rho_i \sim IIDU\,[0.2, 0.4]$, $e_{it} \sim IIDN\left(0, \sigma_i^2\right)$, $\sigma_i^2 \sim IIDU\,[0.5, 1.5]$, and initial values are $\varepsilon_{i,0} = 0$. The unobserved common factor is generated as $f_t \sim IIDN\,(0, 1)$, and factor loadings are generated as $\gamma_i \sim IIDU\,[-1, 3]$.

4.2 CIPS Tests

We investigate four CIPS tests using `xtcipsunb` package: truncated and not truncated versions (option `notruncation`) and cross-averages based on levels, given by (3), or first differences, given by (2) (option `levels_average`). Critical values are computed by simulations using 10,000 replications.

In addition, we consider truncated and not truncated versions of CIPS test statistics implemented by the `pescadf` package. These tests feature cross-section averages computed by averaging levels and critical values are not simulated to match the availability of observations in the sample of unbalanced panel data. Lag order is set to $p = 1$ in all experiments.

4.3 Monte Carlo Findings

Table 2 shows that CIPS tests have good size when cross-section averages are given by (3), with rejection rates slightly below the nominal 5% level, ranging from 2.2% to 4.1% for the truncated version and from 2.8% to 4.9% for the untruncated version. However, when using cross-section averages given by (2) size distortions can be severe, with empirical size up to 49.7% for the highest (N, T) combination.

Using `pescadf` on the same simulated data results in even larger size distortions than using `xtcipsunb` with cross-section averages given by (2). This is especially true when looking at the untruncated results, where the lowest rejection rate reported in Table 2 is 27.3%. While much of the size distortion is driven by distortions from entry and exit of individual cross-section units, inaccurate critical values amplify them even further.

Table 2: Empirical size of CIPS unit root tests using `xtcipsunb` and `pescadf` packages in Monte Carlo experiments with $\phi_0 = 1$

	Truncated CIPS tests			Not truncated CIPS tests		
N/T	**10**	**20**	**30**	**10**	**20**	**30**
`xtcipsunb` package:						
	Cross-section averages given by (3)					
50	0.041	0.036	0.036	0.046	0.049	0.034
100	0.027	0.029	0.037	0.044	0.034	0.036
500	0.033	0.022	0.030	0.045	0.031	0.028
	Cross-section averages given by (2)					
50	0.169	0.265	0.267	0.076	0.158	0.265
100	0.077	0.217	0.340	0.050	0.159	0.332
500	0.122	0.323	0.497	0.056	0.260	0.493
`pescadf` package:						
50	0.129	0.274	0.273	0.384	0.344	0.273
100	0.033	0.392	0.408	0.322	0.478	0.409
500	0.02	0.465	0.615	0.460	0.548	0.615

NOTE: `xtcipsunb` and `pescadf` were used on data generated by (4) with $\phi_i = 1$, (5), and (6). N refers to the number of cross-section units simulated, while T is the number of periods in the observation window and also the largest time dimension. Options `notruncation` and `levels_average` were used to change the averaging and truncation methods for `xtcipsunb`. Cross-section units filtered out by `xtcipsunb` due to too few observations were not used for corresponding `pescadf` experiments, ensuring the same observations were used in both packages.

We compare empirical power only for the tests that achieved good size. In our view, power comparisons for tests that are highly inaccurate in terms of size are unhelpful. This leaves us with two versions of CIPS tests: the truncated and not truncated CIPS tests with cross-section averages given by (3). Table 3 shows their empirical power in experiments with $\phi_0 = 0.5$. As to be expected, the power increases with both T and N, but it is clearly T that is pivotal. The truncated CIPS test achieves better power compared with the untruncated version. These differences are not small. For example, for $N = 500$ and $T = 20$, the truncated version of the CIPS test achieves a 73.9 percent rejection rate compared with a rejection rate of 49.1 percent for the not truncated version.

Table 3: Empirical power of truncated and not truncated CIPS tests

	Truncated CIPS tests			Not truncated CIPS tests		
N/T	**10**	**20**	**30**	**10**	**20**	**30**
50	0.090	0.404	0.976	0.057	0.153	0.975
100	0.104	0.584	1.000	0.050	0.323	1.000
500	0.139	0.739	1.000	0.049	0.491	1.000

NOTE: `xtcipsunb` was used. $\phi_0 = 0.5$. Cross-section averages are based on cumulating cross-section averages of first-differenced variables. See also notes to Table 2.

Overall, Monte Carlo results show that `xtcipsunb` under its default settings has appropriate size and reasonable power, in contrast with the `pescadf`, which can suffer from severe size distortions in the case of unbalanced panels.

5 Empirical Application

We demonstrate the empirical relevance of our code by considering an application from Eberhardt et al. (2013). They construct an unbalanced panel of output, labor, capital, and R&D stock for 119 country-industry pairs, and implement the CIPS test from Pesaran (2007) using `pescadf` as a check prior to the principal regressions of the paper. Our command works easily in this same setting, which we first demonstrate on log capital.

```
.
. use "xtcipsunb_data.dta"
(Eberhardt, Helmers & Strauss: Do Spillovers Matter...?)
.
. xtset id year
Panel variable: id (unbalanced)
 Time variable: year, 1980 to 2005
         Delta: 1 year
.
. xtcipsunb lnk
Panel is unbalanced.
```

```
CIPS test for lnk. 0 additional lags used.
--------------------------------------------------------------------------------
H0: b_i = 0 for all i
H1: b_i < 0, i = 1, ... N_1, b_i = 0, i = N_1+1, ..., N
--------------------------------------------------------------------------------
Number of cross-section units: 119   Avg. number of periods: 22.2
Minimum periods: 11                  Maximum periods: 26
Total sample size: 2637              Used sample size: 2518
--------------------------------------------------------------------------------
CIPS test statistic: -1.598 p value: .7875
1% Critical value: -2.130 5% Critical value: -2.019 10% Critical value: -1.959
.
```

We can accommodate lags and trends in estimation as well:

```
.
. xtcipsunb lnk, trend lag(1)

Panel is unbalanced.
CIPS test for lnk. 1 additional lags used.
--------------------------------------------------------------------------------
H0: b_i = 0 for all i
H1: b_i < 0, i = 1, ... N_1, b_i = 0, i = N_1+1, ..., N
--------------------------------------------------------------------------------
Number of cross-section units: 119   Avg. number of periods: 22.2
Minimum periods: 11                  Maximum periods: 26
Total sample size: 2637              Used sample size: 2399
--------------------------------------------------------------------------------
CIPS test statistic: -2.220 p value: .4665
1% Critical value: -2.627 5% Critical value: -2.516 10% Critical value: -2.454
.
. xtcipsunb lnk, trend lag(1) level

Panel is unbalanced.
CIPS test for lnk. 1 additional lags used.
--------------------------------------------------------------------------------
H0: b_i = 0 for all i
H1: b_i < 0, i = 1, ... N_1, b_i = 0, i = N_1+1, ..., N
--------------------------------------------------------------------------------
Number of cross-section units: 119   Avg. number of periods: 22.2
Minimum periods: 11                  Maximum periods: 26
Total sample size: 2637              Used sample size: 2399
--------------------------------------------------------------------------------
CIPS test statistic: -2.537 p value: .0375
1% Critical value: -2.621 5% Critical value: -2.512 10% Critical value: -2.436
.
```

In the prior example, we computed the CIPS statistic using our preferred method of averaging and with averaging levels. The two methods yield different conclusions, demonstrating the practical relevance of using an appropriate approach to averaging.

One can also add other covariates to the test to account for multiple latent factors in the error term. The following example demonstrates this, while also adjusting the number of draws in the simulation to save time:

```
.
```

```
. xtcipsunb lny lnk lnl lnrd, notrunc n_draws(2000)

Panel is unbalanced.
CIPS test for lny. Additional Covariates: lnk lnl lnrd. 0 additional lags used.
-------------------------------------------------------------------------------
H0: b_i = 0 for all i
H1: b_i < 0, i = 1, ... N_1, b_i = 0, i = N_1+1, ..., N
-------------------------------------------------------------------------------
Number of cross-section units: 119   Avg. number of periods: 22.2
Minimum periods: 11                  Maximum periods: 26
Total sample size: 2637              Used sample size: 2408
-------------------------------------------------------------------------------
CIPS test statistic: -2.932 p value: .012
1% Critical value: -2.961 5% Critical value: -2.656 10% Critical value: -2.547
.
. di "`e(used_obs)´"
2408
.
. xtcipsunb lny lnk lnl lnrd, notrunc n_draws(2000) mint(13)

Panel is unbalanced.
CIPS test for lny. Additional Covariates: lnk lnl lnrd. 0 additional lags used.
-------------------------------------------------------------------------------
H0: b_i = 0 for all i
H1: b_i < 0, i = 1, ... N_1, b_i = 0, i = N_1+1, ..., N
-------------------------------------------------------------------------------
Number of cross-section units: 119   Avg. number of periods: 22.2
Minimum periods: 11                  Maximum periods: 26
Total sample size: 2637              Used sample size: 2264
-------------------------------------------------------------------------------
CIPS test statistic: -2.845 p value: .002
1% Critical value: -2.771 5% Critical value: -2.597 10% Critical value: -2.513
.
. di "`e(used_obs)´"
2264
.
```

The above code also demonstrates the package's ability to trim cross-section units with a smaller sample size than desired and prints the amount of used observations in each. To see which specific units are cut, one can use *matlist e(unused_N)* .

To demonstrate the scope of the differences between our approach and existing implementations, Table 4 compares our outputs (using default options) with those reported in Eberhardt, Helmers, and Strauss (2013) for the variable $\ln(k)$. The conclusions change under alternative specifications, and, in general, the p-values can differ substantially. This suggests that the distortions our program addresses as detailed in the previous section can be relevant in typical applications.

6 Conclusion

This article introduces the `xtcipsunb` command to compute the CIPS test statistic from Pesaran, Smith, and Yamagata (2013) for unbalanced panel data. The command calculates the correct critical values through simulation, since these values may differ

Table 4: p-values of $\ln(k)$ from `pescadf` and `xtcipsunb`

Lags	No trend		Trend		First differences	
	`pescadf`	`xtcipsunb`	`pescadf`	`xtcipsunb`	`pescadf`	`xtcipsunb`
0	1.00	0.78	1.00	1.00	0.00	0.00
1	1.00	0.04	0.00	0.47	0.00	0.00
2	1.00	0.04	1.00	0.67	0.95	0.02
3	1.00	0.03	1.00	0.94	1.00	0.38

NOTE: p-values from different implementations of the CIPS unit root test on a panel of data collected by Eberhardt, Helmers, and Strauss (2013). Results from specifications with 0—3 lags, with and without a trend, and in both levels and first differences are shown.

according to the composition of the panel. The command also lets the user trim data to exclude cross-section units or time periods with too few observations, and it offers optionality to filter out cross-section units with gaps. We also allow for the cross-section averages to be calculated directly by averaging individual variables in levels, or by cumulating cross-section averages of variables in first differences. In unbalanced panels, the former option can lead to size distortions of the CIPS test, which we demonstrate in Monte Carlo experiments.

7 References

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About the authors

Alexander Chudik is an Assistant Vice President at the Federal Reserve Bank of Dallas.

Benjamin Hoham is a Research Analyst at the Federal Reserve Bank of Dallas.