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Panel cointegration analysis with xtpedroni

Timothy Neal University of New South Wales Sydney, Australia timothy.neal@unsw.edu.au

Abstract. In this article, I introduce the new command **xtpedroni**, which implements the Pedroni (1999, Oxford Bulletin of Economics and Statistics 61: 653–670; 2004, Econometric Theory 20: 597–625) panel cointegration test and the Pedroni (2001, Review of Economics and Statistics 83: 727–731) group-mean panel-dynamic ordinary least-squares estimator. For nonstationary heterogeneous panels that are long (large T) and wide (large N), **xtpedroni** tests for cointegration among one or more regressors by using seven test statistics under the null of no cointegration, and it also estimates the cointegrating equation for each individual as well as the group mean of the panel. The test can include common time dummies and unbalanced panels.

Keywords: st0356, xtpedroni, panel cointegration, panel-dynamic ordinary least squares, PDOLS, cointegration test, panel time series, nonstationary panels

1 Introduction

In recent years, it has become increasingly popular to use panel time-series datasets for econometric analysis. These panel datasets are reasonably large in both cross-sectional (N) and time (T) dimensions, as compared with the more conventional panels with very large N yet small T. Theoretical research into the asymptotics of panel time series has revealed two crucial differences from the typical panel: the need for slope coefficients to be heterogeneous (for example, see Phillips and Moon [2000] and Im, Pesaran, and Shin [2003]) and the concern of nonstationarity. Both differences suggest that the usual fixed-effects or random-effects estimators are not appropriate for this application.

The long time dimension in panel time series allows one to use regular time-series analytical tools, such as unit root and cointegration testing, to determine the order of integration and the long-run relationship between variables. Researchers have proposed a variety of tests and estimators that (in varying ways) extend time-series tools for panels while importantly allowing for heterogeneity in the cross-sectional units (as opposed to simply pooling the data). Users have already implemented several of these tests and estimators into Stata (for example, see Blackburne and Frank [2007] and Eberhardt [2012]).

This article and the associated program, xtpedroni, introduce two tools that were developed in Pedroni (1999, 2001, 2004) for use in Stata. The first tool is seven test statistics for the null of no cointegration in nonstationary heterogeneous panels with one or more regressors. The second tool is a between-dimension (that is, group-mean) panel-dynamic ordinary least-squares (PDOLS) estimator. Both tools can include time

dummies (by time demeaning the data) to capture common time effects among members of the panel. Nevertheless, they cannot account for more sophisticated forms of crosssectional dependence.

In this article, I will discuss the theoretical foundations of both tools. I will also introduce the usage and capabilities of **xtpedroni**, and apply the program to replicate the results in Pedroni (2001).

2 Pedroni's cointegration test

Pedroni (1999, 2004) introduced seven test statistics that test the null hypothesis of no cointegration in nonstationary panels. The seven test statistics allow heterogeneity in the panel, both in the short-run dynamics as well as in the long-run slope and intercept coefficients. Unlike regular time-series analysis, this tool does not consider normalization or the exact number of cointegrating relationships. Instead, the hypothesis test is simply the degree of evidence, or lack thereof, for cointegration in the panel among two or more variables.

The seven test statistics are grouped into two categories: group-mean statistics that average the results of individual country test statistics and panel statistics that pool the statistics along the within-dimension. Nonparametric (ρ and t) and parametric (augmented Dickey-Fuller [ADF] and v) test statistics are within both groups.

The test can include common time dummies to address simple cross-sectional dependency, which is applied by time demeaning the data for each individual and variable as follows:

$$\overline{y}_t = \frac{1}{N} \sum_{i=1}^N y_{i,t}$$

All the test statistics are residual-based tests, with residuals collected from the following regressions:

$$y_{i,t} = \alpha_i + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \dots + \beta_{Mi} x_{Mi,t} + e_{i,t}$$
$$\Delta y_{i,t} = \sum_{m=1}^M \beta_{mi} \Delta x_{mi,t} + \eta_{i,t}$$
$$\widehat{e}_{i,t} = \widehat{\gamma}_i \widehat{e}_{i,t-1} + \widehat{\mu}_{i,t}$$
$$\widehat{e}_{i,t} = \widehat{\gamma}_i \widehat{e}_{i,t-1} + \sum_{k=1}^K \widehat{\gamma}_{i,k} \Delta \widehat{e}_{i,t-k} + \widehat{\mu}_{i,t}^*$$

where i = 1, 2, ..., N is the number of individuals in the panel, t = 1, 2, ..., T is the number of time periods, m = 1, 2, ..., M is the number of regressors, and k = 1, 2, ..., K is the number of lags in the ADF regression (selected automatically by **xtpedroni** with

several available options). A linear time trend $\delta_i t$ can be inserted into the regression at the user's discretion.

Next, several series and parameters are calculated from the regressions above.

$$\begin{split} \widehat{s}_{i}^{*2} &= \frac{1}{T} \sum_{t=1}^{T} \widehat{\mu}_{i,t}^{*2}, \qquad \widetilde{s}_{N,T}^{*2} = \frac{1}{N} \sum_{n=1}^{N} \widehat{s}_{i}^{*2} \\ \widehat{L}_{11i}^{-2} &= \frac{1}{T} \sum_{t=1}^{T} \widehat{\eta}_{i,t}^{2} + \frac{2}{T} \sum_{s=1}^{k_{i}} (1 - \frac{s}{k_{i} + 1}) \sum_{t=s+1}^{T} \widehat{\eta}_{i,t} \widehat{\eta}_{i,t-s} \\ \widehat{\lambda}_{i} &= \frac{1}{T} \sum_{s=1}^{k_{i}} (1 - \frac{s}{k_{i} + 1}) \sum_{t=s+1}^{T} \widehat{\mu}_{i,t} \widehat{\mu}_{i,t-s} \\ \widehat{s}_{i}^{2} &= \frac{1}{T} \sum_{t=1}^{T} \widehat{\mu}_{i,t}^{2}, \quad \widehat{\sigma}_{i}^{2} = \widehat{s}_{i}^{2} + 2\widehat{\lambda}_{i}, \quad \widetilde{\sigma}_{N,T}^{2} = \frac{1}{N} \sum_{n=1}^{N} \widehat{L}_{11i}^{-2} \widehat{\sigma}_{i}^{2} \end{split}$$

The seven statistics can then be constructed from the following equations. (See Pedroni [1999] for a complete discussion on how these statistics are constructed.)

panel
$$v: T^2 N^{\frac{3}{2}} (\sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2)^{-1}$$

panel $\rho: T\sqrt{N} (\sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2)^{-1} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i)$
panel $t: (\tilde{\sigma}_{N,T}^2 \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2)^{-\frac{1}{2}} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i)$
panel ADF: $(\tilde{s}_{N,T}^{*2} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*2})^{-\frac{1}{2}} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^* \Delta \hat{e}_{i,t}^*$
group $\rho: T \frac{1}{\sqrt{N}} \sum_{i=1}^N (\sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2)^{-1} \sum_{t=1}^T (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i)$
group $t: \frac{1}{\sqrt{N}} \sum_{i=1}^N (\hat{\sigma}_i^2 \sum_{t=1}^T \hat{e}_{i,t-1}^2)^{-\frac{1}{2}} \sum_{t=1}^T (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i)$
group ADF: $\frac{1}{\sqrt{N}} \sum_{i=1}^N (\sum_{t=1}^T \hat{s}_i^{*2} \hat{e}_{i,t-1}^{*2})^{-\frac{1}{2}} \sum_{t=1}^T \hat{e}_{i,t-1} \Delta \hat{e}_{i,t}$

The test statistics are then adjusted so that they are distributed as N(0,1) under the null. The adjustments performed on the statistics vary depending on the number of regressors, whether time trends were included, and the type of test statistic.

Because the null of no cointegration is rejected, the panel v statistic goes to positive infinity while the other test statistics go to negative infinity. Baltagi (2013, 296) provides a formal interpretation of a rejection of the null: "Rejection of the null hypothesis means that enough of the individual cross-sections have statistics 'far away' from the means predicted by theory were they to be generated under the null."

The relative power of each test statistic is not entirely clear, and there may be contradictory results between the statistics. Pedroni (2004) reported that the group and panel ADF statistics have the best power properties when T < 100, with the panel v and group ρ statistics performing comparatively worse. Furthermore, the ADF statistics perform better if the errors follow an autoregressive process (see Harris and Sollis [2003]).

3 Pedroni's PDOLS

Consider the following model:

$$y_{i,t} = \alpha_i + \beta_i x_{i,t} + \mu_{it}$$

The PDOLS estimator is an extension of the individual time-series dynamic ordinary least squares (DOLS), which is a simple yet efficient single-equation estimate of the cointegrating vector. It can be applied to data that are nonstationary and exhibit a cointegrating relationship between the variables. We can extend this to panel time-series data and conduct a DOLS regression on each individual in the above panel as follows:

$$y_{i,t} = \alpha_i + \beta_i x_{i,t} + \sum_{j=-P}^{P} \gamma_{i,j} \Delta x_{i,t-j} + \mu_{it}^*$$

where i = 1, 2, ..., N is the number of units in the panel, t = 1, 2, ..., T is the number of time periods, p = 1, 2, ..., P is the number of lags and leads in the DOLS regression, β_i is the slope coefficient, and $x_{i,t}$ is the explanatory variable. The β coefficients and associated t statistics are then averaged over the entire panel by using Pedroni's groupmean method.

$$\hat{\beta}_{\rm GM}^{*} = \left[\frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} z_{i,t} z_{i,t}' \right)^{-1} \left\{ \sum_{t=1}^{T} z_{i,t} (y_{i,t} - \overline{y}_{i}) \right\} \right]$$
$$t_{\hat{\beta}_{i}^{*}} = (\hat{\beta}_{i}^{*} - \beta_{0}) \left\{ \widehat{\sigma}_{i}^{-2} \sum_{t=1}^{T} (x_{i,t} - \overline{x}_{i})^{2} \right\}^{\frac{1}{2}}$$
$$t_{\hat{\beta}_{\rm GM}^{*}} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} t_{\hat{\beta}_{i}^{*}}$$

Here $z_{i,t}$ is the $2(p+1) \times 1$ vector of regressors (this includes the lags and leads of the differenced explanatory variable), and σ_i^2 is the long-run variance of the residuals μ_{it}^* . σ_i^2 is computed in the program through the Newey and West (1987) heteroskedasticityand autocorrelation-consistent method with a Bartlett kernel. By default, the maximum lag for the Bartlett kernel is selected automatically for each cross-section in the panel according to $4 \times (T/100)^{(2/9)}$ (see Newey and West [1994]), but it can also be set manually by the user.

In comparison, Kao and Chiang (1997) and Mark and Sul (2003) compute the panel statistics along the within-dimension, with the t statistics designed to test $H_0: \beta_i = \beta_0$ against $H_A: \beta_i = \beta_A \neq \beta_0$. Pedroni's PDOLS estimator is averaged along the

between-dimension (that is, the group mean). Accordingly, the panel test statistics test $H_0: \beta_i = \beta_0$ against $H_A: \beta_i \neq \beta_0$. In the alternative hypothesis, the regressors are not constrained to be a constant β_A . Pedroni (2001) argues that this is an important advantage for between-dimension panel time-series estimators, particularly when one expects slope heterogeneity.

4 The xtpedroni command

4.1 Syntax

xtpedroni depvar indepvars [if] [in] [, notdum nopdols notest extraobs b(#) mlags(#) trend lagselect(string) adflags(#) lags(#) full average(string)]

4.2 Options

Options that affect the cointegration test and the PDOLS estimation

- notdum suppresses time demeaning of the variables (that is, the common time dummies). Time demeaning is turned on by default. This option may be appropriate to use when averaging over the N dimension may destroy the cointegrating relationship or when there are comparability concerns between panel units in the data.
- **nopdols** suppresses PDOLS estimation (that is, reports only the cointegration test results).
- notest suppresses the cointegration tests (that is, reports only PDOLS estimation).
- extraobs includes the available observations from the missing years in the time means used for time demeaning if there is an unbalanced panel with observations missing for some of the variables (at the start or end of the sample) for certain individuals. This was the behavior of Pedroni's original PDOLS program but not of the cointegration test program. It is off by default.
- b(#) defines the null hypothesis beta as #. The default is b(0).
- mlags(#) specifies the number of lags to be used in the Bartlett kernel for the Newey-West long-run variance. If mlags() is not specified, then the number of lags is determined automatically for each individual following Newey and West (1994).

Options that affect only the cointegration test

trend adds a linear time trend.

lagselect(string) specifies the criterion used to select lag length in the ADF regressions. string can be aic (default), bic, or hqic. adflags(#) specifies the maximum number of lags to be considered in the lag selection
process for the ADF regressions. If adflags() is not specified, then it is determined
automatically.

Options that affect only the PDOLS estimation

- lags(#) specifies the number of lags and leads to be included in the DOLS regression.
 The default is lags(2).
- full reports the DOLS regression for each individual in the panel.
- average(string) determines the methodology used to combine individual coefficient estimates into the panel estimate. string can be simple (default), sqrt, or precision. simple takes a simple average and is the behavior of the original Pedroni program. sqrt weighs each estimate according to the square root of the precision matrix, which is the same procedure used for averaging the t statistics. precision weighs each individual's coefficient estimates by its precision.

5 Replicating Pedroni results

Pedroni (2001) applied the group-mean PDOLS estimator empirically to test the purchasing power parity (PPP) hypothesis. Specifically, it tested the weak long-run PPP, which argues that while nominal exchange rates and aggregate price ratios move together, they may not be directly proportional in the long term. Accordingly, the cointegrating slope may be close to yet different from 1. Pedroni used monthly data on nominal exchange rates and Consumer Price Index deflators from the International Monetary Fund's International Financial Statistics database for this test.

We will now replicate the group-mean PDOLS results with the same dataset and **xtpedroni**.

```
use pedronidata
xtset country time
panel variable: country (strongly balanced)
time variable: time, 1973m6 to 1993m11
delta: 1 month
xtpedroni logexrate logratio, notest lags(5) mlags(5) b(1) notdum
Pedroni's PDOLS (Group mean average):
No. of Panel units: 20
Lags and leads: 5
Number of obs: 4700
Avg obs. per unit: 235
Data has not been time-demeaned.
```

Variables	Beta	t-stat
logratio	1.202	9.537

. xtpedroni logexrate logratio, notest lags(5) mlags(5) b(1) Pedroni's PDOLS (Group mean average): No. of Panel units: 20 Lags and leads: 5 Number of obs: 4700 Avg obs. per unit: 235 Data has been time-demeaned.

Variables	Beta	t-stat
logratio_td	1.141	12.76

We computed the results without time dummies (by specifying the notdum option), and then with time dummies. We specified the option notest to suppress the results of the cointegration test, which are not yet relevant. The option b(1) instructed the program to compute all t statistics against the null hypothesis that the slope coefficient is equal to 1, which is appropriate for economic interpretation when testing the weak long-run PPP hypothesis. In accordance with Pedroni's original use of the group-mean PDOLS estimator to calculate these results, we set the number of lags and leads in the DOLS regression to 5 by specifying lags(5), and we set the number of lags used in the Bartlett kernel for the Newey–West long-run variance of the residuals to 5 by specifying mlags(5).

We can now replicate the individual DOLS results for each country in the panel as follows:

Individual DOIS results

Individual DOLS results					
Country	β	t statistic	Country	β	t statistic
UK	0.67	-1.91	Japan	1.75	5.03
Belgium	0.23	-1.96	Greece	0.99	-0.37
Denmark	1.90	2.85	Portugal	1.09	2.46
France	2.21	8.09	Spain	1.02	0.18
Germany	0.91	-0.60	Turkey	1.11	5.84
Italy	1.08	1.12	NZ	1.02	0.61
Holland	0.66	-2.06	Chile	1.37	10.95
Sweden	1.16	0.82	Mexico	1.03	3.60
Switzerland	1.36	2.25	India	2.06	7.80
Canada	1.43	1.88	South Korea	0.88	-1.46

. xtpedroni logexrate logratio, full notest lags(4) mlags(4) b(1) notdum $(output\ omitted\,)$

The output was compressed into a formatted table for brevity. We specified several options to obtain the exact results. The option full displays the results of estimation for each individual panel unit. Emulating Pedroni's original use of the program for this empirical application, we set the number of lags and leads in the DOLS regression to 4 by

specifying lags(4) and the number of lags used in the Bartlett kernel for the Newey-West long-run variance of the residuals to 4 by specifying mlags(4). No common time dummies were used for the individual country results (notdum option).

Pedroni (2004) applied the seven panel cointegration test statistics to the PPP hypothesis. We repeat this procedure as follows:

. xtpedroni logexrate logratio, nopdols Pedroni´s cointegration tests: No. of Panel units: 20 Regressors: 1 No. of obs.: 4920 Avg obs. per unit: 246 Data has been time-demeaned.

v 4.735 rho -2.027 -2.8 t -1.434 -2.13 adf9087 -1.75	35

All test statistics are distributed N(0,1), under a null of no cointegration, and diverge to negative infinity (save for panel v).

The results will be inconsistent with those found in Pedroni (2004), because those results relied on a larger sample period than did the Pedroni (2001) dataset we are currently using. The only option we specified here is nopdols, which suppresses the PDOLS estimation results.

Overall, the results indicate a cointegrating relationship between the log of the exchange rate and the log of the aggregate Consumer Price Index ratio. Statistical inference is straightforward because all the test statistics are distributed N(0,1). All the tests, except the panel t and ADF statistics, are significant at least at the 10% level. Furthermore, the PDOLS results support the weak long-run PPP hypothesis. Most of the coefficients are close to 1, but many are notably higher or lower. For a complete discussion of the results, see Pedroni (2001).

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About the author

Timothy Neal is currently a PhD candidate in the Australian School of Business at the University of New South Wales. His research interests include income inequality, panel econometrics, and welfare economics.