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A residual-based bootstrap test for panel cointegration

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Abstract

We address the issue of panel cointegration testing in dependent panels, showing by simulations that tests based on the stationary bootstrap deliver good size and power performances even with small time and cross-section sample sizes and allowing for a break at a known date. They can thus be an empirically important alternative to asymptotic methods based on the estimation of common factors. Potential extensions include test for cointegration allowing for a break in the cointegrating coefficients at an unknown date.

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1. Introduction

The rate of expansion of the literature on the analysis of non-stationary panels is impressive, see for example Breitung and Pesaran (2006). This growing interest is due to many important economic questions that naturally framed in a panel perspective (for instance, the Purchasing Power Parity issue, Pedroni, 2004, and migrations, Fachin, 2007); further, when only small time samples are available, adding the cross-section dimension grants considerable improvements of the small samples properties of testing procedures, provided the possible linkages across units are properly accounted for. This issue is currently actively investigated in the literature following two main approaches: (i) modelling the linkages as due to unobserved common factors; these can be estimated by principal components methods (Bai and Ng, 2004) and then removed from the data so to apply simple procedures for independent panels (Bai and Carrion-i-Silvestre, 2005, Banerjee and Carrion-i-Silvestre 2006, Gengenbach, Urbain and Palm, 2006, Westerlund 2008); (ii) apply bootstrap algorithms designed to deliver estimates of the distribution of the statistics of interest conditional on the cross-section linkages as present in the dataset at hand. Concentrating on (no-)cointegration tests, two bootstrap approaches have been put forth so far. Fachin (2007) applies the Continuous-Path Block bootstrap (Paparoditis and Politis, 2001, 2003) separately to the right- and the left-hand side variables, while Westerlund and Edgerton (2007) develop a Sieve Bootstrap procedure for testing the null of cointegration. Unfortunately, neither the common factor nor the existing bootstrap approaches are fully satisfactory. A first problem with the common factor approach is that, as Gegenbach, Urbain and Palm (2006) explicitly admit, it requires large samples. In many empirical applications the available information set may simply be not rich enough. A second problem is that it hinges upon a series of assumptions which may be very restrictive. Banerjee and Carrion-i-Silvestre (2006) and Westerlund (2008) allow for common factors in the cointegrating residuals but not in the variables themselves. This more general set-up is allowed by Bai and Carrion-i-Silvestre (2005) and Gegenbach, Urbain and Palm (2006), but at the cost of other restrictions: the former assume homogeneous cointegrating vectors, a rather unrealistic condition, and the latter that the matrix of factor loadings is full rank and block-diagonal, hence ruling out the empirically relevant case of a single source of non-stationarity common across units and variables[1]. Block bootstrap, model-free methods were showed by Fachin (2007) to be empirically useful tools in tackling the problems at hand. However his algorithm destroys *any* relationship between the modelled variables, not only long-run ones. On the other hand, the sieve bootstrap (shown to be valid for inference on cointegrating regressions by Chang, Park and Song, 2006) hinges upon the assumption of a linear structure of the cointegrating residuals[2].

In this paper we shall try to improve on the existing bootstrap methods. Our main conjecture is that Parker, Paparoditis and Politis' (2006) Residual-based Stationary

[1]For instance, in the case of regional consumption and income this may be a stochastic trend in national GDP.

[2]Further, the sieve bootstrap cointegration test proposed by Westerlund and Edgerton (2007) may deliver poor power in small samples. Their procedure involves estimating the sieve through the Yule-Walker equations, so to obtain stationary bootstrap residuals obeying the null of cointegration. However, under no cointegration the bootstrap residuals, though stationary, will have a root arbitrarily close to 1, very difficult to distinguish from a unit root in small samples.

Bootstrap test for unit roots may be applied to the estimated cointegrating residuals. In fact, the potential of block bootstrap methods in this field is stressed by Chang *et al.* (2006). In this paper we will thus first outline the our approach (section 2), evaluate its small sample performances by simulation (section 3 and 4), present an empirical illustration (section 5) and finally draw some conclusions (section 6).

2. Single-equation panel cointegration testing via residual based bootstrap: set-up

Parker, Paparoditis and Politis (2006), henceforth PPP[3], developed a bootstrap unit root test based on the Stationary Bootstrap (Politis and Romano, 1994), a resampling method suitable for weakly dependent series. The extension of PPP Residual-based Stationary Bootstrap (RSB) unit root tests to single-equation cointegration testing is straightforward.

Consider for simplicity two $I(1)$ variables, X and Y, linked by a linear relationship

$$y_t = \mu + \beta x_t + \epsilon_t, t = 1, \ldots, T \tag{1}$$

with $\epsilon_t = \rho\epsilon_{t-1} + \nu_t$. It is immediately seen that when H_0 : no cointegration holds $\rho = 1$,while when it does not $|\rho| < 1$. The hypothesis of no cointegration is then equivalent to H_0: $\rho = 1$. Two important remarks are in order here. First, $\epsilon_t = \rho\epsilon_{t-1} + \nu_t$ is *not* a model of the cointegrating residuals; it only defines a parameter expressing the null hypothesis of interest. Second, the $\nu_t's$ are always stationary, either H_0 holds or not: they can thus be resampled via the Stationary Bootstrap. An algorithm along the lines put forth in PPP, mean zero case, may then proceed as follows:

1. Compute $\widehat{\nu}_t = \widehat{\epsilon}_t - \widehat{\rho}\widehat{\epsilon}_{t-1}$, where $\{\widehat{\epsilon}_t\}$ are the estimated residuals and $\widehat{\rho}$ is the OLS estimate of ρ;
2. Resample the series $\{\widehat{\nu}_t\}$ via the stationary bootstrap, obtaining $\{\nu_t^*\}$;
3. Cumulate $\{\nu_t^*\}$ obtaining pseudoresiduals $\{\epsilon_t^*\}$ obeying the null hypothesis of no cointegration;
4. Compute $y_t^* = \widehat{\mu} + \widehat{\beta}x_t + \epsilon_t^*$;
5. Estimate the cointegrating regression on the dataset $\{y_t^*, x_t\}$: $y_t^* = \widehat{\mu}^* + \widehat{\beta}^* x_t + \widehat{\epsilon}_t^*$;
6. Estimate the AR(1) coefficient ρ^* for the residuals $\widehat{\epsilon}_t^*$;
7. Repeat 2-6 B times;
8. Test the hypothesis $\mathrm{H}_0 : \rho = 1$ on the basis of the distribution of the $\rho^{*\prime}s$, which obey it. Note that the consistency results reported in PPP are in fact general enough to allow the use of more general statistics function of ρ, such as the ADF.

[3]Not to be confused with the acronym for Purchasing Power Parity.

Consider now the panel dimension, ignored so far. An essential feature to be taken into account is dependency across units. In order to reproduce it in the pseudoseries we simply need to apply the resampling algorithm to the entire cross-sections. In this way the (short- and long-run) cross-correlation structure of the data is exactly reproduced in the bootstrap data. More precisely, letting $\widehat{\nu}_{it} = \widehat{\epsilon}_{it} - \widehat{\rho}_i \widehat{\epsilon}_{it-1},$ in step 2 of the RSB algorithm we apply the stationary bootstrap to the entire $T \times N$ matrix of the residuals $\mathbf{V} = [\widehat{\nu}_1 \ldots \widehat{\nu}_N]$, where $\widehat{\nu}_j = [\widehat{\nu}_{1j} \ldots \widehat{\nu}_{Tj}]'$, In the final step the statistic of interest becomes some summary statistic of the $\rho' s$ (or the transformation used, e.g. the ADF) and $p^* = prop(S^* < \widehat{S}),$ where S is the summary statistic adopted; the standard choice in the literature (with the only exception of the bootstrap test by Fachin, 2007) is the mean. However, an often overlooked point is that this summary statistic implies the alternative hypothesis H_1 : "$\rho_i < 1$ in most of units *or* $\rho_i << 1$ in a smaller number of units", as these two cases may be observationally equivalent for the mean. In fact, we can define three other different alternative hypothesis to H_0 : no cointegration in all units, $i.e. H_0 : \rho_i = 1$ for $i = 1, \ldots, N$: (i) $H_1 : \rho_i < 1$ in all units; (ii) $H_1 : \rho_i < 1$ in at least one unit; (iii) $H_1 : \rho_i < 1$ in most of the units. Each of these alternative hypothesis implies a specific summary statistics: (i) $G = Max(\rho_i)$; (ii) $G = Min(\rho_i)$; (iii) $G = Median(\rho_i)$. As the first two alternative hypothesis and respective summary statistics are obviously of little interest, the choice is restricted to mean and median. Now, the point is that a panel cointegration testing procedure is supposed to find out which description (cointegration or not) best fits the panel *as a whole.* This means that the alternative hypothesis should be "cointegration in most of the units", case (iii) above, and the individual statistics summarised by the median[4]. However, this statistic is of notoriously difficult treatment by asymptotic methods, so that a bootstrap approach is mandatory.

3. Monte Carlo Design

We will base our simulations on a DGP which is essentially a generalisation of the classical Engle and Granger (1987) DGP to the case of dependent panels, with the design of the panel structure related to those used by Kao (1999), Fachin (2007), and Gegenbach *et al.* (2006)[5]. Since panel DGPs are inevitably very complex, simulation experiments are computationally very demanding, hence, our aim will be that of defining an empirically relevant set-up. We assume a variable of interest, Y, known to be linked by a linear, possibly cointegrating, relationship to a right-hand side variable[6] X:

$$\begin{cases} y_{it} = \mu_{0i} + \beta_i x_{it} + \epsilon_{it}^y \\ \epsilon_{it}^y = \rho_i \epsilon_{it-1}^y + e_{it}^y, \qquad e_{it}^y \sim N(0, \sigma_{iy}^2) \end{cases} \tag{2}$$

where $i = 1, \ldots, N,\ t = 1, \ldots, T$. When X_i and Y_i are not cointegrated $\rho_i = 1$, while $|\rho_i| < 1$ when instead they are; in the power simulations ρ_i will be generated as

[4]Note that using this statistic a rejection would implie (by definition) that cointegration holds in more than half of the units examined, but nothing can more precise can be said. On the other hand, using the mean we do not even know if the cointegrating units are the majority of the panel or not.

[5]Several parameters are in fact fixed at the values used by the latter.

[6]Exploratory simulations showed the performances of the test to be independent on the number of independent variables.

$Uniform(0.6, 0.8)$ across units to mimic a generally rather slow adjustment to equilibrium. To ensure some heterogeneity across units $\sigma^2_{iy} \sim Uniform(0.5, 1.5)$, while with no loss of generality $\mu_{0i} = \beta_i = 1 \; \forall i$.

Long-run growth of X is assumed to be driven by a non-stationary factor common across units (F_1), with short-run deviations caused by a second stationary common factor (F_2) and by an idiosyncratic stationary noise (ϵ^x_{it}):

$$x_{it} = \gamma_1 F_{1t} + \gamma_2 F_{2t} + \epsilon^x_{it} \tag{3}$$

Following Pesaran (2006) the factor loadings are chosen so to ensure substantial cross-correlation in the $X's$: $\gamma_i \sim Uniform(-1, 3) \; \forall i$. The common factors are generated as follows:

$$\begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} = \begin{bmatrix} F_{1t-1} \\ 0.4F_{2t-1} \end{bmatrix} + \begin{bmatrix} f_{1t} \\ f_{2t} \end{bmatrix} \tag{4}$$

where, as in Gegenbach *et al.* (2006), both the common and idiosyncratic shocks are assumed to have a MA(1) structure:

$$\begin{bmatrix} f_{1t} \\ f_{2t} \end{bmatrix} = \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} + \begin{bmatrix} \vartheta_1 & 0 \\ 0 & \vartheta_2 \end{bmatrix} \begin{bmatrix} \eta_{1t-1} \\ \eta_{2t-1} \end{bmatrix} \tag{5}$$

$$\epsilon^x_{it} = e^x_{it} + \varphi e^x_{it-1}, \tag{6}$$

where $\eta_{it} \sim N(0, 1), i = 1, 2$, and $e^x_{it} \sim N(0, \sigma^2_{ix})$, with $\sigma^2_{ix} \sim Uniform(1, 1.4)$. Both φ and the $\vartheta's$ are generated as Uniform deviates in the range [0.5,0.7].

An important remark is that this DGP is more general than those already used in the literature: Gegenbach *et al.* (2006) exclude the possibility of a single source of non stationarity common to both the left- and the right-hand side variables, Westerlund (2008), assumes common factors to be present in the residuals of the cointegrating equation only[7], Bai and Carrion-i-Silvestre (2005) allow for common factors in the X's only if the cointegrating vectors are homogenous. Thanks to its generality it is likely to be representative of many empirical applications: an obvious example is the case of regional consumption and income, with the common factors given by the trend and cycle in national GDP. To shed some light on the performances that can be expected from common factors methods in this type of set-up we shall also examine the performance of Westerlund's Durbin-Hausman group mean DH_g test. For simplicity we are ruling out the possibility of cointegration holding in some units only, but the design could be easily generalised further to include this case also. The sample sizes considered in the experiment are also chosen trying to reproduce empirically relevant conditions. Hence, we assume the data set to cover up to $N = 40$ cross-section units and $T = 20, 40, 80$. In principle an important, and still largely unsettled, aspect of block bootstrap methods is the choice of block size. In practice according to the simulation results reported by PPP the RSB unit root tests appear to be quite robust to this parameter. We will thus fix it at either $0.10T$ (as in Paparoditis and Politis, 2001) or $0.15T$ with a minimum of 4, leaving implementation of data-based methods for future research. Finally, Monte Carlo simulations and bootstrap redrawings have been set to 1000.

[7]Here the X's are always cointegrated across units, while the Y's are when $|\rho_i| < 1$ within units, i.e. X_i and Y_i are cointegrated.

4. Monte Carlo Results

The results are reported in tables 1-4 below. As it can be appreciated from Tables 1-2, the bootstrap tests deliver an overall rather good performance. First of all, Type I errors are generally close to nominal, except for some overrejection for $T = 20$ (recall that with 1000 Monte Carlo simulations approximate 95% confidence intervals around 5% and 10% are respectively 4%-6% and 8%-12%). Second, the power performance is very good: more than the high values of the rejection rates (which are conditional on the specific DGP and signal/noise ratio at hand), the important evidence here is their rapid growth with the cross-section dimension. The good behaviour of the panel tests is confirmed by the results with $T = 80$ and the first five units (Table 3): Type I errors are essentially equal to nominal size and power reaches 100%. Finally, in Table 4 we report the Type I errors of the Durbin-Hausman group mean test DH_g by Westerlund (2008). We stress again that the application of the test is obviously wrong here; a careful common factor analysis of the data would conclude that the residuals have no common factor, while the right-hand side variable does. Though largely expected, the results are nevertheless instructive of the possible consequences of an automatic application of the method: since the common factor procedure fails to remove the dependence across units, the test heavily overejects. In fact, when the X is generated according to the full specification (3)-(6) with two common factors the true null of no cointegration is *always* rejected by DH_g test. Letting $\gamma_2 = 0$ so that there is only one, non stationary common factor, the size bias falls but it is still very large, and, though shrinking with the time dimension, it worsens with the cross-section one for a fixed time sample. The problem is that, since the bias is exactly in the direction most welcome by practitioners (against H_0: no cointegration, hence in favour of the existence of a cointegrating relationship), they will probably be too happy of the results delivered by a routine application of the test to check carefully the validity of its assumptions.

Table 1
Bootstrap Panel Cointegration Tests
Size

		Units			
		5	10	20	40
T	α	$Median(ADF)$			
20	0.05	0.08	0.08	0.10	0.10
	0.10	0.14	0.16	0.20	0.20
40	0.05	0.06	0.07	0.07	0.06
	0.10	0.10	0.14	0.14	0.12
T	α	$Mean(ADF)$			
20	0.05	0.08	0.09	0.12	0.10
	0.10	0.14	0.17	0.22	0.20
40	0.05	0.05	0.07	0.06	0.05
	0.10	0.12	0.13	0.13	0.12

DGP: X_i : cf. (3)-(6) Y_i : cf. (2)
$\rho_i = 1 \forall i$ H_0 :No cointegration
Median(ADF): H_1 : cointegration in most units
Mean(ADF): H_1 : cointegration in a large number of units *or* strong cointegration in a smaller number of units.

Table 2
Bootstrap Panel Cointegration Tests
Power

		Units			
		5	10	20	40
T	α	$Median(ADF)$			
20	0.05	0.74	0.94	1.00	1.00
	0.10	0.85	0.97	1.00	1.00
40	0.05	0.99	1.00	1.00	1.00
	0.10	1.00	1.00	1.00	1.00
T	α	$Mean(ADF)$			
20	0.05	0.57	0.86	0.99	1.00
	0.10	0.83	0.97	1.00	1.00
40	0.05	0.98	1.00	1.00	1.00
	0.10	1.00	1.00	1.00	1.00

DGP: X_i : cf. (3)-(6) Y_i : cf. (2)
$\rho_i \sim Uniform(0.6, 0.8)$
H_0, H_1 : see Table 1.

Table 3
Bootstrap Panel Cointegration Tests
$T = 80$, $N = 5$

	α	0.01	0.05	0.10
$Median(ADF)$	Size	0.01	0.07	0.14
	Power	1.00	1.00	1.00
$Mean(ADF)$	Size	0.01	0.07	0.14
	Power	1.00	1.00	1.00

DGP: see Table 1; H_0, H_1 : see Table 1.
Size: $\rho_i = 1\ \forall i$; Power: $\rho_i \sim Uniform(0.6, 0.8)$.

Table 4
Durbin-Hausman Common Factors
Group Mean DH_g
Panel Cointegration Test
Size

		Units			
T	α	5	10	20	40
20	0.05	0.06	0.42	0.70	0.89
	0.10	0.06	0.47	0.75	0.91
40	0.05	0.03	0.25	0.35	0.49
	0.10	0.04	0.30	0.43	0.58
80	0.05	0.05	0.08	0.09	0.11
	0.10	0.06	0.13	0.13	0.16

DGP: X_i : cf. (3)-(6),$\gamma_2 = 0$.
Y_i : cf. (2), $\rho_i = 1 \forall i$
H_0 : No cointegration.

5. Empirical illustration: the Fisher effect

The so-called "Fisher effect" dates back to Fisher (1930), who put forth the hypothesis that the nominal interest rate (i) adjusts to the sum of expected real interest rate (r^*) and expected inflation rate (p^*):

$$i_t = r_t^* + p_t^* \tag{7}$$

Of course, (7), which involves unobserved variables, cannot be directly tested; however, it suggests an observable direct relationship with unit coefficient between the nominal interest rate and the actual inflation rate ("full Fisher effect"). In practice, this reasonable hypothesis never found consistent support from the data (recent evidence in this direction is provided, *inter alia*, by Bonham, 1991, King and Watson, 1997), although more general specifications with coefficients different from one ("partial Fisher effect") or breaks were shown to be compatible with the data (*e.g.*, Garcia and Perron, 1996). However, as Westerlund (2008) points out, the available empirical studies are weak under two important aspects. First, most studies examined US data only. Second, in the case of long-run studies the economic hypothesis is rejected when the statistical null hypothesis of no cointegration is not. Hence, low power of the statistical procedure used may lead to erroneously reject the economic hypothesis of interest, exactly as it happens with the Purchasing Power Parity theory[8]. To tackle both, Westerlund (2008) applied his Durbin-Hausman panel cointegration tests to a panel of 20 OECD countries[9] for the period 1980:1-2004:4. With a p-value equal to 0.000, the group mean DH_g test provides extremely strong evidence in favour of panel cointegration between interest rates and inflation (which appear to be non-stationary on the basis of both univariate and panel unit root tests). Since the estimated coefficients are different from one the conclusion is that the hypothesis of a partial Fisher effect holding in the examined panel as a whole cannot be rejected. Although this is a certainly reasonable conclusion, in view of the uncertainty prevailing in the literature its strength is somehow suspect. The simulation reported in Table 4 suggests that in the case of common factors in the right-hand side variable, rather than in the residuals as assumed by the test, the DH_g panel cointegration test can be severely oversized. In fact, applying our bootstrap procedure[10] we estimate the p-value of the mean ADF cointegration statistic as 0.03, and that of the median ADF as 0.13. Applying the conventional 5% significance level the hypothesis of no panel cointegration is rejected in mean (hence, in favour of the alternative hypothesis of cointegration in most of the units *or* strong cointegration in a smaller number of units) but not in median (when the alternative hypothesis is cointegration in most of the units). At the 1% level mean and median tests agree to suggest no rejection of the null hypothesis of no Fisher effect in the panel as a whole. Our conclusion is therefore not entirely at odds with Westerlund's, but considerably more cautious and thus more in line with the previous literature: there is some evidence in favour of a partial Fisher effect, but (i) it is weaker than suggested by the Durbin-Hausman DH_g test, and, (ii) it seems to come from some subset of the examined panel of OECD economies. Clearly, as suggested by Garcia and Perron (1996), allowing for breaks may strengthen the evidence in favour of a Fisher effect.

6. Conclusions

The key contribution of this paper is to put forth a test for panel cointegration in dependent panels based upon a residual based unit root test recently proposed by Parker, Paparoditis and Politis (2006). The test procedure is shown by simulation to deliver good size and power performances in panels with long- and short-run dependence due to common factors in the variables examined. The power gains with respect to aggregate tests appear particularly valuable. Applying the procedure to test the Fisher hypothesis on the Westerlund (2008) data we find some weak evidence in favour of a partial Fisher effect; our conclusions are therefore more cautious than Westerlund's. Future research will try to address the issue of data-based choice of block size, the asymptotic properties of the test, as well as generalising the procedure to allow for breaks at an unknown date.

[8] In fact, this empirical issue was an important motivation for the early developments of panel cointegration methods: see e.g. O'Connell (1998).

[9] Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Portugal, Sweden, United States.

[10] Mean block size $T/10$, 1000 redrawings. The results are robust to mean block size.

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