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A sieve bootstrap range test for poolability in dependent cointegrated panels

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Abstract

We develop a sieve bootstrap range test for poolability of cointegrating regressions in dependent panels and evaluate by simulation its performances. Although slightly undersized the test has good power even when only a single unit of the panel is heterogenous.

Keywords: Poolability, Panel cointegration, sieve bootstrap.

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1 Introduction[1]

Estimation and testing of macroeconomic models using the tools of non-stationary panel analysis is becoming increasingly popular. Recent examples include topics as diverse as migrations (Brücker, Fachin and Venturini, 2011), energy consumption and economic growth (Apergis, 2010), human capital spillover effects (Le, 2010) and money neutrality (Westerlund and Costantini, 2009). Consider for simplicity two cointegrated variables, X and Y, observed over N units (indexed by i) and T time periods (indexed by t). The potential of a panel dataset can be best exploited when the long-run slope coefficients are the same across units; in this case pooled long-run models of the type

$$y_{it} = \theta_i + \beta x_{it} + \epsilon_{it} \tag{1}$$

may be estimated[2]. However, the poolability, or homogeneity, hypothesis $H_0 : \beta_i = \beta$ should be tested, rather than imposed a priori, as it is often the case (as *e.g.*, in Adedeji and Thornton, 2008). A naive, indirect way to test the homogeneity hypothesis is to test for cointegration model (1), since in case of heterogeneity its residuals include the non-stationary component $(\beta_i - \beta)x_i$. However, this approach implicitly assumes homogeneity in the speed of adjustment: if this does not hold, the null hypothesis of slope homogeneity may be erronously rejected even if true. Moving to direct tests of the poolability hypothesis, several options are available for stationary panels (for a recent review see Pesaran and Yamagata, 2008). However, the choice is much more limited if we consider tests suitable for non-stationary panels which take into account the dependence across units. Standard likelihood ratio tests can be used when N is small relative to T (see *e.g.*,Groen and Kleibergen, 2003). However, in macro panels the two sample sizes are typically of the same order of magnitude, so that this route is empirically of very little interest. To the best of our knowledge, the only empirically relevant options available are the generalisations by Mark, Ogaki and Sul (2005) and Moon and Perron (2004) of the Wald test by Mark and Sul (2003), the Hausman test by Westerlund and Hess (2009), and the variance test by Trapani (2010). As we shall see, unfortunately none of these tests is fully satisfactory for testing homogeneity in small panels.

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[2]If the short-run dynamic is of interest the PMG estimator by Pesaran, Shin and Smith (1999), which allows for heterogenous short-run coefficients while imposing long-run homogeneity, may be used.

The Wald test, which compares all the restricted and heterogenous estimates, requires either the assumption of independent units[3] or SUR estimation. The former is empirically implausible, and the latter feasible only for large T/N ratios (in some previous work we found that FM-SUR estimates turned out to be unfeasible for a panel with $T = 50$ and $N = 10$; see Di Iorio and Fachin, 2008).

Westerlund and Hess (2009) construct a test based on the maximum distance between the heterogenous and the pooled estimates estimating the variance of the distance by the Hausman approach. The use of the maximum gives the procedure the ability to detect heterogeneity even in a single unit of the panel. However, some problems remain open. Although stationary common factors in the residuals are allowed, the test requires the assumption of independence across units for the right-hand side variables. Westerlund and Hess suggest that the more general case of dependent explanatory variables can be tackled extracting in a first step the common factors with the Bai and Ng (2004) procedure. This is rather straightforward in the case of to stationary factors, examined by simulation by Westerlund and Hess, but less so in the empirically more relevant case of non-stationary factors, not examined. Further, the power of this two-steps test seems to be inversely related to the variance of the common factor. It should also be kept in mind that, as pointed out *e.g.* by Pesaran and Yamagata (2008), Hausman tests generally tend to have low power.

Trapani (2011) suggests to formulate the homogeneity hypothesis as $H_0 : \sigma_\beta^2 = 0$, where σ_β^2 is the variance of the estimates across units, and develops a testing procedure which has many appealing features: for instance, mixed panels in which only some of the units are cointegrated may be considered. Unfortunately, the simulation evidence reported (which, further, is limited to the case of independent units) suggests that its power is likely to be very low for small sample sizes and heterogeneity limited to a small fraction of the units.

Borrowing from both Westerlund and Hess (2009) and Trapani (2011), we suggest to formulate the homogeneity hypothesis as $H_0 : R = 0$, where $R = Max_{i \in [1,N]}(\beta_i) - Min_{i \in [1,N]}(\beta_i)$ is the range of the coefficients over the N units. Measuring the heterogeneity of the estimated set of coefficients in this way is expected to bring some advantages over both Hausman and variance tests. On one hand, we avoid the troublesome estimation of the variance of the difference between the heterogenous and pooled estimates required by the Hausman tests. On the other, we expect to improve the ability to detect violations of the null hypothesis

[3] This also applies to the Hausmann test applied by Pesaran, Shin and Smith (1999).

in a small fraction of the units. Obviously, the disadvantage is that the asymptotic distribution of the Range can be derived only under the assumption that the extremes are independent (the classical reference is Gumbel, 1947), precisely the case we are not interested in. As we will argue below, we conjecture that this problem can be tackled by the sieve bootstrap. Details of the algorithm will be given in section 2, while the results of some Monte Carlo evaluation in section 3. Section 4 concludes.

2 Testing set-up

Assume we are interested in the following cointegration model (Chang, Park and Song, 2006):

$$\begin{aligned} y_{it} &= \theta_i + \beta_i x_{it} + \epsilon_{it} \\ x_{it} &= x_{it-1} + \psi_{it} \\ \begin{bmatrix} \epsilon_{it} \\ \psi_{it} \end{bmatrix} &= \Phi(L) \begin{bmatrix} e^y_{it} \\ e^x_{it} \end{bmatrix} \end{aligned} \tag{2}$$

where $\Phi(L) = \sum_{k=0}^{\infty} \Phi_k z^k$.The following standard assumptions hold: $\mathbf{e}_t = [e^y_{it}\ e^x_{it}]'$ s.t. $E(\mathbf{e}_t) = 0$, $E(\mathbf{e}_t\mathbf{e}_t^{'}) = \Sigma > 0, E|\mathbf{e}_t|^4 < \infty; det\ \Phi(z) \neq 0$ for all $|z| \leq 1, \sum_{k=0}^{\infty} k\,|\Phi_k| < \infty$. Then, let $\widehat{\beta}_i$ any consistent estimate of β_i, *e.g.* OLS ot the more efficiente FM-OLS or DOLS. Since Max and Min are continuous functions, by the Continuous Mapping Theorem (CMT) the sample range $\widehat{R} = Max_{i\in[1,N]}(\widehat{\beta}_i) - Min_{i\in[1,N]}(\widehat{\beta}_i)$ is a consistent estimate of the population range R, and it can be used as a statistic for testing the homogeneity hypothesis $H_0 : R = 0$. As remarked in the Introduction, since the distribution of the Range is known only for independent units, we conjecture that inference can be based on the sieve bootstrap. This conjecture is based upon two elements. First, Hall and Miller (2010) showed that the simple bootstrap yields asymptotically valid inference on extrema of parameters computed from IID datasets. Second, Chang, Park and Song (2006) proved that sieve bootstrap estimators (*i.e.*, estimators applied to datasets constructed by the sieve bootstrap, say β_i^*) have the same limiting distribution as that of the estimators computed on the originary data. Invoking the CMT again we can conclude that this holds for their Max and Min as well: the asymptotic distribution of $\phi(\beta_i^*)$ is the same as that of $\phi(\widehat{\beta}_i)$, where $\phi = Max, Min$. For independent units this trivially extends to their difference as well, the range. We conjecture, and will show by simulation, this holds for dependent units as well. We do not attempt to obtain a formal proof for two reasons. First, such a proof will necessarily be limited to some specific form of dependence, and thus will never be fully satisfactory. Second, the empirical interest of the procedure lies in its small sample performances, which will need to be assessed by simulation anyway.

To assess if the null hypothesis of poolability is compatible with the data we then suggest to construct by the sieve bootstrap pseudodata satisfying the null hypothesis, and compare the range computed on the empirical dataset with the distribution of the bootstrap ranges. To this end, since bootstrap tests should be based on pivotal statistics we make the additional assumption that all coefficients have the same sign (formally, $\beta_i \beta_j > 0 \ \forall i, j$) and define the normalized range $\widehat{R}_N = [Max_{i\in[1,N]}(\widehat{\beta}_i) - Min_{i\in[1,N]}(\widehat{\beta}_i)]/Max_{i\in[1,N]} \left|\widehat{\beta}_i\right|$,which under this assumption falls in the $[0, 1]$ interval.

The details of the algorithm are as follows:

1. Estimate (2) by any consistent procedure, obtaining for each unit i the residuals $\{\widehat{\epsilon}_{it}\}_{t=1}^{T}$;

2. Compute the Range of the N coefficients, $\widehat{R}_N = [Max_{i\in[1,N]}(\widehat{\beta}_i) - Min_{i\in[1,N]}(\widehat{\beta}_i)]/Max_{i\in[1,N]} \left|\widehat{\beta}_i\right|$;

3. Letting $\mathbf{Z}_{it} = [\Delta x_{it} \ \widehat{\epsilon}_{it}]'$, fit VARs of order p_i to each of the N bivariate time series $\{\mathbf{Z}_{it}\}_{t=2}^{T} : \mathbf{Z}_{it} = \sum_{j=1}^{p_i} \mathbf{B}_j \mathbf{Z}_i + \boldsymbol{\nu}_{it}$,where $\boldsymbol{\nu}_{it} = [\nu_{xit} \ \nu_{\epsilon it}]'$.

4. Store the (empirically white noise) residuals $\widehat{\boldsymbol{\nu}}_{it} = [\widehat{\nu}_{xit}, \widehat{\nu}_{\epsilon it}]', t = p_i + 1, \ldots, T$ of the N VARs;

5. Letting $p_M = \max(p_i)$, resample with replacement the rows of the $(T - p_M) \times 2N$ matrix $\mathbf{V} = [\widehat{\boldsymbol{\nu}}_{x1} \ldots \widehat{\boldsymbol{\nu}}_{xN} \ \widehat{\boldsymbol{\nu}}_{\epsilon 1} \ldots \widehat{\boldsymbol{\nu}}_{\epsilon N}]$, where $\widehat{\boldsymbol{\nu}}_{xi} = [\widehat{\nu}_{xip_M+1} \ldots \widehat{\nu}_{xiT}]'$, $\widehat{\boldsymbol{\nu}}_{\epsilon i} = [\widehat{\nu}_{\epsilon ip_M+1} \ldots \widehat{\nu}_{\epsilon iT}]'$, obtaining a matrix of pseudoresiduals $\mathbf{V}^* = [\widehat{\boldsymbol{\nu}}_{x1}^* \ldots \widehat{\boldsymbol{\nu}}_{xN}^* \ \widehat{\boldsymbol{\nu}}_{\epsilon 1}^* \ldots \widehat{\boldsymbol{\nu}}_{\epsilon N}^*]$. Since entire rows swap places with the column fixed, the cross-unit dependence structure of the matrix $\mathbf{V}$ is preserved;

6. Construct recursively the pseudoseries $\mathbf{Z}_{it}^* = \sum_{j=1}^{p_i} \widehat{\mathbf{B}}_j \mathbf{Z}_i^* + \boldsymbol{\nu}_{it}^*$, setting the p_M initial values equal to the observed values ($\mathbf{Z}_{it}^* = [\Delta x_{it} \ \widehat{\epsilon}_{it}]'$, $t = 1, \ldots, p_M$);

7. Cumulate the $\Delta x^{*\prime} s$ to obtain the $x^{*\prime} s$;

8. Compute pseudodata obeying the null hypothesis of slope homogeneity: $y_{it}^* = \widehat{\theta}_i + \beta^0 x_{it}^* + \epsilon_{it}^*, \ i = 1, \ldots, N, \ t = 1, \ldots, T$.

9. Estimate the cointegrating regression (2) on the dataset $\{y_t^*, x_t^*\}$, obtaining estimates of the cointegrating coefficients $\beta_i^*, i = 1, \ldots, N$;

10. Compute the Range of the bootstrap estimates: $R_N^* = [Max_{i\in[1,N]}(\beta_i^*) - Min_{i\in[1,N]}(\beta_i^*)]/Max_{i\in[1,N]}|\beta_i^*|$;

11. Repeat 3-10 B times;

12. Compute the bootstrap p-value as the right tail of the distribution of the $R_{\boldsymbol{\beta}}^{*\prime}s : p^* = prop(R_N^* > \widehat{R}_N)$.

A few remarks are in order;

(i) The poolability hypothesis is empirically meaningful only for coefficients of the same sign. Hence, the assumption $\beta_i\beta_j > 0 \; \forall i, j$ does not introduce any actual limitation to the empirical applications of the test.

(ii) If the $\Delta x_i^{\prime}s$ have a non-zero mean they must be centred, or a constant included in the VAR of step 3.

(iii) The VAR lag lengths p_i may be empirically chosen on the basis of any consistent criterion, such as the AIC, provided they are allowed to grow with the time sample size at some controlled rate (e.g. logarithmic).

(iv) In steps 8 and 9 the constant may be omitted from both the bootstrap DGP and model.

(v) The simplest choice of β^0 is the mean group estimate $\beta_{MG} = N^{-1}\sum_{i=1}^{N}\widehat{\beta}_i$, which does not require estimating a constrained model.

(v) The procedure is immediately extended to the multivariate model $y_{it} = \theta_i + \sum_{j=1}^{k}\beta_{ji}x_{jit} + \epsilon_{it}$. Tests for a subset of the coefficients are obtained constraining only the relevant elements of the vector $\boldsymbol{\beta}^0$, and joint tests as induced tests rejecting $H_0 : \beta_{ji} = \beta_j, j = 1, \ldots, k'$, if $\min(p_j^*) < \alpha'$,where p_j^* is the bootstrap p-value for variable j. Use of Bonferroni individual significance levels $\alpha' = \alpha/k'$ ensures control of the Family Wise Error Rate at α (Savin, 1984)

3 Simulation evidence

3.1 Design

Our Monte Carlo experiment is based on a Data Generating Process (DGP) which is essentially a generalisation of the classic Engle and Granger (1987) DGP to the case of dependent panels. The panel structure is closely related to those used by Kao (1999), Fachin (2007), and Gengenbach *et al.* (2006). Since panel DGPs are inevitably very complex, simulation experiments are computationally very demanding. Hence, rather than aiming at the unfeasible task of a complete design our aim will be that of defining an empirically relevant set-up. We assume the variable of interest, Y, known to be linked in all units of a panel by a cointegrating relationship to a right-hand side variable X, with residuals following stationary autoregressive processes:

$$\begin{cases} y_{it} = \theta_i + \beta_i x_{it} + \epsilon_{it}^y \\ \epsilon_{it}^y = \rho_i \epsilon_{it-1}^y + e_{it}^y, \qquad e_{it}^y \sim N(0, \sigma_{iy}^2) \end{cases} \tag{3}$$

where $i = 1, \ldots, N$, $t = 1, \ldots, T$. The $\rho_i' s$ are generated as $Uniform(0.4, 0.6)$ across units and kept fixed for all Monte Carlo simulations. To ensure some heterogeneity across units we also generate $\sigma_{iy}^2 \sim Uniform(0.5, 1.5)$ and keep them fixed across experiments, while with no loss of generality we set $\theta_i = \beta_i = 1\ \forall i$ under the null hypothesis of homogeneity. The power simulations consider two cases: in the first case there is wide heterogeneity, with $\beta_i = 1$ in the first $\delta = 0.7N$ units and 0.5 in the remaining $0.3N$[4]. In the second case only the last unit of the panel is heterogenous ($\beta_i = 1$ for $i = 1, \ldots, N-1, \beta_N = 0.5$), so that $\delta = N - 1$.

The right-hand side variable X is constructed essentially as the sum of two terms. The first, u^x, is in turn the sum of two non stationary factors, one common across units (F^x) and one idiosyncratic (ϵ_{it}^x). The second term, $a_i(\mu_{0i} + \epsilon_{it}^y)$, captures the feedback from the left-hand side variable, absent when $a_i = 0$. Summing up:

$$\begin{cases} x_{it} = (1 - a_i\beta_i)^{-1}[u_{xt} + a_i(\mu_{0i} + \epsilon_{it}^y)] \\ u_t^x = \gamma_i^x F_t^x + \epsilon_{it}^x \end{cases} \tag{4}$$

To allow for some heterogeneity across units we generate, and keep fixed across experiments, both the $a_i' s$ and the factor loadings γ_i^x as uniform variates. The endogeneity coefficients fall in the range $[0.05, 0.25]$, while the factor loadings, to ensure substantial dependence across units, in the range $[0.50, 3.0]$. Both the common and the idiosyncratic factors are generated as simple random walks:

$$F_t^x = \textstyle\sum_{s=1}^t \eta_s^x \tag{5}$$

$$\epsilon_{it}^x = \textstyle\sum_{s=1}^t e_{is}^x \tag{6}$$

where $\eta_t^x \sim N(0, 1)$ and $e_{it}^x \sim N(0, \sigma_{xi}^2)$, with $\sigma_{xi}^2 \sim Uniform(1.0, 1.50)$.

[4]Fixing the coefficients of the heterogenous units all at the same value allows more reliable comparisons with small cross-section sample sizes.

From the empirical point of view, our DGP is representative of many applications. One obvious example the case of consumption and income in a panel of regions or national economies, with the common factor due respectively to national or global stochastic GDP trend. The sample sizes considered in the experiment are also chosen with the primary aim of reproducing empirically relevant conditions. Since the homogeneity question is mostly relevant for small cross-sections we shall examine $N = 5, 10, 20$, while, considering that most macro datasets include annual, or at most quarterly data, we will let $T = 20, 40$, 80, and, to evaluate asymptotic behaviour under the null hypothesis, $T = 160$. The VAR lengths will be chosen on the basis of AIC with the maximum lag set to $4log(T)$, yielding $5, 6, 8$ respectively for $T = 20, 40, 80$.

Finally, to strike a balance between experimental precision and computing costs the number of both Monte Carlo simulations and bootstrap redrawings has been set to 1000, implying that the approximate confidence intervals around 5% and 10% will respectively be $[3.6\% - 6.4\%]$ and $[8.1\%, 11.9\%]$.

3.2 Results and conclusions

The results are summarised in Tables 1 (size), 2 and 3 (power). The cointegrating coefficients have been estimated by FM-OLS. Even taking account Monte Carlo uncertainty, the test appears somehow undersized. However, turning to Tables 2 and 3 we can see that the power performances are acceptable for $T = 40$ at 10% level and always very good for $T = 80$. The ability to reject false null hypothesis is clearly strictly dependent upon the quality of the coefficient estimates. The power loss from high to low heterogeneity is, as expected, low provided the time sample is at least moderate.

Summing up, the proposed procedure seems to have good size and power properties even with small cross-sections (in which factor methods deliver poor results) and moderate time samples (in which SUR estimation is typically not feasible). Thus it may be a useful addition to the toolkit of the applied econometrician working with non stationary panels.

Work in progress include more extensive Monte Carlo evaluation, and application of the test to the money demand functions of the six countries of the Gulf Cooperation Council (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates) which are planning a monetary union.

Table 1

Rejection rates ×100 of Bootstrap

Poolability Tests

Size

	T	20		40		80		160	
	α	5	10	5	10	5	10	5	10
N	5	4.5	8.5	3.9	8.1	4.3	8.6	3.6	6.8
	10	3.0	7.1	4.3	7.2	4.2	8.3	4.1	7.6
	20	3.2	7.7	3.4	7.8	3.1	6.3	3.6	6.8

DGP: (3)-(6)

$H_0 : \beta_i = \beta \ \forall i$

Table 2

Rejection rates ×100 of Bootstrap

Poolability Tests

Power, High heterogeneity

	T	20		40		80	
	α	5	10	5	10	5	10
N	5	21.7	33.8	60.4	77.9	99.5	100
	10	17.0	28.1	54.3	75.7	99.4	100
	20	11.5	23.2	46.6	70.5	99.8	100

DGP: (3)-(6), $\delta = 0.3N$ heterogenous units;

$H_0 : \beta_i = \beta \ \forall i$.

Table 3

Rejection rates ×100 of Bootstrap

Poolability Tests

Power, one heterogenous unit

	T	20		40		80	
	α	5	10	5	10	5	10
N	5	19.2	28.3	55.0	68.6	97.6	98.6
	10	15.9	24.9	56.4	67.5	97.7	98.7
	20	10.8	18.1	46.2	61.1	97.2	98.3

DGP: (3)-(6),

$H_0 : \beta_i = \beta \ \forall i$.

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