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An intersection test for the cointegrating rank in dependent panel data

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Abstract

This paper takes a multiple testing perspective on the problem of determining the cointegrating rank in macroeconometric panel data with cross-sectional dependence. The testing procedure for a common rank among the panel units is based on Simes' (1986) intersection test and requires only the p -values of suitable individual test statistics. A Monte Carlo study demonstrates that this simple test is robust to cross-sectional dependence and has reasonable size and power properties. A multivariate version of Kendall's tau is used to test an important assumption underlying Simes' procedure for dependent statistics. The method is illustrated by testing the validity of the monetary exchange rate model for 8 OECD countries in the post-Bretton Woods era.

Keywords: panel cointegration rank test, cross-sectional dependence, multiple testing, common factors, likelihood-ratio

JEL classification: C12, C15, C33

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1 Introduction

Testing for unit roots and cointegration is an essential pre-modelling step in the analysis of Vector Autoregressive (VAR) models, which have become a primary tool for empirical macroeconometric analyses. Cointegration describes the existence of a long-run linear relationship between two or more integrated time series, which is integrated of a lower order than the series themselves. In most applications the series are integrated of order one (i.e. $I(1)$, or unit-root nonstationary), while their cointegrating relation is stationary (i.e. $I(0)$). The number of linearly independent cointegrating relations between multiple time series is called a cointegrating rank.

Panel unit root and cointegration tests have been developed to improve the power of tests based on individual time series when extension of the data in the time dimension is not possible. The increased information set, however, comes at a price. One of the major difficulties inherent in panel data is the presence of dependence between the cross-sectional units, as it may distort the performance of the so called “first-generation” panel cointegration tests which rely on the assumption of independence.¹

The common factor framework has grown increasingly popular in describing the co-movements of macroeconomic time series, and has therefore become widely adopted as a tool to model the cross-sectional dependence in second-generation panel unit-root and cointegration tests. In testing for cointegration it has been employed by Gengenbach et al. (2006), Westerlund and Edgerton (2008), Westerlund (2008), Carrion-i Silvestre and Surdeanu (2011), Bai and Carrion-i Silvestre (2013), Arsova and Örsal (2017) and Banerjee and Carrion-i Silvestre (2015) to name but a few. The only two studies on panel rank testing among them (Carrion-i Silvestre and Surdeanu, 2011 and Arsova and Örsal, 2017), however, focus on the unobserved idiosyncratic components of the data, and their tests can thus yield information on the rank of the observed variables only when the common factors are $I(0)$.

In the present work we avoid the latter issue and propose a simple panel test for the common cointegrating rank of the observed variables, which are of primary interest in empirical work. The test is easy to implement, not requiring estimation of unobserved components or resampling schemes. It belongs to the class of meta-type tests based on p -values and hence allows for more flexibility (e.g. heterogeneous lag orders and/or different deterministic terms over cross-sections) than tests based on pooled statistics. The test builds on the improved Bonferroni procedure for combining significance levels of independent individual tests developed by Simes (1986). The independence assumption has been relaxed by Sarkar (1998), who proves the Simes’ conjecture for statistics whose joint distribution is *multivariate totally positive of order 2* (MTP_2). Simes’ procedure has recently been applied to panel unit root testing by Hanck

¹Theoretical implications of factor-driven dependence for first-generation tests are discussed in Gengenbach et al. (2006); Wagner and Hlouskova (2010) provide simulation evidence of size distortions for several first-generation panel cointegration tests under different dependence structures.

(2013). He demonstrates by simulation its applicability to panels with various types of cross-sectional dependence without a formal proof of whether the MTP_2 condition holds. We go a step further and provide a measure and numerical evidence of the suitability of the MTP_2 assumption in panels where the cross-sectional dependence is driven by common factors. In a Monte Carlo study we show that the proposed panel cointegration rank test has reasonable size and power properties in dependent panels of sizes typically encountered in practice.

The paper is organised as follows. Section 2 presents the panel testing procedure, whose finite sample properties are examined by Monte Carlo simulations in Section 3. Section 4 applies it to test the validity of the monetary exchange rate model for eight OECD countries, and Section 5 concludes.

2 The intersection-type panel cointegration rank test

Simes' procedure can be applied to any test from which p -values are available. In view of our empirical application, below we describe it in a panel setting employing a likelihood-ratio (LR) cointegration rank test for a system with a linear time trend. Two such tests are the well-known Johansen's (1995) (henceforth J) LR trace test and its GLS detrended counterpart proposed by Saikkonen and Lütkepohl (2000) (henceforth SL). The test statistic for the latter is computed as Johansen's LR trace statistic, but from trend-adjusted observations obtained by subtracting GLS estimates of the deterministic terms from the observed data. Saikkonen and Lütkepohl (2000) demonstrate by Monte Carlo simulations that in some situations their test has better finite-sample properties than Johansen's test. It is worth noting that both tests are implemented in the free software JMulTi, which makes the LR J and SL trace statistics and their p -values easily obtainable in practice.

In the panel setting, assume that there exist N cross-sectional units, with the observed variables in each one following an m -variate $VAR(s_i)$ process $Y_{it} = (Y_{1i,t}, \dots, Y_{mi,t})'$. It is further assumed that $Y_{it} \sim I(1)$ and it has at most a linear time trend:

$$Y_{it} = \mu_{0i} + \mu_{1i}t + X_{it}, \quad t = 1, \dots, T; \quad i = 1, \dots, N, \quad (1)$$

$$X_{it} = A_{i1}X_{i,t-1} + \dots + A_{i,s_i}X_{i,t-s_i} + u_{it}. \quad (2)$$

The error terms u_{it} form a martingale difference sequence such that $\mathbb{E}(u_{it}|u_{is}, s < t) = 0$ and $\mathbb{E}(u_{it}u'_{it}|u_{is}, s < t) = \Omega_i$, $\forall i = 1, \dots, N$. The deterministic terms μ_{0i} , μ_{1i} , the coefficient matrices A_{ij} ($j = 1, \dots, s_i$), the covariance matrices Ω_i and the lag orders s_i are assumed to be heterogeneous across units. Letting $\Pi_i = -(I_m - A_{i1} - \dots - A_{i,s_i})$, the null and alternative hypotheses are:

$$H_0 : \text{rk}(\Pi_i) = r_0, \quad \forall i = 1, \dots, N, \quad (3)$$

$$H_1 : \text{rk}(\Pi_i) > r_0 \quad \text{for at least one } i = 1, \dots, N.$$

In general, the LR trace statistic for unit i is computed as

$$LR_i(r_0) = -T \sum_{j=r_0+1}^m \ln(1 - \lambda_{i,j}), \quad (4)$$

where $\lambda_{i,1} \geq \dots \geq \lambda_{i,m}$ are the ordered solutions to the generalized eigenvalue problem $|\lambda S_{i,11} - S_{i,10} S_{i,00}^{-1} S_{i,01}| = 0$. The matrices $S_{i,kl}$ for $k, l = 0, 1$ are defined as $S_{i,kl} = \frac{1}{T} \sum_{t=1}^T R_{i,kt} R'_{i,lt}$, where $R_{i,0t}$ and $R_{i,1t}$ are the vectors of residuals from regressing the first-differenced and lagged processes ΔY_{it} and $Y_{i,t-1}$, respectively, on the deterministic terms and the lagged first differences of Y_{it} .²

Ordering the p -values of the individual LR test statistics as $p_{(1)} \leq \dots \leq p_{(N)}$, the joint null hypothesis in (3) is rejected by Simes' test at significance level α if

$$p_{(i)} \leq \frac{i\alpha}{N} \text{ for any } i = 1, \dots, N. \quad (5)$$

Simes' test can be applied for evaluating the joint significance of the test statistics at each step of the sequential rank testing procedure, i.e. for $r_0 = 0, \dots, m-1$.

Simes shows that the test is conservative under independence of the individual test statistics, that is

$$P_{H_0} \left\{ p_{(i)} \geq \frac{i\alpha}{N}, i = 1, \dots, N \right\} \geq 1 - \alpha. \quad (6)$$

In practice, however, we would expect the cointegration test statistics to exhibit positive dependence. This would be the case when the processes in the individual units are influenced by unobserved common factors, for example. The common shocks would generate more or less similar dynamics of the Y_{it} 's across units, which, in turn, would induce positive dependence among the individual cointegration statistics.

A general class of multivariate distribution functions, which are positively dependent, is defined by the MTP_2 condition. For convenience we next give the definition of MTP_2 as it appears in Sarkar (1998).

Definition 2.1. An N -dimensional random vector $X = (X_1, \dots, X_N)'$ is said to have an MTP_2 (TP_2 when $N = 2$) distribution if the corresponding probability density, $f(\mathbf{x})$, satisfies the following condition:

$$f(\mathbf{x} \vee \mathbf{y}) f(\mathbf{x} \wedge \mathbf{y}) \geq f(\mathbf{x}) f(\mathbf{y}) \quad \text{for all } \mathbf{x}, \mathbf{y} \in \mathbb{R}^N, \quad (7)$$

where, with $\mathbf{x} = (x_1, \dots, x_N)'$ and $\mathbf{y} = (y_1, \dots, y_N)'$, $\mathbf{x} \vee \mathbf{y} = (\max(x_1, y_1), \dots, \max(x_N, y_N))'$ and $\mathbf{x} \wedge \mathbf{y} = (\min(x_1, y_1), \dots, \min(x_N, y_N))'$.

²For more details on the computation of the J and SL trace test statistics we refer to Johansen (1995) and Saikkonen and Lütkepohl (2000).

Sarkar (1998) proves Simes' conjecture (6) for MTP₂ distributions with common marginals. However, whether the joint distribution function $F(x_1, \dots, x_N)$ of the individual LR trace statistics satisfies the MTP₂ property is difficult to establish analytically. The challenge is the unknown functional form of $F(x_1, \dots, x_N)$. The individual LR trace statistics of the J and SL tests are complex non-linear functions of the observations Y_{it} and have non-standard distributions. It has been established by Doornik (1998) and Trenkler (2008) that the limiting (as $T \rightarrow \infty$) distributions of these statistics, i.e. the univariate marginal distributions $F_i(x_i) = P(LR_i(r_0) \leq x_i)$, $i = 1, \dots, N$, are well approximated by gamma distributions. As the parameters of the gamma distributions are functions only of the dimension of the system m and the cointegrating rank under the null hypothesis r_0 , under the null hypothesis of a common cointegrating rank (3) the marginal distribution functions $F_i(\cdot)$ would be the same for each i . For Simes' conjecture to be valid, also the joint distribution function $F(x_1, \dots, x_N)$ has to be MTP₂. The form of $F(x_1, \dots, x_N)$ depends on both the marginals $F_i(x_i)$ and the dependence structure among them, which then is carried by the copula C : $F(x_1, \dots, x_N) = C\{F_1(x_1), \dots, F_N(x_N)\}$.

Various families of copulas have been proposed in the literature. Parametric ones often use only one or two parameters to describe the dependence structure, which may not be enough to capture the heterogeneity in the dependencies between the individual LR cointegration statistics. Also, in practice the true copula of the individual test statistics would be unknown, hence assuming a particular functional form for which to analytically establish the MTP₂ condition seems quite restrictive.³

To circumvent this problem we propose to empirically measure the suitability of the MTP₂ assumption for the vector of LR (trace) statistics $L = (LR_1(r_0), \dots, LR_N(r_0))'$ in the practically relevant case when the cross-sectional dependence is modelled by common factors. This is achieved by a multivariate version of Kendall's tau, defined in Nelsen (1996) as

$$\tau_N = \frac{1}{2^{N-1} - 1} \left(2^N \int_{[0,1]^N} C(u) dC(u) - 1 \right), \quad (8)$$

where $C(u)$ denotes the copula of the random vector L , and $[0,1]^N$ is the N -dimensional unit interval.

Nelsen (1996) shows that this measure of concordance, initially proposed by Joe (1990), is also a measure of *average multivariate total positivity of order two*. In particular, he argues that

$$f(\mathbf{x} \vee \mathbf{y})f(\mathbf{x} \wedge \mathbf{y}) - f(\mathbf{x})f(\mathbf{y}), \quad \mathbf{x}, \mathbf{y} \in \mathbb{R}^N, \quad (9)$$

³Even *factor copula models*, newly developed by e.g. Krupskii and Joe (2013) and Oh and Patton (2015), may not be suitable as they either assume specific parametric copulas, or lack closed-form density in general. These models further assume linear relationship between the random variables of interest and the common factors, which may or may not be true for the elements of $L = (LR_1(r_0), \dots, LR_N(r_0))$. The latter is impossible to verify in practice due to the single available observation on L , in contrast to the assumption of multifactor error structure for the process innovations u_{it} .

measures “local” MTP₂ for a distribution with density f . Denoting its average by

$$T_N = \int_{\mathbb{R}^2} \int_{\mathbb{R}^2} [f(\mathbf{x} \vee \mathbf{y})f(\mathbf{x} \wedge \mathbf{y}) - f(\mathbf{x})f(\mathbf{y})] dx_1 dx_2 \dots dx_N dy_1 dy_2 \dots dy_N, \quad (10)$$

he shows that τ_N , defined by (8), is a scaled version of T_N , bounded between $-\frac{1}{2^{N-1}}$ and 1. τ_N takes value 0 when the components of the random vector L are independent and achieves its upper bound under perfect positive dependence. A non-negative value of τ_N can thus be interpreted as an indicator that, on average,

$$f(\mathbf{x} \vee \mathbf{y})f(\mathbf{x} \wedge \mathbf{y}) - f(\mathbf{x})f(\mathbf{y}) \geq 0 \quad \text{for } \mathbf{x}, \mathbf{y} \in \mathbb{R}^N, \quad (11)$$

i.e. that the joint distribution of L satisfies the MTP₂ condition.

Although the true copula of L will be unknown in practice, if a sample of n independent observations on L were available, then an estimator $\hat{\tau}_N$ based on the empirical copula $\hat{C}_n(u)$ could be computed. The empirical copula has been introduced by Deheuvels (1979) and is given by the empirical distribution function of the sample of rank-transformed data:

$$\hat{C}_n(u_1, \dots, u_n) := \frac{1}{n} \sum_{j=1}^n \prod_{i=1}^N \mathbb{1}(\hat{U}_{ij,n} \leq u_i), \quad (12)$$

where $\mathbb{1}(\cdot)$ denotes the indicator function, $u = (u_1, \dots, u_N) \in [0, 1]^N$ and the pseudo-observations $\hat{U}_{ij,n}$ are estimated as

$$\hat{U}_{ij,n} = \frac{1}{n+1} (\text{rank of } LR_{ij}(r_0) \text{ in } LR_{i1}(r_0), \dots, LR_{in}(r_0)). \quad (13)$$

Using the expression for $\hat{C}_n(u)$ in (12), τ_N can be estimated as

$$\hat{\tau}_N = \frac{1}{2^{N-1} - 1} \left[\frac{2^N}{n^2} \sum_{j=1}^n \sum_{\substack{k=1 \\ k \neq j}}^n \prod_{i=1}^N \mathbb{1}(\hat{U}_{ij,n} \leq \hat{U}_{ik,n}) - 1 \right]. \quad (14)$$

Genest et al. (2011) show that $\hat{\tau}_N$ is asymptotically normally distributed around its true value τ_N and provide an expression for its finite-sample variance $\sigma_{\hat{\tau}_N}^2$:

$$\sigma_{\hat{\tau}_N}^2 = \left(\frac{2^{N-1}}{2^{N-1} - 1} \right)^2 \frac{2}{n(n-1)} [2(n-2)(Q - P^2) + P(1 - P)] \quad (15)$$

with

$$P = 2 \int_{[0,1]^N} C(u) dC(u), \quad (16)$$

$$Q = \int_{[0,1]^N} [C(u) + \bar{C}(u)]^2 dC(u), \quad (17)$$

where $\bar{C}(u)$ denotes the survival function of a random vector U with distribution $C(u)$. The estimators of P and Q in terms of the empirical copula can be computed as

$$\hat{P} = \frac{2}{n(n-1)} \sum_{j=1}^n \sum_{\substack{k=1 \\ k \neq j}}^n \prod_{i=1}^N \mathbb{1} \left(\hat{U}_{ij,n} \leq \hat{U}_{ik,n} \right), \quad (18)$$

$$\begin{aligned} \hat{Q} = \frac{1}{n^2(n-2)} & \left[\sum_{j=1}^n \sum_{k=1}^n \sum_{\substack{l=1 \\ l \neq j,k}}^n \prod_{i=1}^N \mathbb{1} \left(\hat{U}_{ij,n} \leq \hat{U}_{il,n}, \hat{U}_{ik,n} \leq \hat{U}_{il,n} \right) \right. \\ & + 2 \sum_{j=1}^n \sum_{k=1}^n \sum_{\substack{l=1 \\ l \neq j,k}}^n \prod_{i=1}^N \mathbb{1} \left(\hat{U}_{ij,n} \leq \hat{U}_{il,n}, \hat{U}_{ik,n} > \hat{U}_{il,n} \right) \\ & \left. + \sum_{j=1}^n \sum_{k=1}^n \sum_{\substack{l=1 \\ l \neq j,k}}^n \prod_{i=1}^N \mathbb{1} \left(\hat{U}_{ij,n} > \hat{U}_{il,n}, \hat{U}_{ik,n} > \hat{U}_{il,n} \right) \right]. \quad (19) \end{aligned}$$

These expressions enable us to evaluate the significance of the estimated $\hat{\tau}_N$ by means of the t -statistic $t_{\hat{\tau}_N} = \hat{\tau}_N / \hat{\sigma}_{\hat{\tau}_N}$.

In practice only a single observation on the vector L would be available, so computing $\hat{\tau}_N$ would not be feasible. Our aim, however, is rather to illustrate how common factors, despite heterogeneous and possibly negative factor loadings across cross-sections, induce non-negative dependence between the individual statistics as measured by $\hat{\tau}_N$. This would show that the multivariate distribution of L fulfils the MTP₂ condition, thus rendering the Simes' procedure valid for combining the individual cointegration rank tests in the panel setting. We therefore resort to simulation methods to generate samples of independent observations over L in different settings, from which we compute $\hat{\tau}_N$ and $t_{\hat{\tau}_N}$; details are provided in Section 3 below. When cross-sectional dependence between the panel units is present we expect to have a significantly positive $t_{\hat{\tau}_N}$ which would reject $H_0 : \tau_N \leq 0$, while in the absence of dependence we rather expect to get $\hat{\tau}_N$ insignificantly different from 0.

3 Simulation study

We first examine the finite-sample properties of the Simes' procedure employing the J and SL LR trace tests (henceforth Simes-J and Simes-SL, respectively), and then present results for the $t_{\hat{\tau}_N}$ statistics backing up the MTP₂ assumption.

With our empirical application to the monetary exchange rate model in mind, where common factors are present in the observed relative variables by construction, we introduce cross-sectional dependence in the panels by letting multiple common factors affect the innovations to the data generating process.

Preliminary simulations with other correlation structures, e.g. constant positive correlation or spatial-type correlation between the innovations, reveal a very similar picture and are not reported for brevity.

We employ a 3-variate VAR(1) Toda-type process (Toda, 1994, 1995) $Y_{it} = \mu_{0i} + \mu_{1i}t + X_{it}$ with $k = 2$ common factors in the errors:

$$X_{it} = \begin{pmatrix} \psi_{a,i} & 0 & 0 \\ 0 & \psi_{b,i} & 0 \\ 0 & 0 & 1 \end{pmatrix} X_{i,t-1} + u_{it}, \quad (20)$$

$$u_{it} = \lambda_i f_t + \varepsilon_{it}, \quad (21)$$

where $f_t \sim i.i.d. N(0, I_2)$, $\varepsilon_{it} \sim i.i.d. N(0, \Omega_i)$ and $\Omega_i = \begin{bmatrix} 0.47 & 0.20 & 0.18 \\ 0.20 & 0.32 & 0.27 \\ 0.18 & 0.27 & 0.30 \end{bmatrix}$.

The Toda process is frequently used in the literature for investigating the properties of LR cointegration rank tests as it provides an easy way to control the parameters governing the unit-root behaviour of the process (ψ_i). Although it itself is not cointegrated in the classical sense⁴, it is suitable for the task due to the invariance of the LR trace statistics to linear transformations of the type $Z_{it} = HX_{it}$ for a full-rank matrix H . The size of the panel tests is investigated when the true rank is $r = 0$ with $\psi_{a,i} = \psi_{b,i} = 1$ for all units, while power against $H_0 : r = 0$ is examined when the true rank is $r = 1$ with $\psi_{a,i} \sim i.i.d. U[0.7, 1]$ and $\psi_{b,i} = 1$, and against $H_0 : r = 1$ when $r = 2$ with $\psi_{a,i} \sim i.i.d. U[0.7, 1]$ and $\psi_{b,i} = 0.5$. The factor loadings λ_i are simulated as $(m \times k)$ matrices with (a) $i.i.d. U[-0.4, 0.4]$, (b) $i.i.d. U[0, 1]$, or (c) $i.i.d. U[-1, 3]$ entries for every cross-section; for cross-sectional independence we set $\lambda_i = 0, \forall i$.

Throughout we set $\mu_{0i} = \mu_{1i} = (0.2, 0.2, 0.2)', \forall i$; we allow for a linear trend both in the variables and in the cointegrating relations when computing the individual LR trace test statistics. The processes X_{it} are initialised with 0 and the first 30 observations are discarded to mitigate the effect of initial values. The p -values for the J and SL LR trace statistics are obtained by approximating their limiting distributions by gamma distributions as in Doornik (1998) and in Trenkler (2008), respectively. We consider all combinations of $T - 1 \in \{50, 100, 150, 200\}$ and $N \in \{5, 10, 20\}$. The simulations are carried out in GAUSS and the number of replications is 5000.

Table 1 presents the empirical size of the Simes-SL and Simes-J tests in the cases with cross-sectional dependence (a) – (c) and in the independence case. Although both panel tests appear slightly oversized for $T = 50$, we note that this is a consequence of the individual SL and J LR trace tests being size distorted for small T and relatively large systems, and that no size distortions arise due to cross-sectional dependence alone. The size results for the dependence cases are very similar across each other and match those for

⁴An m -dimensional process X_{it} is cointegrated as $CI(d, b)$ if all its elements are $I(d)$, and there exists at least one linear combination of them $\beta' X_{it}$ which is $I(d - b)$, $b > 0$ (Engle and Granger, 1987).

the cross-sectionally independent case. Overall, Simes-SL has slightly better size properties than Simes-J. In terms of power against $H_0 : r = 0$ when $r = 1^5$ (Table 2) both the Simes-SL and Simes-J tests exhibit substantial increase in power as N grows; both tests perform equally well for $T \geq 150$. The Simes-SL test outperforms the Simes-J test for $T = 100$ when no or only weak cross-sectional dependence (as in case (a)) is present; otherwise, for small T ($T = 50$) the Simes-J test performs better, perhaps due to its greater size. The increased power in the cross-sectional dependence cases compared to the independence case may be attributed to the stronger covariances in $\mathbb{E}(u_i u_i') = \Omega_i + \lambda_i \lambda_i'$, which are exploited by both LR tests.

We now turn to assessing the appropriateness of the MTP₂ assumption for the joint distribution of the individual LR trace statistics. Table 3 reports estimated $\hat{\tau}_N$ and their corresponding t -statistics for the simulated N -dimensional vectors L^J and L^{SL} of individual SL and J statistics, respectively, used within the Simes' procedure for $T - 1 \in \{100, 200\}$, $N \in \{5, 10, 20\}$ and $n = 1000$ replications under $H_0 : r = 0, \forall i$.⁶ Results with $T - 1 \in \{50, 150\}$ are qualitatively the same and available upon request.

As may be expected, greater (in absolute value) factor loadings induce a greater degree of positive dependence between the individual statistics, as measured by the estimated values $\hat{\tau}_N$, which are highest for cases with cross-sectional dependence (c) and closest to zero for the case of no dependence. The decreasing values of $\hat{\tau}_N$ over N for fixed T can be explained by its interpretation as a scaled probability of concordance (Nelsen, 1996) – the probability that the elements of an N -vector are all small or all large simultaneously diminishes as N grows. In the cases with cross-sectional dependence $\hat{\tau}_N$ is in general positive and the t -statistic – highly significant, while $\hat{\tau}_N$ is insignificantly different from 0 in most cases where there is no cross-sectional dependence.

An illustration of this point is provided by Figures 1 and 2. Figure 1 presents the estimates of τ_N under $H_0 : r = 0$ for a DGP with constant correlation ρ_ε between the panel units. This process is a modification of the DGP (20), such that $u_{it} \equiv \varepsilon_{it}$. The $(Nm \times 1)$ vector of innovations $\varepsilon_t = (\varepsilon'_{1t}, \dots, \varepsilon'_{Nt})'$ is simulated as $\varepsilon_t \sim i.i.d.N(\mathbf{0}, \Sigma)$ with $\Sigma = \rho_\varepsilon I \otimes \Omega_i, \forall t$, where \otimes denotes the Kronecker product. We note that $\rho_\varepsilon \geq -\frac{1}{N-1}$ in order for Σ to be positive definite. In Figure 1 $\hat{\tau}_N$ remains non-negative even for negative values of ρ_ε . The same observation holds for the graphs in Figure 2, which present the estimated $\hat{\tau}_N$ for DGP (20) with multifactor error structure and various factor loadings under $H_0 : r = r_0$ for $r_0 = 0, 1, 2$. Hence the non-negative average MTP₂-dependence between the individual LR test statistics

⁵Results for power against $H_0 : r = 1$ when $r = 2$ are similar and not reported for brevity. They are available upon request.

⁶It turns out that $n = 1000$ replications are enough for a good approximation of the empirical distribution function of the vectors L^J and L^{SL} in order to illustrate our point. We refrain from using a higher number of replications to avoid precision issues in the computation of $\hat{\sigma}_{\hat{\tau}_N}^2$ in the cross-sectional independence case. Results with $n \in \{100, 200, 500\}$ reveal a similar picture, with estimates of τ_N of the same magnitude, but with t -statistics generally smaller in absolute value due to the larger estimated variance. These results are available upon request.

is present regardless of the null hypothesis under investigation.

In order to evaluate how well $\hat{\sigma}_{\hat{\tau}_N}$, computed in terms of \hat{P} and \hat{Q} (eqs. (18) and (19)), approximates the true variance of $\hat{\tau}_N$, we have computed the t -statistics for the cross-sectionally independent case using the expression for $\sigma_{\hat{\tau}_N}$ in the special case of the independence copula derived by Genest et al. (2011, p. 164):

$$\sigma_{\tau_N}^{2,ind} = \frac{n(2^{2N+1} + 2^{N+1} - 4 \times 3^N) + 3^N(2^N + 6) - 2^{N+2}(2^N + 1)}{3^N(2^{N-1} - 1)^2 n(n-1)}. \quad (22)$$

As the lowest panel of Table 3 shows, the t -statistics computed with $\sigma_{\tau_N}^{ind}$ are quite similar to those computed with $\hat{\sigma}_{\hat{\tau}_N}$, despite some discrepancies when $\hat{\tau}_N$ is negative, which increase with the absolute value of $\hat{\tau}_N$.

To summarise, these findings corroborate our conjecture that the MTP₂ condition is met for the multivariate distribution of the individual LR trace statistics when the variables in the panel are influenced by unobserved common factors.

4 The monetary exchange rate model

In this section we apply the Simes-SL and the Simes-J tests to assess the validity of the monetary exchange rate model in the post-Bretton Woods era. The model postulates a stationary long-term relationship between nominal exchange rate and monetary fundamentals, assuming that the purchasing power parity and the uncovered interest rate parity hold. The empirical evidence whether the monetary exchange rate model holds in practice is rather mixed. For example, Rapach and Wohar (2002) find only limited support for the model on a country-by-country basis for 14 industrialized countries, while using panel error-correction-based techniques Dąbrowski et al. (2014) report evidence of cointegration in a recent panel of 8 central and eastern European countries.

In our study we follow Dąbrowski et al. (2014) and define the testable equation of the model as

$$s_{it} = d_{it} + \beta_{i1}(m_{it} - m_{it}^*) + \beta_{i2}(y_{it} - y_t^*) + \beta_{i3}[(p_{it} - p_{it}^T) - (p_t^* - p_t^{T*})] + u_{it}, \quad (23)$$

where s_{it} is nominal exchange rate between country i and the numéraire country, m_{it} is nominal money supply, y_{it} is real output, p_{it} and p_{it}^T are domestic general and tradable goods price levels respectively, and d_{it} is a country-specific deterministic term. The asterisk symbol denotes the corresponding quantities for the numéraire country, which in our study is the USA. All variables are taken in natural logarithms. The price level of non-tradables for country i , approximated by $(p_{it} - p_{it}^T)$, is included in the model to mitigate possible Balassa-Samuelson effects.

We employ monthly data in the period 1995/01 – 2007/12 ($T = 156$) for 8 OECD countries: Canada, Denmark, Japan, Korea, Norway, Sweden, Switzerland and the UK; a brief description of the data is given in Table 4. As monthly

GDP figures are unavailable, national income y_{it} has been approximated by the industrial production index (IPI). Unlike other studies, we refrain from including Eurozone countries in our analysis due to their adoption of a common currency in 1999 or later. The sample window is restricted by the data availability in order to obtain a balanced panel: the IPI series for Switzerland start in 1995/01 and end in 2007/12, along with the producer price index series for Norway.

Before testing for cointegration, all four relative variables in (23) are tested for nonstationarity in levels and in first differences using panel unit root tests. We employ Pesaran's (2007) simple panel unit root test and Breitung and Das' (2005) panel unit root test, both of which are robust to cross-sectional dependence.⁷ With only two exceptions for relative output, which is rather classified as trend-stationary when a small lag order (2 or less) is chosen,⁸ and for exchange rate at lags 2 and 3 according to Pesaran's (2007) test, there is predominant evidence in favour of the unit root null hypothesis. Therefore we proceed with the cointegration analysis assuming that the relative variables are $I(1)$.

In order to assess the appropriateness of the common factor structure for capturing the cross-sectional dependence of the series, we follow Banerjee and Carrion-i Silvestre (2015) and look at the average cross-sectional correlation coefficient $\hat{\rho}$ before and after extracting common factors by principal components. We compute $\hat{\rho}$ from the panel of residuals from the individual 4-variate VAR models under $H_0 : r = 0$ ⁹. From a maximum number of six common factors, the criterion of Onatski (2010) selects three, which together account for 37.6% of the total variance of the standardized residuals. To assess the significance of the estimated $\hat{\rho}$, we employ the CD test for weak cross-sectional dependence of Pesaran (2015). We note that we have modified the computation of the CD statistic to fit the current multivariate setting excluding correlations between the residuals within the same individual units as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)m^2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \sum_{k=1}^m \sum_{l=1}^m \hat{\rho}_{ij,kl}.$$

Here $\hat{\rho}_{ij,kl}$ is the estimated sample correlation of the residuals corresponding to the k -th variable in unit i and the l -th variable in unit j , where $k, l = 1, \dots, m$, $i, j = 1, \dots, N$.

The results are summarised in Table 5. While the CD statistic is highly significant before extracting common factors, it becomes insignificant at the 5% level after extracting two or three factors. This leads us to conclude that the multifactor error structure with two or three factors adequately captures the cross-sectional dependence in the panel.

⁷We have used their implementations in `pescadf` by Piotr Lewandowski and `xtunitroot` in Stata. Unit root test results are available upon request.

⁸Trend in relative output is visible only for Korea, Norway and the UK.

⁹ $H_0 : r = 0$ is the starting point in the sequential rank testing procedures of Johansen (1995) and Saikkonen and Lütkepohl (2000).

Finally, Table 6 presents the results of the Simes-SL and Simes-J tests. Both reject $H_0 : r = 0$ at the 5% level (that is, at least one p -value satisfies condition (5)), but neither rejects $H_0 : r = 1$ (when the corresponding p -values would be in ascending order). Hence both tests point to the existence of a single cointegrating relationship between the nominal exchange rate and the macroeconomic fundamentals at the panel level.

5 Conclusion

In this paper we employ Simes' (1986) p -values intersection procedure to propose a new and computationally simple likelihood-based panel cointegration rank test. A crucial assumption for the validity of the intersection test when the individual test statistics are dependent is that their multivariate distribution should be *multivariate totally positive of order 2*.

Following Nelsen (1996), we adopt a multivariate version of Kendall's tau (τ_N) as a measure for the suitability of the MTP₂ assumption. Estimating τ_N by means of the empirical copula, in our Monte Carlo study we show that the MTP₂ condition is met in panels where the dependence is driven by unobserved common factors – an assumption which is commonly made in applied work. The simulation study as well demonstrates that the new panel rank testing procedure is robust to cross-sectional dependence and exhibits good size and power in finite samples. These properties, along with its simple computation, make the intersection panel cointegration rank test an attractive tool for empirical analysis.

As an application, we employ the intersection test to explore the validity of the monetary exchange rate model for eight OECD countries. Implementations of the test with both Johansen's (1995) and Saikkonen and Lütkepohl's (2000) individual LR trace tests point to the existence of a single cointegrating relationship between the nominal exchange rate and macroeconomic fundamentals at the panel level.

Table 1: Empirical size of Simes-SL and Simes-J LR trace tests, true rank $r = 0$, $\forall i = 1, \dots, N$

$T \backslash N$	Simes-SL test				Simes-J test			
	1	5	10	20	1	5	10	20
Cross-sectional dependence (a): $\lambda_i \sim i.i.d. U[-0.4, 0.4]$								
50	0.056	0.066	0.074	0.078	0.070	0.079	0.090	0.104
100	0.054	0.062	0.061	0.071	0.062	0.066	0.067	0.073
150	0.062	0.066	0.059	0.068	0.058	0.064	0.064	0.066
200	0.053	0.057	0.066	0.069	0.060	0.055	0.063	0.070
Cross-sectional dependence (b): $\lambda_i \sim i.i.d. U[0, 1]$								
50	0.056	0.072	0.073	0.079	0.068	0.081	0.091	0.095
100	0.055	0.063	0.063	0.074	0.066	0.066	0.070	0.072
150	0.051	0.058	0.064	0.068	0.055	0.062	0.069	0.072
200	0.055	0.053	0.063	0.068	0.060	0.060	0.061	0.068
Cross-sectional dependence (c): $\lambda_i \sim i.i.d. U[-1, 3]$								
50	0.060	0.067	0.068	0.062	0.070	0.076	0.074	0.084
100	0.058	0.061	0.056	0.065	0.063	0.064	0.065	0.066
150	0.054	0.061	0.059	0.059	0.057	0.056	0.059	0.058
200	0.056	0.054	0.057	0.063	0.059	0.059	0.060	0.054
Cross-sectional independence								
50	0.056	0.070	0.074	0.082	0.072	0.087	0.095	0.106
100	0.057	0.061	0.067	0.065	0.062	0.067	0.071	0.077
150	0.056	0.061	0.069	0.070	0.060	0.062	0.069	0.072
200	0.056	0.055	0.061	0.068	0.053	0.065	0.071	0.067

Notes: Rejection frequencies at 5% significance level.

Table 2: Empirical power of Simes-SL and Simes-J LR trace tests against $H_0 : r = 0$, true rank $r = 1$, $\forall i$

$T \backslash N$	Simes-SL test				Simes-J test			
	1	5	10	20	1	5	10	20
Cross-sectional dependence (a): $\lambda_i \sim i.i.d. U[-0.4, 0.4]$								
50	0.109	0.156	0.178	0.211	0.110	0.168	0.183	0.220
100	0.273	0.475	0.591	0.713	0.262	0.455	0.560	0.679
150	0.437	0.787	0.924	0.983	0.436	0.783	0.910	0.980
200	0.554	0.926	0.990	1.000	0.562	0.934	0.992	1.000
Cross-sectional dependence (b): $\lambda_i \sim i.i.d. U[0, 1]$								
50	0.204	0.361	0.461	0.568	0.216	0.393	0.494	0.601
100	0.452	0.820	0.930	0.977	0.468	0.850	0.952	0.991
150	0.604	0.956	0.993	1.000	0.623	0.965	0.998	1.000
200	0.711	0.987	1.000	1.000	0.728	0.992	1.000	1.000
Cross-sectional dependence (c): $\lambda_i \sim i.i.d. U[-1, 3]$								
50	0.369	0.739	0.882	0.958	0.418	0.817	0.938	0.991
100	0.597	0.960	0.995	0.999	0.622	0.972	0.999	1.000
150	0.715	0.992	1.000	1.000	0.738	0.994	1.000	1.000
200	0.786	0.996	1.000	1.000	0.801	0.999	1.000	1.000
Cross-sectional independence								
50	0.111	0.153	0.181	0.201	0.121	0.169	0.196	0.231
100	0.269	0.473	0.596	0.725	0.252	0.453	0.547	0.667
150	0.434	0.798	0.926	0.985	0.443	0.791	0.920	0.982
200	0.552	0.930	0.991	0.999	0.564	0.940	0.992	1.000

Notes: Rejection frequencies at 5% significance level.

Table 3: Empirical estimates of $\hat{\tau}_N$ for the Simes-SL and Simes-J tests under $H_0 : r = 0$, true rank $r = 0$, $\forall i$

$T \backslash N$	Simes-SL test			Simes-J test		
	5	10	20	5	10	20
Cross-sectional dependence (a): $\lambda_i \sim i.i.d. U[-0.4, 0.4]$						
100	0.015	0.001	0.000	0.019	0.004	0.000
	(2.66)	(2.41)	(1.03)	(3.49)	(4.44)	(1.93)
200	0.013	0.001	0.000	0.028	0.002	0.000
	(2.33)	(2.62)	(0.72)	(4.61)	(2.93)	(2.17)
Cross-sectional dependence (b): $\lambda_i \sim i.i.d. U[0, 1]$						
100	0.036	0.007	0.000	0.049	0.016	0.001
	(5.66)	(5.39)	(2.81)	(7.43)	(7.14)	(4.04)
200	0.027	0.005	0.000	0.053	0.009	0.001
	(4.51)	(5.10)	(3.20)	(7.37)	(6.25)	(3.22)
Cross-sectional dependence (c): $\lambda_i \sim i.i.d. U[-1, 3]$						
100	0.107	0.048	0.009	0.143	0.072	0.020
	(12.30)	(9.76)	(6.62)	(14.6)	(12.3)	(7.76)
200	0.135	0.039	0.010	0.162	0.068	0.021
	(14.6)	(10.8)	(6.43)	(15.8)	(13.4)	(7.68)
Cross-sectional independence						
100	0.007	-0.001	0.000	0.002	0.000	0.000
	(1.48)	(-3.61)	($-\infty$)	(0.41)	(0.24)	(0.03)
	[1.60]	[-2.02]	[-0.81]	[0.43]	[0.26]	[0.03]
200	-0.007	0.000	0.000	0.011	0.000	0.000
	(-1.48)	(-1.56)	(0.03)	(2.07)	(-0.28)	(0.03)
	[-1.42]	[-1.10]	[0.03]	[2.33]	[-0.27]	[0.03]

Notes: t -statistics computed as $\hat{\tau}/\hat{\sigma}_{\hat{\tau}_N}$ shown in parentheses.

t -statistics computed as $\hat{\tau}/\sigma_{\tau_N}^{ind}$ shown in square brackets.

Figure 1: Estimated $\hat{\tau}_N$ for the vector of LR trace statistics for DGP with equal correlation between the innovations of the individual units ρ_ε , $T = 100$, $n = 1000$ replications under $H_0 : r = 0$

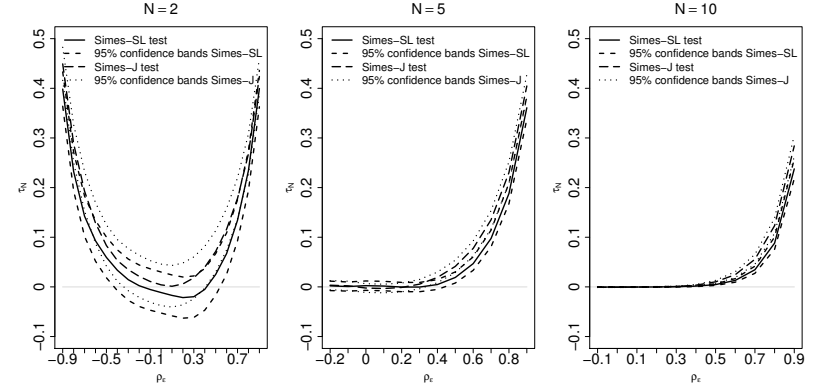


Figure 2: Estimated $\hat{\tau}_N$ for the vector of LR trace statistics for DGP (20) with multifactor error structure under the true null hypothesis $H_0 : r = r_0$, $T = 100$, $N = 10$, $n = 1000$ with factor loadings $\lambda_i \sim i.i.d. U[-k, k]$

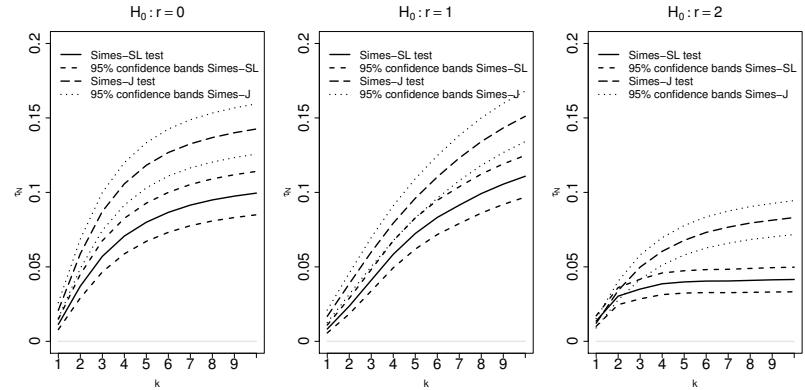


Table 4: Data description

Variable	Description	Source
s	Nominal exchange rate per 1 USD; end-of-period	IMF IFS
y	Industrial production index	
p	Consumer price index	
p^T	Producer price index	
m	M2 for Switzerland, UK and US	OECD
	M2+ for Canada, M1 for Denmark, M3 for Sweden	Macrobond
	M2 for Norway and Korea	
	Monetary base for Japan	Bank of Japan

Table 5: Average cross-sectional correlation coefficient and Pesaran's (2015) CD statistic before and after extracting common factors from estimated residuals of individual VAR models under $H_0 : r = 0$

	k	Avg. corr. coef. $\hat{\rho}$	CD statistic	% expl. variance	Cum. % expl. variance
Before extracting factors		0.066	17.17	—	—
After	1	0.096	24.86	0.18	0.18
extracting	2	−0.001	−0.24	0.12	0.29
k factors	3	−0.001	−0.32	0.08	0.38

Notes: The CD statistic has a $N(0, 1)$ distribution under the null hypothesis of weak cross-sectional dependence.

Table 6: Simes-SL and Simes-J panel cointegration tests

Country	\hat{p}_i^{AIC}	Det. terms	$LR_{r=0}$	p -value	$LR_{r=1}$	p -value	Simes' sign. level	
							5 %	10%
Simes-SL test								
Canada	2	trend	71.11	0.000**	28.88	0.045	0.006	0.013
Switzerland	1	trend	57.04	0.002**	14.30	0.812	0.013	0.025
Denmark	3	const	43.60	0.020*	15.82	0.400	0.019	0.038
Korea	4	trend	47.57	0.029*	29.35	0.039	0.025	0.050
Japan	2	trend	45.64	0.046*	20.24	0.376	0.031	0.063
Norway	5	trend	42.09	0.104	17.01	0.619	0.038	0.075
Sweden	3	const	35.16	0.148	16.63	0.342	0.044	0.088
UK	2	trend	39.81	0.164	17.64	0.570	0.050	0.100
Simes-J test								
Canada	2	trend	95.08	0.000**	44.73	0.031	0.006	0.013
Switzerland	1	trend	85.68	0.000**	32.99	0.342	0.013	0.025
Denmark	3	const	60.57	0.011**	24.71	0.423	0.019	0.038
Korea	4	trend	68.97	0.016**	42.51	0.053	0.025	0.050
Norway	5	trend	57.62	0.150	29.18	0.557	0.031	0.063
Japan	2	trend	56.95	0.167	31.91	0.400	0.038	0.075
UK	2	trend	55.91	0.195	33.91	0.297	0.044	0.088
Sweden	3	const	42.87	0.339	22.21	0.585	0.050	0.100

Notes: ** and * denote significance at the corresponding Simes' 5% and 10% nominal levels, respectively.

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