

Jean-Pierre Urbain, Joakim Westerlund

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Maastricht research school of **E**conomics
of **T**Echnology and **O**Rganizations

Universiteit Maastricht
Faculty of Economics and Business Administration
P.O. Box 616
NL - 6200 MD Maastricht

phone : ++31 43 388 3830
fax : ++31 43 388 4873

Spurious Regression in Nonstationary Panels with Cross-Unit Cointegration*

Jean-Pierre Urbain[†] and Joakim Westerlund[‡]

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Abstract

This paper illustrates analytically the effects of cross-unit cointegration using as an example the conventional pooled least squares estimate in the spurious panel regression case. The results suggest that the usual result of asymptotic normality depends critically on the absence of cross-unit cointegration.

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1 Introduction

The use of nonstationary panel data techniques to infer both spurious and cointegrated regressions has basically exploded during the last couple of years. The main reason for this being the more powerful and straightforward asymptotic results based on pooling across a large cross-section of independent units. In fact, as shown by Phillips and Moon (1999), since this independence effectively works by smoothing out the usual unit root dependency for each unit, normal inference is usually possible, even in the usually so difficult spurious regression case.

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[†]Corresponding author: Department of Quantitative Economics, Universiteit Maastricht, P.O. Box 616, 6200 MD Maastricht, The Netherlands. Telephone: +31 43 388 3660; Fax: +31 43 388 48 74; E-mail address: j.urbain@ke.unimaas.nl

[‡]Department of Economics, Lund University, P.O.Box 7082, S-220 07 Lund, Sweden. Telephone: +46 46 222 8670; Fax: +46 46 222 4118; E-mail address: joakim.westerlund@nek.lu.se.

However, as argued by Banerjee *et al.* (2006), assuming independence in this way is usually not warranted, especially when considering macroeconomic or financial data with strong intra-economic linkages. In particular, by using simulation methods, they show that the presence of cross-unit cointegration, a reasonable assumption in most applications, can have quite drastic effects on inference.

In this paper, we complement analytically the simulation results of Banerjee *et al.* (2006) taking as an example the pooled least squares slope estimator in the simple bivariate case.¹ We consider two possibilities, one is when the cointegration occurs across the whole panel, while the other is when the cointegration occurs within groups that are otherwise independent of each other, which seems like a reasonable scenario when studying for example convergence clubs. In both cases, it is shown that the presence of cross-unit cointegration in both the dependent and independent variables leads to statistics that diverge with the size of the cross-section. On the other hand, if at least one of the variables does not cointegrate across units, then normality is again possible, with the center of the distribution located at the long-run average regression coefficient. For the case with cointegration within groups, this naturally leads to the definition of a long-run average group coefficient.

The next two sections present our main findings, while Section 4 concludes. All proofs are relegated to the appendix.

2 Panel common unit roots

Suppose that y_{it} and x_{it} are two a scalar variables such that

$$x_{it} = \lambda_{xi}f_{xt} + \delta_{xi}e_{xit} + u_{xit} \quad \text{and} \quad y_{it} = \lambda_{yi}f_{yt} + \delta_{yi}e_{yit} + u_{yit}, \quad (1)$$

where $t = 1, \dots, T$ and $i = 1, \dots, N$ indexes the time series and cross-sectional units, respectively. Note that while the first term on the right-hand side of these equations are common across i , the second is not. The parameters λ_{xi} , δ_{xi} , λ_{yi} and δ_{yi} are assumed to be mutually independent, and randomly distributed across i with expected values λ_x , δ_x , λ_y and δ_y , respectively. We further assume that the disturbances u_{xit} and u_{yit} are stationary processes, while the remaining right-hand side variables in (1) are pure unit root processes that satisfy the following invariance principles as $T \rightarrow \infty$ for each i

$$\frac{1}{\sqrt{T}} \begin{bmatrix} f_{xt} \\ f_{yt} \end{bmatrix} \Rightarrow \begin{bmatrix} B_x \\ B_y \end{bmatrix} \quad \text{and} \quad \frac{1}{\sqrt{T}} \begin{bmatrix} e_{xit} \\ e_{yit} \end{bmatrix} \Rightarrow \begin{bmatrix} B_{xi} \\ B_{yi} \end{bmatrix},$$

where \Rightarrow signifies weak convergence. The vectors of common and idiosyncratic Brownian motions, B and B_i say, are assumed to be independent with covariance matrices Ω^f and Ω_i^e , respectively, where Ω_i^e is a random matrix with expectation

¹This work is related to that of Gengenbach *et al.* (2006). However, while they focus specifically on the case when testing for cointegration, our focus is more conceptual, and our interest in the least squares slope estimate is just for illustration.

Ω^e . All variables and random parameters indexed by i are independent along the cross-sectional dimension.

Although very simple, as we shall see, this data generating process yields significant insight. In particular, note how (1) nests a variety of spurious regression cases both with and without cross-unit cointegration, depending on the values taken by λ_{xi} , δ_{xi} , λ_{yi} and δ_{yi} .² In fact, it is not difficult to see that (1) is actually a system of two Bai and Ng (2004) factor models, one for x_{it} and one for y_{it} . Define

$$\widehat{\beta} = \left(\sum_{i=1}^N \sum_{t=1}^T x_{it} y_{it} \right) / \left(\sum_{i=1}^N \sum_{t=1}^T x_{it}^2 \right).$$

The objective of this paper is to show how $\widehat{\beta}$, the conventional pooled least squares slope estimator in a regression of y_{it} on x_{it} , behaves in this context.

Let us define the following two quantities

$$\begin{aligned} Q_{xx} &= \lambda_x^2 \left(\int B_x^2 \right) + \frac{1}{2} \delta_x^2 \Omega_{xx}^e, \\ U_{xy} &= \frac{1}{6} \left(\lambda_x^2 \delta_y^2 \Omega_{xx}^f \Omega_{yy}^e + \lambda_y^2 \delta_x^2 \Omega_{yy}^f \Omega_{xx}^e + \delta_y^2 \delta_x^2 \Omega_{yy}^e \Omega_{xx}^e \right) \\ &\quad + \frac{1}{2} \lambda_y \lambda_x \delta_y \delta_x \Omega_{xy}^f \Omega_{xy}^e. \end{aligned}$$

Given Q_{xx} and U_{xy} , if we let \rightarrow_p signify convergence in probability, then the asymptotic distribution of $\widehat{\beta}$ can be summarized in the following way.

Theorem 1. Under the assumptions laid out above, as $N, T \rightarrow \infty$

$$\begin{aligned} \text{(a)} \quad \widehat{\beta} &\rightarrow_p \frac{1}{Q_{xx}} \left(\lambda_y \lambda_x \int B_y B_x + \frac{1}{2} \delta_x \delta_y \Omega_{xy}^e \right) \\ \text{(b)} \quad \sqrt{N} \widehat{\beta} - \sqrt{N} \frac{1}{Q_{xx}} \left(\lambda_y \lambda_x \int B_y B_x + \frac{1}{2} \delta_x \delta_y \Omega_{xy}^e \right) &\Rightarrow N \left(0, \frac{1}{Q_{xx}^2} U_{xy} \right) \end{aligned}$$

Note how Theorem 1 expresses the asymptotic distribution of $\widehat{\beta}$ in terms of the parameters of (1). This is very instructive.

Firstly, note that the mean of the distribution depends critically on the common components of x_{it} and y_{it} . In particular, note that if λ_x is zero, so that only y_{it} has a common component, then $\sqrt{N} \widehat{\beta}$ converges to a normal variate with mean $\delta_y \Omega_{xy}^e / \delta_x \Omega_{xx}^e$, which is the long-run average regression coefficient derived by Phillips and Moon (1999) in the cross-sectionally independent case. On the other hand, if λ_x and λ_y are both nonzero, then $\widehat{\beta}$ is no longer consistent for $\delta_y \Omega_{xy}^e / \delta_x \Omega_{xx}^e$, and in fact diverges as N grows. This suggests that much of the empirical work based on the pooled least squares estimator in nonstationary panel data with a possible common factor structure needs to be reevaluated, see for example Coakley *et al.* (2005).

²The case with cointegration between y_{it} and x_{it} at is also covered, and amounts for example to setting λ_{xi} and λ_{yi} to zero for all i while imposing equality or proportionality of the idiosyncratic unit roots e_{xit} and e_{yit} .

This clearly illustrates the importance of the common components, both for inferential and cointegration testing purposes. For example, with both y_{it} and x_{it} affected, the asymptotic distribution of $\sqrt{N}\widehat{\beta}$ is no longer normal, but dependent on Brownian motion, which makes it look more like something that one would expect to see in the conventional time series case. Similarly, it is not difficult to see how tests for the absence of cointegration based on the consistency of $\widehat{\beta}$, such as those of Kao (1999), become invalid in this case.

Secondly, the variance of the asymptotic distribution of $\sqrt{N}\widehat{\beta}$ depends on both the idiosyncratic and common components. However, note that if there are no common components, then the variance reduces to $2\delta_y^2\Omega_{yy}^e/3$, which is likely to be smaller than for the case with common components, and it is definitely smaller than $2(\lambda_y^2\Omega_{yy}^f + \delta_y^2\Omega_{yy}^e)/3$, the variance when λ_x is zero. Hence, the presence of the common components affects the asymptotic distribution of $\sqrt{N}\widehat{\beta}$ by increasing its variance.

3 Group specific unit roots

Next, we examine the case with group specific common unit roots. Specifically, suppose that there are M groups with K units in each, and let f_{xjt} be the common unit root component of x_{it} for group $j = 1, \dots, K$ containing the units $i = 1 + (j - 1)K, \dots, jK$. The group specific common component of y_{it} is constructed in the same way, and is denoted f_{yjt} . Let B_{xj} and B_{yj} be the Brownian motions associated with f_{xjt} and f_{yjt} , and assume that these have covariance Ω_j^f and that they are independent across j .

In view of Theorem 1, it is not difficult to see that as $N, T \rightarrow \infty$ with M fixed

$$\widehat{\beta} \rightarrow_p \left(\lambda_y \lambda_x \frac{1}{M} \sum_{j=1}^M \int B_{yj} B_{xj} + \frac{1}{2} \delta_x \delta_y \Omega_{xy}^e \right) / \left(\lambda_x^2 \frac{1}{M} \sum_{j=1}^M \int B_{xj}^2 + \frac{1}{2} \delta_x^2 \Omega_{xx}^e \right).$$

By contrast, if M is permitted to grow with N , then we get

$$\widehat{\beta} \rightarrow_p \left(\lambda_y \lambda_x \Omega_{xy}^f + \delta_x \delta_y \Omega_{xy}^e \right) / \left(\lambda_x^2 \Omega_{xx}^f + \delta_x^2 \Omega_{xx}^e \right),$$

where Ω^f is the expected value of Ω_j^f . This second result is very interesting. Specifically, suppose that δ_x is zero so that x_{it} has no idiosyncratic unit root, then the probability limit of $\widehat{\beta}$ reduces to $\lambda_y \Omega_{xy}^f / \lambda_x \Omega_{xx}^f$, which might be thought of as a long-run average group coefficient. Thus, if the number of groups are permitted to grow with N , then we end up with something that is very similar to what we had earlier in the case with panel common unit roots. This seems very reasonable since in this case the group essentially takes the role of the individual unit. Moreover, as in Section 2, it is possible to show that if M is permitted to grow with N and T , then $\sqrt{N}\widehat{\beta}$ is asymptotically normal.

4 Concluding remarks

It is now well-known that the conventional assumption of independent cross-sections is very hard to maintain when conducting inference in nonstationary panels.

In this paper, we study the effects of cross-unit cointegration taking as an example the pooled least squares estimator in the spurious regression case. We consider both the case when the cointegration takes place across the panel as a whole, and when it takes place within groups. Our findings suggest that the presence of cross-unit cointegration can have dramatic effects for the usual asymptotic results based on cross-section independence, and that the consistency and asymptotic normality of the pooled least squares estimator may even be lost. These results have important implications, not only for theoretical, but also for applied work. Take for example the study of Coakley *et al.* (2005), in which the authors seek to infer purchasing power parity using pooled least squares methods in the presence of common factors. Our results indicate that this type of analysis can be potentially very deceptive.

As a final note, although the simplicity of the data generating process used in this paper naturally raises some concerns, we would like to stress that most assumptions are only for ease of exposure, and can in principle be relaxed without affecting the main conclusions. For example, it can be easily generalized to accommodate deterministic intercept, trend terms and additional dynamics.

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Mathematical appendix

In this appendix, Theorem 1 is proven. For brevity, only necessary details are provided. Unreported results can be obtained from the corresponding author upon request.

Proof of Theorem 1.

Consider (a). The least squares estimator of β can be written as

$$\sqrt{N}\hat{\beta} = \left(\frac{1}{NT^2} \sum_{i=1}^N \sum_{t=1}^T x_{it}^2 \right)^{-1} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T x_{it} y_{it}. \quad (\text{A1})$$

Consider the denominator, whose limit as $N, T \rightarrow \infty$ is given by

$$\begin{aligned} \frac{1}{NT^2} \sum_{i=1}^N \sum_{t=1}^T x_{it}^2 &= \lambda_{xi}^2 \frac{1}{T^2} \sum_{t=1}^T f_{xt}^2 + \delta_{xi}^2 \frac{1}{NT^2} \sum_{i=1}^N \sum_{t=1}^T e_{xit}^2 \\ &+ 2\lambda_{xi}\delta_{xi} \frac{1}{NT^2} \sum_{i=1}^N \sum_{t=1}^T f_{xt} e_{xit} + O_p(T^{-1}) \\ &\rightarrow_p \lambda_x^2 \left(\int B_x^2 \right) + \delta_x^2 E \left(\int B_{ix}^2 \right) + 2\lambda_x \delta_x E \left(\int B_x B_{ix} \right) \\ &= \lambda_x^2 \left(\int B_x^2 \right) + \frac{1}{2} \delta_x^2 \Omega_{xx}^e, \end{aligned} \quad (\text{A2})$$

where the last equality follows from the independence of B_x and B_{ix} , and the moments of Brownian motion.

Similarly, for the numerator, we have

$$\begin{aligned} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T x_{it} y_{it} &= \sqrt{N} \lambda_{xi} \lambda_{yi} \frac{1}{T^2} \sum_{t=1}^T f_{xt} f_{yt} + \lambda_{xi} \delta_{yi} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T f_{xt} e_{yit} \\ &+ \lambda_{yi} \delta_{xi} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T f_{yt} e_{xit} \\ &+ \delta_{yi} \delta_{xi} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T e_{yit} e_{xit} + O_p(T^{-1}), \end{aligned} \quad (\text{A3})$$

which has the following limit as $T \rightarrow \infty$

$$\begin{aligned} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T x_{it} y_{it} &\Rightarrow \sqrt{N} \left(\lambda_{xi} \lambda_{yi} \int B_x B_y \right) \\ &+ \frac{1}{\sqrt{N}} \sum_{i=1}^N \left(\lambda_{xi} \delta_{yi} \int B_x B_{yi} + \lambda_{yi} \delta_{xi} \int B_y B_{xi} + \delta_{yi} \delta_{xi} \int B_{yi} B_{xi} \right) \\ &= \sqrt{N} \left(\lambda_{xi} \lambda_{yi} \int B_x B_y \right) + \frac{1}{\sqrt{N}} \sum_{i=1}^N U_i, \text{ say.} \end{aligned} \quad (\text{A4})$$

Thus, passing $N \rightarrow \infty$, it is clear that

$$\frac{1}{NT^2} \sum_{i=1}^N \sum_{t=1}^T x_{it} y_{it} - \left(\lambda_x \lambda_y \int B_x B_y \right) = \frac{1}{N} \sum_{i=1}^N U_i \xrightarrow{p} \frac{1}{2} \delta_x \delta_y \Omega_{xy}^e.$$

This establishes (a).

Next, consider (b). By using (a) and the Lindberg-Lévy theorem, as $N, T \rightarrow \infty$

$$\begin{aligned} \frac{1}{\sqrt{NT^2}} \sum_{i=1}^N \sum_{t=1}^T x_{it} y_{it} - \sqrt{N} \left(\lambda_x \lambda_y \int B_x B_y + \frac{1}{2} \delta_x \delta_y \Omega_{xy}^e \right) \\ \Rightarrow N \left(0, \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N E(U_i^2) \right). \end{aligned}$$

For the variance, we have

$$\begin{aligned} E(U_i^2) &= E \left(\left(\lambda_x \delta_y \int B_x B_{yi} + \lambda_y \delta_x \int B_y B_{xi} + \delta_y \delta_x \int B_{yi} B_{xi} \right)^2 \right) \\ &= \lambda_x^2 \delta_y^2 E \left(\int B_x B_{yi} \right)^2 + \lambda_y^2 \delta_x^2 E \left(\int B_y B_{xi} \right)^2 + \delta_y^2 \delta_x^2 E \left(\int B_{yi} B_{xi} \right)^2 \\ &\quad + 2 \lambda_y \lambda_x \delta_y \delta_x E \left(\int B_x B_{yi} \right) \left(\int B_{xi} B_y \right) \\ &= \frac{1}{6} \left(\lambda_x^2 \delta_y^2 \Omega_{xx}^f \Omega_{yy}^e + \lambda_y^2 \delta_x^2 \Omega_{yy}^f \Omega_{xx}^e + \delta_y^2 \delta_x^2 \Omega_{yy}^e \Omega_{xx}^e \right) \\ &\quad + \frac{1}{2} \lambda_y \lambda_x \delta_y \delta_x \Omega_{xy}^f \Omega_{xy}^e. \end{aligned} \tag{A5}$$

where the second equality follows from the fact that all cross-products except the squared ones have expectation zero, while the second follows from the moments of Brownian motion.

Putting everything together, we obtain

$$\sqrt{N} \hat{\beta} - \sqrt{N} \frac{1}{Q_{xx}} \left(\lambda_x \lambda_y \int B_x B_y + \frac{1}{2} \delta_x \delta_y \Omega_{xy}^e \right) \Rightarrow N \left(0, \frac{1}{Q_{xx}^2} U_{xy} \right).$$

This completes the proof of (b). ■