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On the use of panel cointegration tests in energy economics☆

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ABSTRACT

There is a burgeoning literature based on using panel cointegration techniques to study the relationship between energy consumption and GDP. Most panel cointegration tests employed take no cointegration as the null hypothesis. The current paper illustrates how a rejection by such a test cannot be taken as evidence of cointegration for the panel as a whole, a fact that seems to have gone largely unnoticed in the literature. Hence, even if the no cointegration null is rejected, this evidence is not enough to ensure that the relationship can be meaningfully estimated, as most (if not all) estimators in the literature require that the panel is cointegrated as a whole.

1. Introduction

Recent years have witnessed an immense proliferation of research based on panel data asking whether GDP and energy consumption are cointegrated (see Payne, 2010a, 2010b, for surveys of this literature). The conventional way in which earlier studies have been trying to test the cointegration hypothesis is to first run a time series regression of GDP for a particular country onto a constant and energy consumption for the same country, and then to test whether the resulting least squared (LS) residuals contain a unit root. This test is then repeated for each country in the sample, each time using only the sample information for that particular country. As more recent research has shown, however, this is wasteful. Indeed, there are many reasons for preferring a joint panel data approach. First, in many studies, it is the group of countries that is of main interest and not the individual countries by themselves, which means that little is lost by taking the panel perspective. Second, the use of panel rather than time series data not only increases the total number of observations and their variation but also reduces the noise coming from the individual time series regressions. This is reflected in the power of the resulting panel cointegration test, which is increasing in both the number of cross-section units, N, and the number of time periods, T, as opposed to a time series/unit-by-unit approach where power is only increasing in T. Thus, from a power/precision point of view, a joint (panel) approach is always preferred. Third, since power is increasing in both N and T, this means that in panels one can effectively compensate for a relatively small T by having a relatively large N. This is particularly true when considering developing countries where data availability is an issue and, whenever data are available, they are usually for a short time span, often insufficient for fitting time series regressions. Fourth, unlike the unit-by-unit approach, the joint panel approach accounts for the multiplicity of the testing problem. It is therefore correctly sized.

For these reasons, in recent years, there has been a shift towards the panel data approach, which is now the workhorse of the industry with a very large number of panel cointegration-based studies being published (see Narayan and Smyth, 2014, and the references provided therein). However, while appealing in many regards, the pooling along the cross-section is at the same time the source of the greatest weakness of the panel approach. Most panel cointegration tests take as their null hypothesis that all the cross-section units are not cointegrated, which seems like a rather natural formulation. The problem lies with alternative hypothesis, which is typically formulated such that at least some units are cointegrated. In particular, while a non-rejection can be straightforwardly interpreted as that the cointegration is absent, the alternative hypothesis is too broad for any interesting economic

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conclusions; it could be that cointegration holds for all countries, but it could also be that there is onlya small fraction of countries for which cointegration holds (see Pesaran, 2012, for a discussion in the context of unit root testing). This is important for the interpretation of the test outcome. However, the main concern is that all known estimators of cointegrated (panel) regressions assume that all the cross-section units are in fact cointegrated, and their properties become suspect when this assumption is not met. Hence, only in the case of full panel cointegration is it appropriate to proceed with estimation and inference.

In the current paper, we take the above weakness of the panel data approach as our starting point. The purpose is to illustrate the effects of erroneous conclusion regarding the presence of cointegration. This is done using both simulated and real data. We begin by describing the econometric model. This is done in Section 2. To make the analysis as transparent as possible, the model is intentionally very simple, yet insightful. This is demonstrated in Section 3, where we study the effect of non-full panel cointegration when using a test that takes no cointegration as the null hypothesis. The effect of non-full cointegration on estimation and inference is studied in Section 4. Section 5 draws some concluding implications for empirical work.

2. The econometric model

Consider the scalar and $m \times 1$ vector panel data variables $y_{i,t}$ and $x_{i,t}$, respectively, which are observable for $t = 1,\dots, T$ time periods and $i = 1,\dots, N$ cross-section units. Suppose that these variables admit to the following data-generating process (DGP):

$$y_{i,t} = \beta_i' x_{i,t} + u_{i,t}, \tag{1}$$

$$u_{i,t} = \rho_i u_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

$$x_{i,t} = x_{i,t-1} + v_{i,t}, \tag{3}$$

where $\rho_i \in (-1, 1]$, and $e_{i,t} = (\varepsilon_{i,t}, v_{i,t}')'$ is independent and identically distributed (iid) with $E(e_{i,t}) = 0_{(m+1)\times 1}$ and $E(e_{i,t}e_{i,t}') = \Sigma_i$ is a positive definite matrix. In this DGP, $y_{i,t}$ and $x_{i,t}$ are cointegrated with cointegrating vector $(1, -\beta_i')'$ when $|\rho_i| < 1$, and they are non-cointegrated when $\rho_i = 1$.

Note here that $x_{i,t}$ is assumed to follow a unit root process. Hence, in terms of applied work, in this paper, we assume that the researcher has already established that $x_{i,t}$ has a unit root. Note that, in contrast to testing for cointegration, when testing for a unit root, the most natural formulation of the null hypothesis is that of a unit root, such that if the null is not rejected, all the units are unit root non-stationary (which is the relevant condition in cointegration analysis).

3. Cointegration testing

Most of the panel cointegration tests employed in the literature are residual-based tests that seek to infer the null hypothesis $H_0 : \rho_1 = \dots = \rho_N = 1$. Since this hypothesis involves N restrictions, the tests are joint hypotheses tests. As in any other testing situation of this type, the alternative hypothesis is that at least one of the restrictions under the null fails, suggesting that the appropriate alternative hypothesis can be formulated as $|\rho_i| < 1$ for at least some i. It is convenient to assume that the first N_0 units are non-cointegrated ($\rho_i = 1$) and that the remaining $N_1 = N - N_0$ units are cointegrated ($|\rho_i| < 1$). In this notation, the above formulation of the alternative hypothesis is equivalent to requiring that $N_1 > 0$. In order to study the appropriateness of this formulation, we consider a sequence of test statistics $\theta_{1,T},\dots, \theta_{N,T}$, where $\theta_{i,T}$ tests the restriction that $\rho_i = 1$. Typically, $\theta_{i,T}$ is the t-statistic for a unit root in $\hat{u}_{i,t} = y_{i,t} - \hat{\beta}_i' x_{i,t}$, where $\hat{\beta}_i$ is the least squares (LS) estimator of β_i. A common way to combine $\theta_{1,T},\dots, \theta_{N,T}$ (into a joint test) is to take the average; $\overline{\theta}_T = N^{-1}\sum_{i=1}^{N}\theta_{i,T}$. Define the normalized joint test statistic $Z_{\theta,T} = \sqrt{N}(\overline{\theta}_T - \mu_\theta)/\sigma_\theta$, where $\theta_i = lim_{T\to y}\theta_{i,T}$, $\mu_\theta = E(\theta_i)$ and $\sigma_\theta^2 = E[(\theta_i - \mu_\theta)^2]$. In terms of the terminology of Pedroni (2004), this is a "group mean" (or "between") type statistic. Using $\delta_{0,N} = N_0/N \in [0, 1]$ ($\delta_{1,N} = N_1/N = 1 - \delta_{0,N}$) to denote the fraction of non-cointegrated (cointegrated) units, it is not difficult to see that

$$\begin{aligned} Z_{\theta,T} &= \frac{1}{\sqrt{N}\sigma_\theta}\sum_{i=1}^{N}\left(\theta_{i,T} - \mu_\theta\right) = \sqrt{\delta_{0,N}}\frac{1}{\sqrt{N_0}\sigma_\theta}\sum_{i=1}^{N_0}\left(\theta_{i,T} - \mu_\theta\right) \\ &\quad + \sqrt{\delta_{1,N}}\frac{1}{\sqrt{N_1}\sigma_\theta}\sum_{i=N_0+1}^{N}\left(\theta_{i,T} - \mu_\theta\right), \end{aligned} \tag{4}$$

whose limit as $T \to \infty$ is given by

$$Z_\theta = \lim_{T\to\infty} Z_{\theta,T} = \sqrt{\delta_{0,N}}\frac{1}{\sqrt{N_0}\sigma_\theta}\sum_{i=1}^{N_0}(\theta_i - \mu_\theta) + \sqrt{\delta_{1,N}}\frac{1}{\sqrt{N_1}\sigma_\theta}\sum_{i=N_0+1}^{N}(\theta_i - \mu_\theta). \tag{5}$$

Assuming that θ_i is iid with $E(\theta_i^4) < \infty$, it is clear that

$$\frac{1}{\sqrt{N_0}\sigma_\theta}\sum_{i=1}^{N_0}(\theta_i - \mu_\theta) \to_d N(0, 1) \tag{6}$$

as $N \to \infty$, where $\to_d$ signify convergence in distribution. Thus, if $N_1 = 0$ and therefore H_0 is true, $Z_\theta \to_d N(0, 1)$ as $N \to \infty$, or

$$Z_{\theta,T} \to_d N(0, 1) \tag{7}$$

as $T \to \infty$ and then $N \to \infty$. We say that $Z_{\theta,T}$ has $N(0, 1)$ as its sequential limiting distribution.

Under $|\rho_i| < 1$, $\theta_{i,T}$ is divergent as $T \to \infty$. The rate at which this happens depends on the type of test statistic considered. For example, if $\theta_{i,T}$ is a t-statistic, then $\theta_{i,T} = O_p\left(\sqrt{T}\right)$, where $X_{i,T} = O_p(1)$ signifies that that the random variable $X_{i,T}$ converges in distribution. Therefore,

$$Z_{\theta,T} = \sqrt{\delta_{0,N}}\frac{1}{\sqrt{N_0}\sigma_\theta}\sum_{i=1}^{N_0}\left(\theta_{i,T} - \mu_\theta\right) + \sqrt{\delta_{1,N}}\sqrt{N_1}O_p\left(\sqrt{T}\right), \tag{8}$$

suggesting that for the joint statistic to be divergent and hence also consistent we need $\delta_1 = lim_{N\to\infty}\delta_{1,N} > 0$. Indeed, if the second term on the right-hand side was negligible $Z_{\theta,T}$ would converge to $N(0, 1)$ under both the null and alternative hypotheses, and therefore the test would be unable to discriminate between the two. The appropriate formulation of the alternative hypothesis is therefore not that $N_1 > 0$, but rather $H_1 : \delta_1 > 0$, which will be the case if $N_1 = \alpha N$, where $\alpha \in (0, 1]$, such that $\delta_1 = \alpha \in (0, 1]$. That is, for the test to be able to discriminate between H_0 and H_1 as N increases, the number of cointegrated units cannot remain constant but must be allowed to increase with N.

The above discussion clarifies that the conventional interpretation in which a rejection is taken to imply that all the units of the panel are cointegrated ($\delta_1 = 1$) is incorrect. The test will reject whenever $\delta_1 > 0$, which clearly does not require $\delta_1 = 1$. In order to illustrate this fact, we report some Monte Carlo results in Table 1 for the simulated 5% rejection frequency of the five tests developed by Pedroni (2004), here denoted as Z_t^{GM}, Z_ρ^{GM}, Z_t^{P},Z_ρ^{P} and Z_v^{P}. While the first two are based on the group mean principle, the remaining statistics are based on the so-called "panel" (or "within") principle. These tests are the most commonly used ones by far and represent the workhorses of the literature.