COMPARING COINTEGRATING REGRESSION ESTIMATORS: SOME ADDITIONAL MONTE CARLO RESULTS*

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ABSTRACT

This paper compares the finite sample performance of two recently proposed cointegrating vector estimators: the canonical cointegration regression estimator (Park [6]) and Stock and Watson's [9] dynamic ordinary least squares estimator (DOLS). The set up for the Monte Carlo experiment is the same used by Inder [3]. The results show that the canonical cointegration regression estimator has smaller bias and mean square root error than the OLS and the fully modified estimator. In addition, Stock and Watson's estimator performs sistematically better than the CCR estimator.

KEY WORDS: Cointegration, canonical regression, simulation.

RESUMEN

Este trabajo compara las propiedades en pequeñas muestras de dos estimadores de vectores de cointegración propuestos recientemente en la literatura: el estimador de la regresión de cointegración canónica (CCR)(Park (1992)) y el llamado estimador dínamico por mímimos cuadrados propuesto por Stock y Watson (1993). El estudio de Monte-Carlo se basa en el proceso generador utilizado por Inder (1993). Los resultados muestran que el estimador de la regresión de cointegración canónica tiene un sesgo y un error cuadrático medio menores que el estimador por mínimos cuadrados y el estimador conocido como "fully modified". Además, la simulación permite comprobar que el estimador propuesto por Stock y Watson (1993) tiene un sesgo menor que el estimador CCR para todos los modelos examinados.

PALABRAS CLAVE: Cointegración, regresión canónica, simulación.

1 Introduction

The estimation of long run relationship involving cointegrated variables has been the focus of a lot of recent papers. Many studies have reported alternative cointegrating vector estimators and its asymptotic properties [e.g., Phillips and Loretan (1991)]. The general result is that those asymptotic properties are not affected by endogeneity or serial correlation if the estimators are properly corrected. However, the applied researcher does not usually have enough data to justify the application of asymptotic theory. For this reason it is important to consider the small sample performance of alternative cointegrating vector estimators. On the one hand, the general result points to large bias in small samples for any estimator that ignores short run dynamics. On the other, the error correction mechanism (ECM) estimator, that considers explicitly knowledge of the short run dynamics, has problems in terms of t-statistics far from their theoretical distributions.

The purpose of this paper is to compare the finite sample performance of two recently proposed cointegrating vector estimators: the canonical cointegration regression estimator (CCR) (Park [6]) and Stock and Watson's dynamic OLS estimator (DOLS) [9]. In order to analyze the small sample properties we avoid to use "our" particular generating process and adopt the one proposed by Inder [3]. This choice has the added advantage of allowing the comparation with other estimators reported by Inder [3][1].

The conclusions are the following:

- Althoug the CCR estimator is generally consider as a modification of Phillips and Hansen's fully modified estimator [7], its performance is much better that the fully modified in terms of bias and mean square root error.
- The refinements do not help in reducing the bias of the CCR estimator.
- The DOLS estimator shows substantial bias for some of the generating processes. Nevertheless, it performs better than the CCR in every single experiment.

[1]Inder [3] reports, among others, the Monte Carlo results for the ECM and the modified ECM estimator. See also Kremers, Ericsson and Dolado (1992)[4].

2 The estimators.

2.1 The specification of the model.

Let $y_t = (y_{1t}, y_{2t})$ be a m-dimensional I(1) process. The generating mechanism for y_t is the cointegrated system in its triangular form

$$\begin{aligned} y_{1t} &= \beta' y_{2t} + u_{1t} && (1) \\ \Delta y_{2t} &= u_{2t} && (2) \end{aligned}$$

where $u_t = (u'_{1t}, u'_{2t})$ is, in the general case, strictly stationary with zero mean and finite covariance matrix

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \tag{3}$$

The benchmarck case can be defined by u_t being $IIDN(0, \Sigma)$ and Σ block diagonal. In this situation Δy_{2t} is strictly exogenous and the OLS estimator of β in (1) is the MLE. In the general case, whenever Σ is not block diagonal and/or the u_t process is weakly dependent, the OLS estimator is not efficient.

2.2 The CCR estimator.

The CCR estimator is based on a transformation of the variables in the cointegrating regression that removes the second order bias of the OLS estimator in the general case mentioned in (2.1).

An additional advantage of the CCR estimator is the asymptotic normality of the t-statistic derived from it.

The long run covariance matrix corresponding to (1) and (2) can be written as

$$\Omega = \lim_{n \to \infty} \frac{1}{n} E(\sum_{t=1}^{n} u_t)(\sum_{t=1}^{n} u_t)' \tag{4}$$

The matrix Ω can be represented as the following sum

$$\Omega = \Sigma + \Gamma + \Gamma' \tag{5}$$

where

$$\Sigma = \lim_{n\to\infty} \frac{1}{n}\sum_{t=1}^{n} E(u_t u_t') \tag{6}$$

$$\Gamma = \lim_{n\to\infty} \frac{1}{n}\sum_{k=1}^{n-1}\sum_{t=k+1}^{n} E(u_t u_{t-k}') \tag{7}$$

$$\Lambda = \Sigma + \Gamma = (\Lambda_1, \Lambda_2) \tag{8}$$

The canonical cointegration regression is obtained transforming the variables using the following partition of Ω and Λ.

$$\Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix} \quad \Lambda = \begin{bmatrix} \Lambda_{11} & \Lambda_{12} \\ \Lambda_{21} & \Lambda_{22} \end{bmatrix} \tag{9}$$

The transformed series are obtained as [2]

$$y_{2t}^* = y_{2t} - (\Sigma^{-1}\Lambda_2)' u_t \tag{10}$$

$$y_{1t}^* = y_{1t} - (\Sigma^{-1}\Lambda_2\beta + (0, \Omega_{12}\Omega_{22}^{-1})')' u_t \tag{11}$$

The canonical cointegration regression takes the following form

$$y_{1t}^* = \beta' y_{2t}^* + u_{1t}^* \tag{12}$$

where

$$u_{1t}^* = u_{1t} - \Omega_{12}\Omega_{22}^{-1} u_{2t} \tag{13}$$

Therefore, in this context, the OLS estimator of (12) is asymptically equivalent to the ML estimator. The reason is that the transformation of the variables eliminates asymptotically the endogeneity caused by the long run correlation of y_{1t} and y_{2t}. In addition, (13) shows how the transformation of the variables eradicates the asymptotic bias due to the possible cross correlation between u_{1t} and u_{2t}. Section 3 presents the practical implementation of this estimator.

[2] The fully modified estimator transforms only the dependent variable and then, corrects in the second step the OLS estimate in the regression of the modified y_{1t}.

2.3 Stock and Watson's approach.

Stock and Watson [9] have proposed to estimate β running the following regression

$$y_{1t} = \beta' y_{2t} + d(L)\Delta y_{2t} + v_t \tag{14}$$

where $d(L)$ is two sided.

This approach is motivated as a MLE for the triangular representation in (1) and (2) assuming that u_t is a Gaussian linearly regular stationary stochastic process[3]. The basic idea is to transform u_{1t} in such a way that the resulting transformation is independent of $\mathcal{F}(u_{2t})$, where $\mathcal{F}(u_{2t})$ contains the past, present and future values of u_{2t}. This is obtained by calculating

$$E(u_{1t}|\mathcal{F}(u_{2t})) = d(L)\Delta y_{2t} \tag{15}$$

Therefore, $\mathcal{F}(u_{2t})$ and $u_{1t}^{*} = u_{1t} - E(u_{1t}|\mathcal{F}(u_{2t}))$ are independent and the likelihood function of this model can be decomposed as

$$f(Y_1, Y_2|\beta, \theta_1, \theta_2) = f(Y_1|Y_2, \beta, \theta_1) f(Y_2|\theta_2) \tag{16}$$

where $\theta = (\theta_1, \theta_2)$ are the parameters of the marginal distribution of u_1 and the parameters of $d(L)$ respectively. Under this conditions the MLE of β is calculated by maximizing the firs part of the likelihood function in (16). Therefore, the GLS estimator of (14) delivers that MLE. An asymptotically equivalent estimator is an OLS estimator of (14) or what Stock and Watson define as the dynamic OLS estimator.

3 Monte Carlo results.

The economic literature has proposed many different generating processes in order to asses the small sample properties of alternative cointegrating vector estimators. This paper adopts the generating process in Inder [3] to discuss the finite sample properties of the CCR and the DOLS estimators. Inder [3]

[3]In precise terms we also need to assume that $\Delta y_{2,-i} = \Delta y_{2,T+1-i} = 0 \quad i = 0, 1, ...,$

uses this process to point out the problems of the fully modified estimator and "blames" the particular generating mechanism used by Phillips and Hansen [7] as the reason why the fully modified performs so well in their Monte Carlo experiment[4]. The generating process is

$$\begin{aligned} y_{1t} &= \mu + \beta_0 y_{2t} + \beta_1 y_{2,t-1} + \alpha_1 y_{1,t-1} + u_{1t} && (17) \\ y_{2t} &= y_{2,t-1} + u_{2t} && (18) \\ u_{1t} &= \rho_{11}\eta_{1t} && (19) \\ u_{2t} &= \rho_{21}\eta_{1t} + \rho_{22}\eta_{2t} + \rho_{23}\eta_{1,t-1} && (20) \end{aligned}$$

where η_{1t} and η_{2t} are independently and identically distributed standard normal variables.

This DGP can also be written as

$$y_{1t} = \lambda_1 + \lambda_2 y_{2t} + \lambda_3 \Delta y_{1t} + \lambda_4 u_{2t} + u_{1t} \tag{21}$$

where

$$\begin{aligned} \lambda_1 &= \frac{\mu}{(1-\alpha_1)} && (22) \\ \lambda_2 &= \frac{\beta_0 + \beta_1}{(1-\alpha_1)} && (23) \\ \lambda_3 &= \frac{-\alpha_1}{(1-\alpha_1)} && (24) \\ \lambda_4 &= \frac{-\beta_1}{(1-\alpha_1)} && (25) \end{aligned}$$

Inder [3] defines 18 models corresponding to different values of the vector $(\beta_0, \beta_1, \alpha_1)$ and the vector $\rho = (\rho_{21}, \rho_{22}, \rho_{23})$. The value of ρ_{11} is set to 0.2 for all the experiments. The set of parameter values are included in tables I

[4] Inder [3] reports that the bias of the fully modified estimator is as large as the bias of the OLS estimator. Stock and Watson [9] also indicate that, for their generating processes, the fully modified estimator tends to have biases comparable to the OLS estimator.

and II. The benchmark case considered in section 2 is presented in the first panel of tables I and II [5].

Tables I and II compare four estimators:

- OLS: ordinary least squares estimator. It is reported for the sake of comparison.
- CCR: canonical cointegration regression estimator. In order to obtain a consistent estimator of the long run covariance matrix we need to estimate consistently its two components, Σ and Γ. A consistent estimator of Σ is

$$\hat{\Sigma} = \frac{1}{n} \sum_{t=1}^{n} \hat{u}_t \hat{u}_t' \tag{26}$$

where $\hat{u}_t$ is the vector containing the first stage OLS residual.

There are several ways to estimate Γ consistently. The CCR results in tables I and II are obtained using a nonparametric estimator as

$$\hat{\Gamma} = \frac{1}{n} \sum_{k \geq 1} c(k) \sum_{t=k+1}^{n} \hat{u}_t \hat{u}_{t-k}' \tag{27}$$

In principle there are many possible choices for the weight function $c(k)$. Any well behaved kernel would be an appropriate choice. We have taken the QS kernel[6] with an automatic bandwidth.

Given the estimators of $\hat{\Sigma}$ and $\hat{\Gamma}$ the rest of the matrices needed for the CCR transformation can be calculated as

$$\hat{\Omega} = \hat{\Sigma} + \hat{\Gamma} + \hat{\Gamma}' \tag{28}$$

[5] $(\beta_0 = 1, \beta_1 = 0, \alpha_1 = 0)$ and $(\rho_{21} = 0, \rho_{22} = 1, \rho_{23} = 0)$.

[6] This kernel has some large sample optimality properties: it generates positive semi-definite estimates, as the Bartlett kernel, but it has a quicker rate of convergence [1] than the Barlett kernel.

and

$$\hat{\Lambda} = \hat{\Sigma} + \hat{\Gamma} \tag{29}$$

- CCRPW: CCR estimator using a VAR prewithened kernel estimator of the long run covariance matrix [7]. The idea is to fit a VAR model to u_t as

$$u_t = \sum_{k=1}^{p} \Psi_k u_{t-k} + \nu_t \tag{30}$$

From the residuals of this VAR, ν, we can obtain a consistent estimate of the long run variance by recoloring the spectrum of the prewithened residuals, using the fact that

$$\Omega = \Psi(1)^{-1}\Omega_\nu \Psi(1)^{-1} \tag{31}$$

where Ω_ν is the long run covariance matrix of the residuals.

- DOLS: dynamic OLS estimator[8]. The set of regressors contains one lead and one lag of the first difference of y_{2t} for T=50 and two for T=100.

The results in tables I and II show the following facts[9]:

1. The CCR estimator performs much better than the OLS estimator for all the models. Therefore,

   even though the CCR estimator is generally consider jointly with the fully modified in terms of theoretical considerations, its finite sample performance is much better than the fully modified. The efficiency improvement of the CCR estimator over the fully modified, measured as the ratio of the root mean squared error, ranges from a 20% improvement to a 200%. The smallest improvement corresponds to high values of α_1.

[7] Andrews and Monahan [2] and Park and Ogaki [5].

[8] Among all the estimators reported by Stock and Watson [9] we have choosen the DOLS because it has the smallest bias in the general case excluding, of course, Johansen's MLE

[9] The number of replications is equal to 5.000.

2. The CCRPW estimator does not improve over the performance of the standard CCR for the models considered in tables I and II. The prewithening procedure does not help to reduce the bias of the CCR estimator and, in several models, the estimator shows larger bias and root mean squared error than the CCR estimator.

3. The DOLS estimator has substantial bias when α_1 is set to the high value (0.8). However, it has smaller bias and root mean squared error than the other estimators presented in tables I and II.

4 Conclusions.

When estimating a cointegrating vector that relates I(1) variables, the applied researcher needs to rely on an estimator that has some reasonable good small sample properties. The economic literature has proposed many alternative estimators that are asymptotically as efficient as Johansen's MLE. However, their small sample performance is not the same.

Inder [3] has showns that the fully modified OLS estimator presents large biases in the presence of dynamic structure. This paper reports the results of a Monte Carlo experiment that uses Inder's generating processes [3] and shows that the CCR estimator performs much better than the fully modified estimator. This result is interesting because the only difference between the fully modified and the CCR estimator is that the former transforms data and estimator while the later transforms only the data.

The DOLS estimator has smaller bias than the CCR estimator. However, when α_1 is large, the relative efficiency of this estimator with respect to the CCR estimator, measured as the ratio of their respective root mean squared error, is largely reduced.

4 CONCLUSIONS.

TABLE I						
T=50	ρ =(0,1,0)		ρ =(0.5,0.866,0)		ρ =(0.5,0.707,0.5)	
Estimator	Bias	RMSE	Bias	RMSE	Bias	RMSE
β_0=1 β_1=0 α_1=0						
OLS	-0.0000	0.013	0.0092	0.016	-0.0002	0.008
CCR	-0.0007	0.015	0.0020	0.013	-0.0000	0.007
CCRPW	-0.0006	0.014	0.0025	0.013	-0.0000	0.007
DOLS	-0.0000	0.015	0.0001	0.013	0.0018	0.008
β_0=0.6 β_1=0 α_1=0.4						
OLS	-0.0648	0.081	-0.0482	0.061	-0.0425	0.054
CCR	-0.0293	0.049	-0.0209	0.036	-0.0169	0.027
CCRPW	-0.0273	0.047	-0.0209	0.036	-0.0173	0.027
DOLS	-0.0112	0.030	-0.0092	0.024	-0.0079	0.015
β_0=0.2 β_1=0 α_1=0.8						
OLS	-0.2880	0.332	-0.2518	0.291	-0.2282	0.266
CCR	-0.2228	0.281	-0.1935	0.246	-0.1729	0.210
CCRPW	-0.2323	0.293	-0.1969	0.248	-0.1734	0.219
DOLS	-0.2008	0.245	-0.1743	0.214	-0.1627	0.201
β_0=0.6 β_1=0.4 α_1=0						
OLS	-0.0405	0.052	-0.0300	0.040	-0.0274	0.036
CCR	-0.0069	0.019	-0.0051	0.015	-0.0058	0.012
CCRPW	-0.0073	0.019	-0.0065	0.017	-0.0058	0.012
DOLS	-0.0003	0.016	0.0001	0.014	0.0020	0.008
β_0=0.4 β_1=0.2 α_1=0.4						
OLS	-0.0952	0.118	-0.0788	0.099	-0.0670	0.086
CCR	-0.0502	0.076	-0.0436	0.065	-0.0321	0.048
CCRPW	-0.0506	0.075	-0.0439	0.066	-0.0320	0.048
DOLS	-0.0150	0.032	-0.0135	0.027	-0.0118	0.019
β_0=0.1 β_1=0.1 α_1=0.8						
OLS	-0.3244	0.373	-0.2875	0.332	-0.2610	0.306
CCR	-0.2519	0.317	-0.2281	0.286	-0.2002	0.252
CCRPW	-0.2629	0.327	-0.2341	0.291	-0.2082	0.259
DOLS	-0.2292	0.280	-0.2035	0.246	-0.1862	0.226

TABLE II

T=100	ρ =(0,1,0)		ρ =(0.5,0.866,0)		ρ =(0.5,0.707,0.5)	
Estimator	Bias	RMSE	Bias	RMSE	Bias	RMSE
β_0=1 β_1=0 α_1=0						
OLS	0.0000	0.006	0.0054	0.009	-0.0000	0.004
CCR	0.0001	0.007	0.0006	0.006	-0.0000	0.003
CCRPW	0.0002	0.007	0.0006	0.006	-0.0000	0.003
DOLS	0.0002	0.008	0.0001	0.007	-0.0000	0.004
β_0=0.6 β_1=0 α_1=0.4						
OLS	-0.0343	0.045	-0.0255	0.033	-0.0233	0.030
CCR	-0.0101	0.020	-0.0068	0.015	-0.0062	0.011
CCRPW	-0.0103	0.020	-0.0068	0.015	-0.0062	0.011
DOLS	-0.0031	0.013	-0.0019	0.011	-0.0020	0.006
β_0=0.2 β_1=0 α_1=0.8						
OLS	-0.1713	0.209	-0.1475	0.182	-0.1390	0.169
CCR	-0.1054	0.149	-0.0988	0.138	-0.0820	0.112
CCRPW	-0.1115	0.153	-0.0954	0.133	-0.0778	0.109
DOLS	-0.094	0.122	-0.0837	0.107	-0.0779	0.098
β_0=0.6 β_1=0.4 α_1=0						
OLS	-0.0218	0.029	-0.0154	0.021	-0.0144	0.019
CCR	-0.0022	0.008	-0.0014	0.006	-0.0018	0.005
CCRPW	-0.0022	0.008	-0.0016	0.007	-0.0015	0.004
DOLS	-0.0000	0.007	0.0001	0.011	-0.0002	0.004
β_0=0.4 β_1=0.2 α_1=0.4						
OLS	-0.0495	0.064	-0.0407	0.052	-0.0364	0.047
CCR	-0.0182	0.031	-0.0154	0.026	-0.0121	0.019
CCRPW	-0.0195	0.033	-0.0157	0.027	-0.0117	0.018
DOLS	-0.0033	0.014	-0.0027	0.011	-0.0028	0.007
β_0=0.1 β_1=0.1 α_1=0.8						
OLS	-0.1902	0.230	-0.1746	0.209	-0.1650	0.199
CCR	-0.1253	0.172	-0.1125	0.155	-0.0962	0.133
CCRPW	-0.1287	0.178	-0.1106	0.153	-0.0994	0.137
DOLS	-0.1100	0.140	-0.0951	0.122	-0.0948	0.118

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