SCIENTIFIC LETTERS

Econometrics Letters Volume (1), 1, 2014, June.

Cross-section Dependency and the Effects of Nonlinearity in Panel Unit Testing

Furkan Emirmahmutoglu[1]

ABSTRACT

In this study, we have analyzed the Cross Section Dependence (CSD) problem that is frequently encountered in a panel unit root setting by using the Pesaran (2004, 2008) CD tests. For this purpose we have generated cross sectionally dependent data and investigated the effects of nonlinear modeling on the cross section dependency problem inherited in panel analysis. The simulation study shows us that the nonlinear models remedy some part of this CSD.

Keywords: Panel Unit Root; Cross Section Dependency Bias; Cross Section Dependency Test.
Jel Classification: C1,C12

[1] Gazi University Department of Econometrics 06500, Ankara, Turkey. Tel: +90 312 216 13 27- Fax: +90 312 213 20 36, e-mail: furkan@gazi.edu.tr

1. Introduction

In this study we are investigating the effects of nonlinear model structure for remedying the cross section dependence (CSD) problem. Cross section dependency is mainly a problem of large time dimension in the panel data analysis and may arise due to spatial correlations, spill-over effects, omitted global/multilateral variables, common unobserved shocks or general residual interdependence. In the existence of cross-sectionally correlated error terms, traditional OLS-based estimations are inefficient and nullify much inferential theory of panel data models. In presence of CSD, SURE-GLS (Seemingly Unrelated Regression Equations and Generalized Least Squares) can be used as a remedy and is feasible when the cross-section dimension N is smaller then the time series dimension T. Omay *et al.* (2014) used the SURE-GLS approach for the CSD bias. They have demonstrated that the system SURE-GLS eliminates the cross sectional dependence and endogeneity bias together. The typical approach is to consider the equations from the different cross-sectional units as a system of seemingly unrelated regression equations and then estimate the system by Generalized Least Squares (GLS) method (Omay et al, 2014). If both of these dimensions (N and T) are similar, the disturbance covariance matrix will be rank deficient (Omay and Kan, 2010). Nevertheless, when the covariances between the errors of different cross-sectional units are non-zero due to common omitted variables, it is not obvious that SURE-GLS is always the right approach Coakley *et al.*(2002). The other popular approach is Pesaran's (2006) common correlated effect estimator approach, which suggests a method that makes use of cross-sectional averages to offer valid inference for stationary panel regressions with multifactor error structure. On the other hand, Pesaran (2007) proposes a new panel unit root test (called as the CADF statistic) that tackles the cross sectional dependence problem by using CC estimator and shows that the standard IPS test that does not allow for cross-sectional dependence can be seriously biased if the degree of cross-section dependence is sufficiently large[2]. We know that, remedying cross sectional dependence across individual units is crucial in developing a panel unit root test because ignoring cross sectional dependence would create important power losses and size distortions (O'Connell, 1998)

There are some recent attempts to show the bias reduction properties of different remedies. One of them is the study by Kapetanios et al. (2011). They show that the CCE estimators have better small sample properties than the factor-based estimators. Besides, Westerlund and Urbain (2011) have also presented that the CCE estimator is less biased than the principal component estimator, although these two estimators have the equal variances. Furthermore, Pesaran and Tosetti (2011) have proven that the CCE estimator yields consistent estimates of the slope coefficients for the panel data model with both the multifactor error structure and the spatial error correlation. All these studies have used an estimation of parameter in interest strategy which involves explicitly estimating the coefficient and deciding whether it is biased or not. Fortunately, the other method may be the usage of CD test for showing the bias reduction in the panel unit root test. The first cross-section dependence test was proposed by Pesaran (2004). By using this test and the Pesarans' adjusted CD-LM test; we aim to show the reduction of CSD bias in panel unit root tests when nonlinear structures are introduced into the testing process. Omay and Kan (2010) have shown this bias reduction in the case of static nonlinear panel data model, namely the heterogeneous panel smooth transition model (PSTR). Specifically, they have documented that in each stage (linear model,

[2] Phillips and Sul (2003), Bai and Ng (2004), Moon and Perron (2004), Bai and Carrion-i-Silvestre (2009) have applied the principal component analysis to deal with cross sectional correlations. Alternatively, the bootstrap-based panel unit root tests have been suggested to deal with the general structure of cross sectional correlations, e.g., Maddala and Wu (1999), Chang (2004), Smith et al. (2004) and Ucar and Omay (2009).

linearized model, nonlinear model and the nonlinear model plus CCE estimation), the cross-sectional dependence diminishes. According to these authors the progress of the test statistics reveals that non-linear estimation eliminates some part of the cross-section dependence due to model misspecification. Furthermore, when they apply the CCE estimator, the cross-sectional dependence is fully removed from their PSTR estimations. Depending on the findings of Omay and Kan (2010) we extend this study to the panel unit root testing. From our simulation study we have also shown that that non-linear estimation eliminates some part of the cross-sectional dependence due to model misspecification. The model misspecification is CSD if we estimate the panel unit root test by using the cross sectional independent panel assumption such as IPS. However, when an Ucar and Omay (2009) type of nonlinearity is taken into account, some part of the CSD that is remedied this time imposes pseudo nonlinearity.

The rest of the paper is organized as follows. Section 2 gives the CD-LM tests along with the Monte-Carlo experiment design and the simulation results. Section 3 concludes.

2. The simulation study and the CD tests

In this section, we introduce the CD-LM test of the CSD bias. Pesaran (2004) shows that his cross-sectional dependence test (CD test) can also be applied to models including small or large N and T. Moreover, this diagnostic CD test does not require an a priori specification of connection or spatial matrix. The CD test is based on a simple average of all pair-wise correlation coefficients of the OLS residuals from the individual regressions in the panel:

$$\Delta y_{it} = \mu_i + \beta_i^{'} x_{\mathrm{it}} + u_{it} \tag{1}$$

where, on the time domain t = 1,2,…,T, for the cross-section units i = 1,2,…,N. $x_{\mathrm{i,t}}$ is a kx1 vector of observed time-varying regressors. The individual intercepts, μ_i and slope coefficients β_i are defined on a compact set permitted to vary across i. For each i, $u_{it} \sim iid(0, \sigma_{i,u}^2)$ and for all t, although they could be cross-sectionally correlated. The sample estimate of the pair-wise correlation in the residuals is:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{1/2}} \tag{2}$$

while the e_{it} is the OLS estimates of u_{it}, defined as:

$$e_{it} = \Delta y_{it} - \hat{\mu}_i - \hat{\beta}_i^{'} x_{\mathrm{it}} \tag{3}$$

The proposed CD test by Pesaran (2004) yields:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{4}$$

The second CD test, which is used in Pesaran (2004), is proposed by Breusch and Pagan (1980):

$$CD_{LM1} = T \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{5}$$

following the scaled version of CD_{LM1} which can be considered for testing the hypothesis of cross-sectional dependence even for large N and T:

$$CD_{LM2} = \sqrt{\frac{1}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T.\hat{\rho}_{ij}^2 - 1) \right) \tag{6}$$

By using these CD tests we organize some Monte Carlo experiments. The first design is as follows:

Linear model with single factor:

$$y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + \eta_{it} \tag{7}$$

where

$$\eta_{it} = \gamma_i f_t + u_{it} \tag{8}$$

and $u_{it} \sim N(0,\sigma_i^2)$ with $\sigma_i^2 \sim iidU[0.5,1.5]$

Notice here that f_t is a factor variable that affects dependent and independent variables, respectively. We used this data generating process and apply the IPS test, UO test and UO test with CCE estimation and obtain CD-LM tests. We have used the UO test because Omay and Kan (2010) have used the linearized version of the PSTAR and obtained a bias reduction in the CD-LM test. This indicates that any nonlinear structure included into the panel unit root test under cross-sectionally dependent panels reduce some part of the CSD imposed by factor variable.

Table 1. CD test for different remedies

T/N		*5*			*25*			100	
	NR	LRR	LRRCC	NR	LRR	LRRCC	NR	LRR	LRRCC
30	2.027	1.999	-3.891	22.029	21.724	-3.412	64.888	64.107	-3.291
50	2.728	2.688	-5.219	29.046	28.711	-4.612	85.281	84.397	-4.471
70	3.260	3.212	-6.271	34.666	34.274	-5.561	101.743	100.727	-5.403
100	3.865	3.809	-7.574	41.718	41.279	-6.737	122.173	121.026	-6.561
150	4.785	4.722	-9.347	51.225	50.744	-8.336	149.943	148.674	-8.124
200	5.549	5.477	-10.845	59.383	58.832	-9.678	173.605	172.282	-9.428

Note: NR means not remedied, we use only IPS test while obtaining the residuals, LRR means the linearized version of the nonlinear model. We use the UO test for linearized version. LRRCC means the linearized version with CCE estimator.

As it can be seen readily from Table 1, the CD test is decreasing in every step, which means that the nonlinearity imposed into the model limits the potential cross section dependency bias. This finding lends a support for the results obtained by Omay and Kan (2010) for the nonlinear static panel data model.

3. Conclusion

In this study we have investigated the cross-sectionally dependent panels and the effects of nonlinear modeling on cross-sectional dependence problem inherited in panel analysis. The simulation study shows us that the nonlinear models remedy some part of the CSD in dynamic panel data models. For future research these findings can be analyzed by using different data generating processes and remedies.

References

Omay, T., Kan, Ö. E., 2010. Re-examining the threshold effects in the inflation-growth nexus with cross-sectionally dependent non-linear panel: Evidence from six industrialized economies. Economic Modelling 27, 996-1005.

Pesaran, M.H., 2004. General diagnostic tests for cross-section dependence in panels. Cambridge Working Papers in Economics 0435. Faculty of Economics, University of Cambridge.

Pesaran, M. H., 2007. A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics 22(2), 265-312.

Ucar, N., Omay, T., 2009. Testing for unit root in nonlinear heterogeneous panels. Economics Letters 104, 5 –8.