2. A Note on the Examination of the Fisher Hypothesis by Using Panel Co-Integration Tests with Break

Tolga OMAY[1]
Mubariz HASANOV[2]
Asli YUKSEL[3]
Aydin YUKSEL[4 *]

Abstract

One problem encountered when examining the Fisher hypothesis is that various policy changes and economic shocks may induce structural shifts in the long-run relation. We explore the argument that panel cointegration tests based on common correlated effect estimators have reasonably good power and size properties, even in the presence of structural breaks, if the timing of structural shifts roughly coincide to each other across individual group members. Using the data from Omay et al. (2015), which pays special attention to cross-section dependence issue but ignores the possibility of structural break in the data, we provide support to the argument above.

Keywords: Fisher hypothesis; panel cointegration with structural break; cross section dependency; common correlated effect estimators; sieve bootstrap

JEL Classification: G10; C10

I. Introduction

The generalized Fisher hypothesis as applied to common stocks states that common stocks should provide a hedge against inflation. Early research not taking into account the potential nonstationarity and cointegration properties of stock and consumer price indices has revealed mixed results. There are studies reporting that the relation between stock returns and inflation is positive and in other studies the relation is found to be insignificant or even negative. The next wave of studies using cointegration framework

[1] *Department of Management, Turk Hava Kurumu University, Ankara, Turkey.*
[2] *Department of Banking and Finance, Okan University, Istanbul, Turkey.*
[3] *Department of Management, Bahcesehir University, Istanbul, Turkey.*
[4] Department of Management, Isik University, Sile, Istanbul, 34980, Turkey. E-mail: yuksel@isikun.edu.tr.

such as Anari and Kolari (2001) and Luintel and Paudyal (2006) provide supportive evidence for the generalized Fisher hypothesis. These studies report that, in general, long-run generalized Fisher elasticity of stock prices with respect to consumer prices exceeds unity. These findings are consistent with the argument in Anari and Kolari (2001) that nominal stock returns must exceed the inflation rate to compensate tax-paying investors.[5] Recent papers, Gregoriou and Kontonikas (2010) and Omay *et al*. (2015) examine the hypothesis within a panel cointegration framework to utilize the dataset in the most efficient manner. The estimated Fisher elasticities in these two papers are in the range between 0.7 and 1.3.

One problem encountered in examining the Fisher hypothesis is that various policy changes and economic shocks may induce structural shifts in the long-run relation. Ignoring a structural shift may lead to incorrect inferences about the existence of cointegration as documented by a limited number of non-panel cointegration studies. One such study is Luintel and Paudyal (2006), which uses eight UK industry-level stock indices to examine the generalized Fisher hypothesis. The study shows that there occurs a structural shift in the cointegrating relation for five industries in the sample. Moreover, the inclusion of a structural shift dummy in the model specification results in detecting cointegration for a larger number of industries.

Beyer *et al*. (2009), which examines the original Fisher hypothesis, namely that a permanent change in inflation will lead to a one-for-one change in the nominal interest rate in the long run, is another such study. In the paper, the use of trace and maximum-eigenvalue tests of Johansen (1995) provides, consistent with previous studies, evidence against cointegration for nine of 14 countries in the sample. Nonetheless, Carrion-Silvestre and Sans´o (2006) test for structural change cannot reject the null hypothesis that there is a cointegrating relationship with a break for any of those nine countries for which Johansen tests finds the absence of cointegration. Moreover, once the authors account for these breaks, the pre-break and post-break samples reveal clear evidence in favor of cointegration.

Similar problem is likely to exist in panel cointegration testing. In fact, the evidence in one of the above-mentioned papers that examine the generalized Fisher hypothesis, is in line with this conjecture. One notable finding in Omay *et al*. (2015) is that different panel cointegration tests yield dramatically different results. The paper disaggregates the large country set into eight different sub-panels and uses recently proposed second generation panel cointegration tests to deal with the potential cross-section dependence problem in the data. While Banerjee and Carrion-Silvestre (2011) test (henceforth BCS test) indicates that stock prices and goods prices are cointegrated for the whole sample as well as for five sub-panels, another test based on a bootstrap procedure does not provide support for the existence of cointegration neither for the whole sample nor for any of the sub-panels.

One possible explanation for the superior performance of the BCS test for the sample examined in Omay *et al*. (2015) may be the existence of a structural break in the cointegration relationship. Banerjee and Carrion-Silvestre estimator is basically a common correlated effects (CCE) estimator[6], which augments the observed regressors

[5] See Darby (1975) for the derivation of the tax-adjusted version of the Fisher hypothesis.

[6] *Common correlated effects estimators were introduced by Pesaran (2006).*

with cross-sectional averages of the dependent variable and the individual-specific regressors. As noted by Omay *et al*. (2013), the cross-sectionally augmented stationarity test procedure proposed by Pesaran (2007) has reasonably good power and size properties in detecting stationary in the presence of structural breaks. In particular, cross-section averages of the series may approximate breaks in the series if the timing of structural shifts roughly coincide to each other across individual group members. In fact, as Smith and Fuertes (2010) also point out "… apparent structural changes may result from having left out an unobserved global variable". Therefore, it is not surprising that the BCS test, which is based on the CCE estimator, displays relatively good properties even in the presence of structural breaks.

However, Omay *et al*. (2013) also points out that the CCE-type estimators have good power properties only when the break parameters are relatively homogenous across cross-sectional units. Moreover, as the heterogeneity of break parameters increase, especially the parameter that determines location of structural shift, the power of the CCE-based stationarity tests falls drastically.

Motivated by the above reasoning, this paper re-examines the Omay *et al*. (2015) data to answer two empirical questions. The first question is whether or not it is the existence of structural break in the data that makes it hard to detect cointegration. For that purpose, we use Omay *et al*. (2013) panel unit root test (henceforth the OHS test) as residual based cointegration test that takes into consideration both the potential cross-section dependence and structural break problems in the data. Following Leybourne *et al*. (1998), this test models structural change as a smooth transition between different regimes over time, rather than an instantaneous break. The second question to be pursued is whether the sub-panels for which the BCS test detects cointegration are characterized as having break parameters that are relatively homogenous across cross-sectional units. To explore this issue, we examine for each sub-panel the distribution of the parameter that determines the timing of the transition midpoint (henceforth the location parameter).

The results indicate that cointegration exists in all the sub-panels as shown by the OHS test. This finding shows the importance of accounting for structural breaks in the data. Moreover, consistent with the argument in Omay *et al*. (2013), we find that the sub-panels for which the BCS test fails to detect cointegration are those in which the variability of the parameter that determines the location of structural shift is large. This finding gives supporting evidence to the prior claim that inferences based on CCE estimators display some robustness to the existence of breaks in the data.

The remainder of the paper is organized as follows. The next section discusses the econometric framework. The third section presents the data and discusses the empirical results. The last section provides the concluding remarks.

II. Econometric Methodology

Consider following panel regression model:

$$y_{i,t} = \alpha_i + \boldsymbol{\beta_i}\mathbf{x_{i,t}} + u_{i,t} \tag{1}$$

where: $y_{i,t}$ and $\mathbf{x}_{i,t}$ denote observable $I(1)$ variables, $\boldsymbol{\beta}_i = (\beta_1, \dots, \beta_k)$ are parameters to be estimated, and $u_{i,t}$ is the error term. $y_{i,t}$ is scalar, and $\mathbf{x}_{i,t} = (x_{1,t}, x_{2,t}, \dots, x_{k,t})$ is an $(k\text{x}1)$ vector and finally α_i is fixed effect (heterogeneous intercept).

If the error term $u_{i,t}$ in regression (1) is stationary, then the $(n\text{x}1)$ vector $\mathbf{z}'_{i,t} = (y_{i,t}, \mathbf{x}'_{i,t})$ is said to be co-integrated, and $u_{i,t}$ is called equilibrium error (Engle and Granger, 1987). In this paper, we assume that the deviations from the long-run equilibrium are subject to regime shifts. In particular, we assume that the equilibrium error process $u_{i,t}$ can be modelled as follows:

$$u_{i,t} = \mu_{i1} + \mu_{i2} S_{it}(\gamma_i, \tau_i) + \varepsilon_{i,t} \tag{2}$$

$$\Delta\varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + \xi_{it} \tag{3}$$

The errors ξ_{it} in equation (3) are assumed to be a martingale difference with respect to the history of the vector $\mathbf{z}_{i,t}$ up to time $t-1$, that is, $E\{\xi_{it} | \mathrm{z}_{i,t-1}, \mathrm{z}_{i,t-2}, \dots, \mathrm{z}_{i,t-p}, \dots\} = 0$ and that the conditional variance of the error term is constant, i.e., $E\{\xi_{it}^2 | \mathrm{z}_{i,t-1}, \mathrm{z}_{i,t-2}, \dots, \mathrm{z}_{i,t-p}, \dots\} = \sigma_i^2$. Note that we allow for contemporaneous correlation across the errors of the N equations (i.e., $\mathrm{cov}(\xi_{it}, \xi_{jt}) \neq 0$ for $i \neq j$). Now, the null hypothesis of unit root in $u_{i,t}$, i.e., the null of no cointegration in $\mathbf{z}'_{i,t}$, can be formulated as $H_0: \rho_i = 0$ for all i, against the alternative hypothesis of cointegration $H_1: \rho_i < 0$ for some i. Notice that the component representation, eq. (2)-(3), allows for a deterministic trend function both under the null and alternative hypotheses without introducing any irrelevant parameters (see Schmidt and Phillips, 1992).

The transition function $S_{it}(\gamma_i, \tau_i)$ given in equation (2) is continuous, bounded between zero and one, and governs the regime shift in the equilibrium error process $u_{i,t}$. Following Leybourne *et al.* (1998), the individual-specific logistic smooth transition functions based on a sample of size T are given as:

$$S_{it}(\gamma_i, \tau_i) = [1 + \exp\{-\gamma_i(t - \tau_i T)\}]^{-1}, \gamma_i > 0 \tag{4}$$

The parameters γ_i and τ_i determine the smoothness and location, respectively, of the transition from one regime to the other. For small values of γ_i, the transition between two regimes occur very slowly. In the limiting case when $\gamma_i = 0$, $S_{it}(\gamma_i, \tau_i) = 0.5$ for all values of t. As the smoothness parameter γ_i becomes very large, the transition function approaches a Heaviside step function, and consequently, the change from one regime to the other becomes almost instantaneous at time $t = \tau_i T$. Thus, the transition function $S_{it}(\gamma_i, \tau_i)$ nests the no-break and the instantaneous break models as special cases. In particular, if $\gamma_i = 0$, then the transition function $S_{it}(\gamma_i, \tau_i)$ collapses to constant, and hence, equation (2)-(3) reduce to a conventional linear regression models. On the other extreme, as γ_i approaches infinity, the model allows for an instantaneous break at time $t = \tau_i T$, as analysed by Perron (1989). If it is assumed that u_t is a mean-zero $I(0)$ process, then $u_{i,t}$ will be stationary process around the mean that changes from an initial value μ_{i1} to the final value $\mu_{i1} + \mu_{i2}$.[7] See also Leybourne *et al.* (1998).

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[7] *Note that the above specification of the error process also allows for a regime shift only in the intercept of the cointegrating vector. In a more general framework, one may also consider the possibility of regime shifts in the cointegrating vector allowing for shifts in the entire coefficient*

Stationarity of the error term $u_{i,t}$, and hence, cointegration in $\mathbf{z}'_{i,t}$ can be tested in three steps following Leybourne *et al*. (1998) and Omay *et al*. (2013) as follows:

Step 1. Estimate equation (1) by ordinary least squares and collect the equilibrium error process $\hat{u}_{i,t}$:

$$\hat{u}_{i,t} = y_{i,t} - \hat{\alpha}_i - \widehat{\boldsymbol{\beta}}_i \mathbf{x}_{i,t} \tag{5}$$

Step 2. Using the equilibrium error process $\hat{u}_{i,t}$ obtained in step 1, estimate the deterministic components of the model given in equation (2) for each of the cross-section units by the nonlinear least squares (NLS), and collect the residuals $\hat{\varepsilon}_{i,t}$:

$$\hat{\varepsilon}_{i,t} = \hat{u}_{i,t} - \hat{\mu}_{i1} - \hat{\mu}_{2i} S_{it}(\hat{\gamma}_i, \hat{\tau}_i) \tag{6}$$

Step 3. For each individual, compute the ADF t-statistic for ρ_i form the following regression:

$$\Delta\hat{\varepsilon}_{it} = \rho_i \hat{\varepsilon}_{i,t-1} + \sum_{j=1}^{p_i} \varphi_{ij} \Delta\hat{\varepsilon}_{i,t-j} + \xi_{it} \tag{7}$$

which is obtained by

$$t_i = \frac{\Delta x_i' M_t x_{i,-1}}{\hat{\sigma}_i \left(x_{i,-1} M_t x_{i,-1}\right)^{1/2}} \tag{8}$$

where:$\hat{\sigma}_i^2 = \Delta x_i' M_t \Delta x_i/(t-1)$, $M_t = I_t - \tau_T(\tau_T'\tau_T)^{-1}\tau_T'$, $\Delta x_i = \left(\Delta x_{i,1}, \Delta x_{i,2}, \ldots, \Delta x_{i,T}\right)'$ and $\tau_T = (1,1,\ldots,1)'$. As is common in the literature, in order to accommodate a higher order residual serial correlation, we included the lagged differences in test equation (7) above. Now, the mean-group test statistic for testing the null of no cointegration, denoted as $\bar{t}$, can be computed as the cross-section average of the individual ADF test statistics t_i:

$$\bar{t} = \frac{\sum t_i}{N} \tag{9}$$

One of the frequently encountered problems in panel regression models is the presence of cross-section dependence. The cross-section dependence may arise due to spatial correlations, spill-over effects, economic distance, omitted global variables and common unobserved shocks (see, e.g., Omay and Kan, 2010). Ignoring the existence of such dependence may lead to wrong inferences from unit root and cointegration tests in panel data models. Banerjee *et al*. (2004 and 2005) assess the finite sample performance of the available tests and find that all tests experience severe size distortions when panel members are cointegrated. To overcome this issue, some remedies have been proposed. For example, Bai and Ng (2004) and Bai *et al*. (2009) propose to augment the regression equation by principal components. Pesaran (2006 and 2007), on the other hand, uses cross-section averages of dependent and independent variables to proxy unobserved factors. Maddala and Wu (1999), Chang (2004), Ucar and Omay (2009) and OHS (2013), among others, use bootstrap

vector as proposed by Gregory and Hansen (1996). Such a general regime shift would imply that the Fisher coefficient is not time-invariant. In this study, however, we pre-assume that the Fisher coefficient is constant but the adjustment to the equilibrium might have shifted. In fact, given relatively small time span of the data, one may reasonable expect that the Fisher coefficient remained constant during the period under consideration.

simulation to obtain good size properties. In this study, we choose to use the bootstrap approach to remedy cross-section dependency problem. For details of the bootstrap methodology applied in this paper, see Ucar and Omay (2009) and Omay *et al*. (2013).

III. Data and Empirical Analysis

We use the same data and the same data grouping as in Omay et al. (2015). Monthly data for goods prices, measured by the national consumer price index, nominal stock prices, measured by the national stock price index are collected from Datastream. The sample period covers 11 years, running from January 1997 until December 2007. This results in a sample of 52 countries with 132 monthly observations.

Our analysis is conducted not only for the full sample, but also for different subgroups of countries. We classify the sample countries as developed, emerging and other based on Morgan Stanley Capital International (MSCI) classification of markets.[8] According to this classification, our data set contains 21 developed (Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, and United States), 19 emerging (Argentina, Brazil, Chile, China, Czech Republic, Egypt, Hungary, India, Israel, Jordan, Malaysia, Morocco, Philippines, Poland, Russian Federation, South Africa, Taiwan, Thailand, and Turkey) and 12 other (Croatia, Estonia, Iran, Jamaica, Latvia, Mauritius, Slovakia, Sri Lanka, Saudi Arabia, Trinidad and Tobago, Venezuela, and Zambia) markets.

We also classify countries based on the average level of realized inflation during the sample period. We use two classifications for that purpose. The first classification (hereafter INF1) divides countries into two groups. Depending on whether a country's average inflation level is above or below the sample median, a country is classified as either high inflation (INF1 H) or low inflation (INF1 L) country. Each of these two groups contains 26 countries. The second classification (hereafter INF2) divides countries into three groups. These are high inflation (INF2 H), moderate inflation (INF2 M) and low inflation (INF2 L) groups.[9] These three groups contain, 12, 26 and 14 countries, respectively. The use of subgroups will allow us to provide additional evidence on the robustness of the long-run relation between stock prices and goods prices.

In their analysis of the Fisher hypothesis, Omay *et al*. (2015) first examine the extent of cross-section dependence in their data by applying the CD test proposed by Pesaran (2004). Given overwhelming evidence of cross-section dependence, the authors use methods that allow for cross-section dependence in their analysis. After confirming that consumer price and stock price indices are first-difference stationary processes, they use two panel cointegration tests, namely the BCS test and Omay *et al*. (2014) bootstrap procedure. These tests reveal dramatically different results.

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[8] Other countries group contains the sample countries that are neither developed nor emerging based on MSCI classification.

[9] INF2 H group contains countries in which average monthly inflation exceed 0.5%, while INF2 L group contains countries in which average monthly inflation is below 0.16%. INF2 M group contains the remaining countries.

We start the analysis by examining the question whether the limited evidence provided by the tests used in Omay *et al*. (2015) in favor of cointegration is caused by their lack of accounting for structural breaks. For that purpose, we employ the OHS test that takes into consideration both the potential cross-section dependence and structural break problems in the data and compare the results to those of the BCS test reported in Omay *et al*. (2015). Table 1 presents the results.[10] As can be seen from the second column, the BCS test rejects the null of no cointegration in five sub-panels, not supporting the validity of the Fisher hypothesis for country groups classified as Others, INF1H, and INF2H. On the other hand, the OHS test statistics, shown in the third column, indicate the existence of cointegration for all the panels. This finding implies that the inability of Omay *et al*. (2014) bootstrap procedure to detect cointegration for any of the sub-panels may be due to the lack of accounting for any type of structural break. Moreover, the partial success of the BCS test may be due to its ability to deal with breaks if the timing of structural shifts roughly coincide to each other across individual group members.

Table 1

Cointegration test results

Country Groups	BCS	Bootstrap OHS
All	-2.446*	-2.467 (0.000)
Developed	-2.722*	-2.350 (0.000)
Emerging	-2.460*	-2.774 (0.000)
Others	-2.053	-2.136 (0.000)
INF1 H	-2.069	-2.605 (0.000)
INF1 L	-2.978*	-2.361 (0.000)
INF2 H	-1.908	-2.325 (0.000)
INF2 M	-2.738*	-2.587 (0.000)
INF2 L	-2.660*	-2.030 (0.000)

Notes: BCS denotes Banerjee and Carrion-Silvestre (2011) common correlated effect estimator to IPS. The BCS tests are taken from Omay et al. (2015). At 5% significance level Banerjee and Carrion-Silvestre test has critical values for T=100 and N equals 10, 15, 20,30 and 50 are -2.39, -2.30, -2.24, -2.20 and -2.15, respectively. At 10% significance level the corresponding figures are -2.27, -2,20, -2.16, -2.12 and -2.08. An asterisk denotes rejection of the null hypothesis of no cointegration at 5% significance level. Bootstrap OHS denotes Omay et al. (2013) residual based panel cointegration test. For OHS p-values are shown in parentheses. The bootstrap empirical distribution of OHS statistics, generated by employing 2,000 replications, are used to obtain the p-values.

Given the above finding that after accounting for both the potential cross-section dependence and the structural break problems, cointegration is found in all sub-panels, we next examine the second question whether the sub-panels for which the BCS test detects cointegration are characterized as having break parameters that are relatively homogenous across cross-sectional units. To explore this issue graphically, for each

[10] *To save space the coefficient estimates,* $\mu_{i1}, \mu_{i2}, \gamma_i$ *and* τ_i*, for individual countries are not reported in the paper. They are available from the authors upon request.*

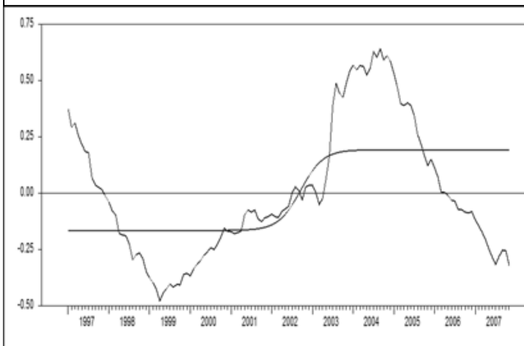
country we plot the estimated equilibrium error terms $\hat{u}_{i,t}$ and the fitted deterministic part of the model given in equation (2) on the same graph. Figure 1 presents this graph for six selected countries, namely Ireland, Turkey, Poland, Russian Federation, UK and US. As can readily be seen from the figure, both the magnitude and the timing of break vary considerably across the six selected countries. This finding supports the explanation that the heterogeneity of breaks may be the reason for the limited success of the BCS test in detecting cointegration.

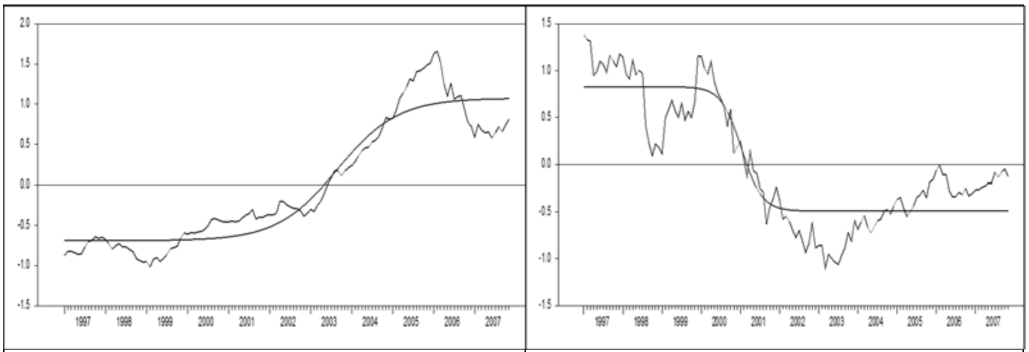
To provide additional evidence, we examine the variability of location parameters, τ_i, given in equation (4) above across the countries within each panel. Table 2 presents the calculated values of the standard deviation and range of estimated location parameter $\hat{\tau}_i$ for all panels. As the table shows, the standard deviation of the location parameter is higher for those groups for which the BCS test fails to detect cointegration. In particular, the standard deviation of τ_i for the INF2H panel is the highest (0.268) among all panels. The second and third highest standard deviations are associated with the OTHERS (0.244) and INF1H

(0.239) panels, respectively. This result once more underlines the importance of taking account of possible structural breaks in testing integration properties of series. In particular, if series are subject to regime shifts and the timing of such breaks vary considerably across cross-section units, then conventional integration tests, as well as CCE-based tests, are likely to have little power. In such cases, one must instead apply other test procedures such as the OHS test that explicitly

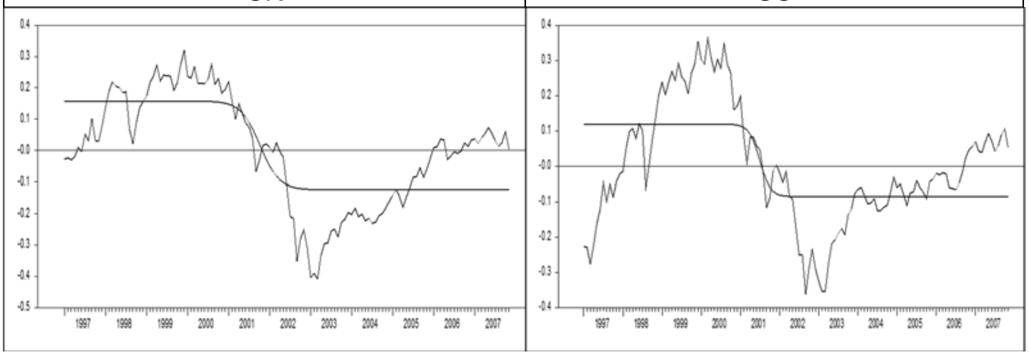
Figure 1

Graph of equilibrium error process and fitted break

Ireland	Turkey
	
Poland	Russia



UK	US



allows for possible breaks in the data generating process as well as remedies cross-section dependence among the panel units.

Table 2

The variability of location parameter, τ_i, within each subsample

Country Groups	Standard Deviation of τ_i	Range of τ_i
All	0.216	0.859
Developed	0.193	0.593
Emerging	0.225	0.758
Others	0.244	0.801
INF1 H	0.239	0.801
INF1 L	0.196	0.638
INF2 H	0.268	0.801
INF2 M	0.193	0.758
INF2 L	0.210	0.638

Note: τ_i denotes the location parameter in the country-specific logistic smooth transition functions given in Eq. (4).

The OHS test based on Leybourne *et al*. (1998) framework does not directly test for the existence of break(s). It is basically a procedure for testing whether a series is I(1) against the alternative of I(0) around a deterministic component which changes gradually and smoothly between two regimes. To check for robustness of our findings, we have also used the break tests proposed by Bai and Perron (1998). The results are reported in the Appendix. Overall, the comparison of break dates obtained from this test to those implied by the Leybourne *et al*. (1998) framework shows that the two approaches consistently estimate break dates for very smooth, smooth and moderate transitions. [11] The two methods disagree, however, for sharp (threshold) breaks. This finding is consistent with the argument in Becker et al. (2006) that the Bai and Perron (1998) test has little power to detect u-shaped breaks or breaks located at the end of the series.[12]

IV. Conclusions

In this paper, we explore the argument made by Omay et al. (2013) that panel unit root tests based on common correlated effect estimators have reasonably good power and size properties even in the presence of structural breaks if the timing of structural shifts roughly coincide to each other across individual group members. In the analysis, we employ Omay *et al*. (2013) residual based panel cointegration test as the benchmark test that takes into consideration both the potential cross-section dependence and structural break problems in the data. Using the data from Omay *et al*. (2015), which pays special attention to cross-section dependence issue but ignores the possibility of structural break in the data, we provide support to the argument above. Specifically, our results show that structural break exists in the data examined. Moreover, the three sub-panels for which the BCS test fails to detect cointegration are those in which the variability of the parameter that determines the location of structural shift is large.

Overall, our results indicate that CCE estimators can proxy structural breaks not only in unit root testing but also in cointegration testing. Moreover, they emphasize that the Fisher hypothesis must be analyzed considering the structural break in testing and estimating the relationship. For example, a time varying FMOLS model can be used in estimating the Fisher equation.

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[11] Assuming the existence of instantaneous break, the Leybourne et al. (1998) framework implies a break date at $t = \tau_i T$

[12] For further analysis of Becker et al. (2006), see Omay (2015).

Appendix

Table A1

Estimated break dates in cointegration relations

Country	Transition Speed, γ		Location, τ	Break Date	
	Level	Category		LNV	Bai-Perron
Argentina	1.270	Moderate	0.333	Jul-2000	Jul-2000
Austria	0.162	Smooth	0.730	Dec-2004	Nov-2004
Belgium	13.236	Sharp	0.386	Feb-2001	Aug-2005
Brazil	0.095	Very Smooth	0.885	Aug-2006	Aug-2005
Canada	0.150	Smooth	0.778	May-2005	May-2005
Chile	0.087	Very Smooth	0.778	May-2005	Jun-2004
China	8.613	Sharp	0.632	Nov-2003	Aug-2006
Croatia	0.077	Very Smooth	0.882	Aug-2006	Dec-2004
Czech R.	0.147	Smooth	0.728	Nov-2004	Oct-2004
Denmark	0.149	Smooth	0.787	Jul-2005	Apr-2005
Egypt	0.260	Smooth	0.720	Nov-2004	Nov-2004
Estonia	0.179	Smooth	0.691	Jun-2004	Sep-2004
Finland	11.345	Sharp	0.482	Feb-2002	Nov-1998
France	11.096	Sharp	0.492	Apr-2002	Mar-1998
Germany	12.901	Sharp	0.424	Jul-2001	Aug-2001
Hong Kong	0.055	Very Smooth	0.979	Aug-2007	Oct-2004
Hungary	1.198	Moderate	0.332	Jul-2000	Jan-2005
India	0.109	Smooth	0.780	Jun-2005	Oct-2004
Iran	0.303	Smooth	0.524	Aug-2002	Apr-2003
Ireland	12.798	Sharp	0.428	Jul-2001	Nov-2005
Israel	0.109	Smooth	0.725	Nov-2004	Nov-2004
Italy	12.882	Sharp	0.425	Jul-2001	Mar-1998
Jamaica	0.137	Smooth	0.500	May-2002	Aug-2002
Japan	0.962	Moderate	0.795	Aug-2005	Aug-2005
Jordan	0.228	Smooth	0.684	May-2004	Jul-2004
Latvia	0.125	Smooth	0.693	Jun-2004	Apr-1998
Luxembourg	1.399	Moderate	0.418	Jun-2001	Jul-2001
Malaysia	0.090	Very Smooth	0.906	Oct-2006	Sep-2006
Mauritius	0.092	Very Smooth	0.925	Jan-2007	Oct-2006
Morocco	0.212	Smooth	0.863	May-2006	Feb-2006
Netherlands	0.427	Smooth	0.470	Jan-2002	Mar-2002
Norway	0.195	Smooth	0.783	Jun-2005	May-2005
Philippines	0.090	Very Smooth	0.148	Jul-1998	Apr-2000
Poland	0.193	Smooth	0.837	Jan-2006	Jan-2006
Portugal	0.776	Moderate	0.397	Mar-2001	Apr-2001
Russian F.	0.081	Very Smooth	0.769	Apr-2005	Jun-2005
Singapore	0.110	Smooth	0.863	May-2006	Feb-2006
Slovakia	0.796	Moderate	0.712	Sep-2004	Oct-2004

Country	Transition Speed, γ		Location, τ	Break Date	
	Level	Category		LNV	Bai-Perron
South Africa	0.169	Smooth	0.788	Jul-2005	Jun-2005
Spain	3.244	Sharp	0.405	Apr-2001	Jan-2006
Sri Lanka	0.224	Smooth	0.645	Dec-2003	Oct-2003
Saudi Arabia	0.113	Smooth	0.612	Aug-2003	Oct-2003
Sweden	13.112	Sharp	0.418	Jun-2001	Oct-2005
Switzerland	3.398	Sharp	0.421	Jul-2001	Nov-2005
Taiwan	4.851	Sharp	0.341	Aug-2000	Sep-2000
Thailand	1.103	Moderate	0.614	Aug-2003	Sep-2003
Trinidad Tobago	0.332	Smooth	0.605	Jul-2003	Sep-2003
Turkey	0.323	Smooth	0.374	Dec-2000	Jun-2001
UK	0.361	Smooth	0.440	Sep-2001	Aug-2001
US	0.631	Smooth	0.416	Jun-2001	Jul-2001
Venezuela	0.578	Smooth	0.120	Mar-1998	Apr-1998
Zambia	*0.486*	*Smooth*	*0.158*	*Aug-1998*	*Sep-1998*

Note: *Bai-Perron shows break dates obtained by using the break tests proposed by Bai and Perron (1998). LNV denotes break dates implied by the Leybourne et al. (1998) framework.*

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