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Short communication

Hidden panel cointegration☆

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ABSTRACT

This paper focuses on an important empirical and methodological research question, namely possibly asymmetric and hence nonlinear cointegrating relationships between variables. It extends the Granger and Yoon (2002) method on hidden cointegration for time series data to a panel data framework. Solutions are provided for transforming the panel data variables with deterministic as well as stochastic trend parts into partial cumulative sums for positive and negative components. The transformed data can then be used to test for the long run relationship between the underlying components. The proposed method is applied to a small panel of three Scandinavian countries examining the presence of a long-term relationship between government consumption and economic growth based on quarterly data. First, the standard method that does not allow for asymmetry was implemented. The results do not provide evidence of a long-term relationship between the two variables. However, the results based on the tests suggested in this paper indicate that the underlying variables are indeed related in the long run. Thus, it might be important to separate the impact of positive shocks from the negative ones when the long run relationships between panel data variables are investigated.

1. Introduction

Since the pioneer work of Granger (1981) cointegration analysis has become an integral part of applied econometrics when the underlying variables are quantities that are measured across time. Based on Granger's definition, cointegration occurs in a situation in which a linear combination between integrated variables has one unit root less than the integration order of the variables in the model. The variables cointegrate if and only if they have common stochastic trends that cancel each other out. There is a massive literature both theoretically and empirically on cointegration indicating its due importance. Cointegration analysis is important in empirical research in order to avoid spurious results based on a regression model. It is also important for analyzing the long-run relationships between the underlying variables combined with the short-run adjustment mechanism. It is crucial to test for cointegration in order to avoid the spurious regression problem. If the variables have unit roots but not cointegrated then any relationship between them in the level form is spurious according to Granger and Newbold (1974).

Testing for cointegration was initiated by Engle and Granger (1987) via implementing residual based tests for cointegration. More powerful tests were suggested by Phillips (1987) as well as Phillips and Ouliaris (1990).[1] Multivariate tests for cointegration were developed by Johansen (1988, 1991), Johansen and Juselius (1990) as well as Stock and Watson (1988). The idea to conduct tests for unit roots within a panel system originates from Quah (1994). Tests for panel cointegration were suggested by Pedroni (1999, 2004), Kao (1999) and Westerlund (2007), among others.[2]

In all previous literature on cointegration testing, there was no separation between the impact of negative and positive shocks

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[1] There are also tests for cointegration that allow of structural breaks. See for example Gergory and Hansen (1996) for tests with one unknown break and Hatemi-J (2008) for tests with two unknown breaks.

[2] For recent contributions on regression modeling the interested reader is referred to AlMuhayfith and Alzaid (2016), Sanaullah and Hanif (2018) and Mohammad and Mudhir (2018), among others.

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until Granger and Yoon (2002) introduced the concept of hidden cointegration for time series data. It is hidden in the sense that it illustrates a situation in which the variables in original form do not cointegrate but when the impact of positive shocks is separated from the impact of negative shocks then cointegration is potentially found between the components of the variables.[3] The aim of this article is to extend the concept of hidden cointegration to panel data analysis. The suggested tests in this paper are applied to investigate the impact of contractionary as well as expansionary fiscal policy on the economic performance in a panel consisting of Denmark, Norway and Sweden. It should be pointed out that allowing for asymmetry accords well with reality. It is widely agreed in the literature that individuals tend to react more powerfully to negative conditions than to positive ones.

The article continues as follows. Section 2 introduces hidden panel cointegration analysis. Section 3 provides an application. The last section concludes the article. Finally, an appendix at the end of the article provides a simple mathematical example that shows the necessary condition for cointegration in a panel system. It also presents the solution for a variable that has deterministic trend parts. It should be mentioned that Gauss codes are available that can be used for transforming a variable into positive partial sums for positive and negative components (see Hatemi-J, 2014). After transforming the data, tests for panel cointegration can be implemented via a number of software packages that exist in the market.

2. Hidden panel cointegration

Consider the following two variables that are integrated of the first degree, with the resultant solution for each that is found by the recursive approach:[4]

$$y_{i,t} = y_{i,t-1} + e_{i1,t} = y_{i,0} + \sum_{j=1}^{t} e_{i1,j}$$

$$x_{i,t} = x_{i,t-1} + e_{i2,t} = x_{i,0} + \sum_{j=1}^{t} e_{i2,j}$$

For $i = 1, \ldots, m$. Where m signifies the cross-sectional dimension and e is the disturbance term that is assumed to be a white noise process. The positive and negative shocks for each panel variable are defined as $e^+_{i1,t} := Max(e_{i1,t}, 0)$, $e^+_{i2,t} := Max(e_{i2,t}, 0)$, $e^-_{i1,t} := Min(e_{i1,t}, 0)$ and $e^-_{i2,t} := Min(e_{i2,t}, 0)$.[5] Using these results, the following expressions can be obtained:

$$y^+_{i,t} = y^+_{i,0} + e^+_{i1,t} = y_{i,0} + \sum_{j=1}^{t} e^+_{i1,j}$$

$$x^+_{i,t} = x^+_{i,0} + e^+_{i2,t} = x_{i,0} + \sum_{j=1}^{t} e^+_{i2,j}$$

$$y^-_{i,t} = y^-_{i,0} + e^-_{i1,t} = y_{i,0} + \sum_{j=1}^{t} e^-_{i1,j}$$

$$x^-_{i,t} = x^-_{i,0} + e^-_{i2,t} = x_{i,0} + \sum_{j=1}^{t} e^-_{i2,j}$$

Assume that our dependent variable is y, and then the two potential panel cointegration equations for the components can be defined as

$$y^+_{i,t} = \alpha^+_i + \beta^+_i x^+_{i,t} + e^+_{i,t} \tag{1}$$

$$y^-_{i,t} = \alpha^-_i + \beta^-_i x^-_{i,t} + e^-_{i,t} \tag{2}$$

The positive cumulative shocks are cointegrated in the panel if $e^+_{i,t}$ is stationary. Likewise, the negative cumulative shocks are cointegrated in the panel if $e^-_{i,t}$ is stationary.[6]

There is potentially a battery of the tests available in the literature that can be used for testing whether $e^+_{i,t}$ or $e^-_{i,t}$ is stationary or not. However, the well-known augmented Dickey-Fuller (ADF) test is the simplest one that can be used for this purpose. Assume that we wish to test for cointegration in the panel model (1). Then, the panel ADF test equation is the following:

$$e^+_{i,t} = \rho^+ e^+_{i,t-1} + \sum_{l=1}^{k} \gamma^+_i \Delta e^+_{i1,t-l} + w^+_{i,t} \tag{3}$$

The optimal lag order l can be determined by minimizing an information criterion. The null hypothesis of no cointegration between the positive components is $\rho^+ = 1$. It is also possible to allow for deterministic components such as individual drifts and trends in Eq. (3) if necessary.[7] Based on the results provided by Kao (1999), the following test statistic can be used to test the null hypothesis of no panel cointegration:

$$ADF = \frac{t_{\rho^+ + \sqrt{6m} \times \frac{\sigma_v}{2\sigma_{0v}}}}{\sqrt{\frac{\sigma^2_{0v}}{2\sigma^2_v} + \frac{3\sigma^2_v}{10\sigma^2_{0v}}}} \tag{4}$$

where t_{ρ^+} is the t-statistic for parameter ρ^+ in Eq. (3). The variance is estimated as $\sigma^2_v = \sigma^2_{e^+_1} - \frac{\sigma^2_{e^+_1, e^+_2}}{\sigma^2_{e^+_2}}$, and the long-run variance is estimated as $\sigma^2_{0v} = \sigma^2_{0e^+_1} - \frac{\sigma^2_{0e^+_1, e^+_2}}{\sigma^2_{0e^+_2}}$.

Let $u_{it} = \begin{bmatrix} e^+_{i1,t} \\ e^+_{i2,t} \end{bmatrix}$. The variance-covariance for u_{it} is estimated as $\Sigma = \begin{bmatrix} \sigma^2_{e^+_1} & \sigma_{e^+_1, e^+_2} \\ \sigma_{e^+_1, e^+_2} & \sigma^2_{e^+_2} \end{bmatrix} = \frac{1}{mT} \sum_{i=1}^{m} \sum_{t=1}^{T} u_{it} u'_{it}$

The long-run variance-covariance matrix is estimated via the kernel estimation approach as

$$\Omega = \begin{bmatrix} \sigma^2_{e^+_1} & \sigma_{e^+_1, e^+_2} \\ \sigma_{e^+_1, e^+_2} & \sigma^2_{e^+_2} \end{bmatrix} = \frac{1}{m} \sum_{i=1}^{m} \left[\frac{1}{T} \sum_{t=1}^{T} u_{it} u'_{it} + \frac{1}{T} \sum_{t=1}^{T} \kappa(\tau/b) \sum_{t=\tau+1}^{T} (u_{it} u'_{it-\tau} + u_{it-\tau} u'_{it}) \right]$$

where κ is representing the kernel function and b is the bandwidth.

[3] Recently, a procedure suggested by Shin et al. (2014) accounts for the hidden cointegration within the non-linear autoregressive distributed lag (NARDL) framework. However, there are two main differences between their approach and the one that is suggested by the current paper. Shin et al. (2014) approach deals with the time series data while the current paper deals with the panel data. Another difference is that Shin et al. (2014) account for the potential asymmetric effects within the same equation while the current one makes use of separate equations for the positive and negative components of both dependent and independent variables.

[4] For the simplicity of expression we concentrate on the case where the panel model consists of two variables. The results can, however, be generalized in the sense that more independent variables can be included in the model.

[5] Based on a similar approach, Hatemi-J (2012, 2014) suggests tests for asymmetric causality as well as estimating the asymmetric generalized impulse response functions for times series data.

[6] If cointegration is found the parameters in Eqs. (1) and (2) can be estimated by the least squares method or any other more efficient approach. It should be mentioned that other combinations are also possible. Such as, cumulative positive changes of y as a function of cumulative negative changes of x, as well as cumulative negative changes of y as a function of cumulative positive changes of x.

[7] As pointed out by an anonymous referee, "*It would be illustrative and clarifying to distinguish clearly between observed variables such as y, x and also y^-, x^-, and constructed variables such as the residuals e^-, e^+. Note that $e^+_{i1,t}$ is observed as it is an increment in a random walk y^+, whereas $e^+_{i,t}$ is a residual in a regression Eq. (1). Also, $e^+_{i1,t}$ is positive, whereas $e^+_{i,t}$ not necessarily.*"

Table 1
The Results of Panel Unit Root Tests.

VARIABLE	H_0: I(1), H_1: I(0)	H_0: I(2), H_1: I(1)
X	0.9945	<0.0001
Y	0.4222	<0.0001
X^+	0.6758	<0.0001
Y^+	0.4457	<0.0001
X^-	0.4410	<0.0001
Y^-	0.7116	<0.0001

Notes
The denotation X stands for the government consumption and Y is representing the GDP. The variables are expressed the logarithmic form. The Im, Pesaran and Shin (2003) test is used to test for panel unit root. The p-values are presented.

Table 2
The Results of Panel Cointegration Tests.

VARIABLES IN THE MODEL	H_0: I(1), H_1: I(0)
(Y,X)	-1.0144
(Y^+,X^+)	-1.6995^*
(Y^-,X^-)	-0.5489
(Y^-,X^+)	-1.8705^*
(Y^+,X^-)	-1.6995^*

Notes
The null hypothesis of no panel cointegration is rejected at the 5% significance level if the estimated test value is lower than -1.64. * means significant at the 5% significance level.

The ADF test statistic as presented in Eq. (4) has a standard normal distribution asymptotically. For a proof see Kao (1999). To test for stationarity in the linear combination between negative components as presented in Eq. (2), a similar ADF test can be conducted. Other combinations are also possible.[8] A Gauss code for constructing partial cumulative sums of positive and negative changes of each variable for each cross sectional unit in the panel is available on request from the author. It should be mentioned that it is also possible to test for hidden panel cointegration using other tests such as seven residual based tests suggested by Pedroni (1999, 2004) as well as the panel version of the multivariate Johansen (1991) test as developed by Maddala and Wu (1999) based on the Fisher (1932) principle of deriving a combined test using the individual test results.

3. An application

The suggested test for hidden panel cointegration is applied to investigating the long-run relationship between government consumption and economic performance in Denmark, Norway and Sweden. Quarterly data is used during the period 1995:Q1-2017:Q4. The source of data is the FRED database that is provided by the Federal Reserve Bank of St. Louis. In order to capture real effects, the variables are expressed at constant prices. The cumulative sums of positive and negative shocks were constructed based on the procedure presented in the previous section. Prior to testing for panel cointegration, panel unit root tests were implemented by using the Im, Pesaran and Shin (2003) test. The results are presented in Table 1, which show that each panel variable has one unit root.

Given that each variable in the panel has one unit root, it is crucial to conduct tests for panel cointegration. First, we tested for concintegration by using the standard tests and then we implemented the tests that are proposed in this paper. The results of these tests are presented in Table 2, which indicate that there is no cointegration between government consumption and output in the panel sample for these three countries when standard tests are performed. However, when the suggested tests for hidden cointegration are implemented, the results indicate that there is panel cointegration between the underlying components.

4. Conclusions

Tests for cointegration are commonly utilized in applied research. The aim of this article is to extend the hidden cointegration tests of time series data as developed by Granger and Yoon (2002) to the hidden cointegration tests of panel data. Panel data combines the time series dimension with the cross-sectional dimension, which results in higher degrees of freedom. It is shown in this paper how partial cumulative sums of positive and negative changes can be constructed for the panel data variables. It is also demonstrated how an augmented Dickey-Fuller test for a panel system can be implemented to test the null hypothesis of no panel cointegration between different components of the underlying variables. A user friendly Gauss algorithm is produced to transform the panel variables into their respective components.

The suggested tests are applied to investigating the impact of government consumption on economic output in a panel of three Scandinavian countries—namely Denmark, Norway and Sweden. The results show that there is no panel cointegration between these variables when the standard tests are applied. However, when the tests suggested in this paper are implemented, it is found that there is indeed a long run relationship between the negative and positive components of the underlying panel data variables. Thus, allowing for asymmetry is crucial in this case in order to avoid misleading empirical inference. It should be pointed out that separating the impact of positive shocks from the negative ones might be informative *per se*, in order to capture the potential asymmetry that might prevail. Another issue that might be relevant within this context is the issue of cross-section dependence, which has not been addressed in this paper. A potential approach to deal with the cross-section dependency in tests for hidden panel cointegration might be using the results suggested by Pesaran (2006). Furthermore, if the assumption of normality is not fulfilled, the simulation based techniques such as the bootstrapping method suggested by Shin (2015) might be useful for creating critical values that are based on resampling of the underlying data set instead of using the asymptotic critical values.

Appendix

An example regarding panel cointegration

Let us be more explicit about panel cointegration between two panel integrated variables by a simple example. Consider the following two non-stationary panel variables:

$$Z_{i,t} = Z_{i,t-1} + \varepsilon_{i1,t} \tag{A1}$$

$$W_{i,t} = Z_{i,t-1} + \varepsilon_{i2,t} \tag{A2}$$

where $\varepsilon_{i1,t}$ and $\varepsilon_{i2,t}$ are two white noise error terms. Assuming that the initial values are zero, continuous substitutions give the following solutions:

$$Z_{i,t} = \sum_{j=1}^{t} \varepsilon_{i1,j} \tag{A3}$$

$$W_{i,t} = \sum_{j=1}^{t-1} \varepsilon_{i1,j} + \varepsilon_{i2,t} \tag{A4}$$

[8] That is, one can consider $y^+_{i,t}$ as a function of $x^-_{i,t}$ or $y^-_{i,t}$ as a function of $x^+_{i,t}$.

By taking the first difference of each variable, we obtain

$$\Delta Z_{i,t} = Z_{i,t} - Z_{i,t-1} = \sum_{j=1}^{t}\varepsilon_{i1,j} - \sum_{j=1}^{t-1}\varepsilon_{i1,j} = \varepsilon_{i1,t} \tag{A5}$$

$$\Delta W_{i,t} = W_{i,t} - W_{i,t-1} = \sum_{j=1}^{t}\varepsilon_{i1,j} + \varepsilon_{i2,t} - \left(\sum_{j=1}^{t-1}\varepsilon_{i1,j} + \varepsilon_{i2,t-1}\right)$$
$$= \varepsilon_{i1,t} + \varepsilon_{i2,t} - \varepsilon_{i2,t-1} \tag{A6}$$

That is, each panel variable becomes stationary after taking the first difference. Hence, the variables are integrated of the first order, denoted I(1). Now, the question is whether or not these two panel variables are cointegrated. Denote $Y_{i,t}$ as the difference between the two variables, i.e.

$$Y_{i,t} = W_{i,t} - Z_{i,t} = \sum_{j=1}^{t}\varepsilon_{i1,j} - \left(\sum_{j=1}^{t-1}\varepsilon_{i1,j} + \varepsilon_{i2,t}\right) = \varepsilon_{i1,t} - \varepsilon_{i2,t} \tag{A7}$$

This difference is clearly a stationary process. That is, a linear combination of the non-stationary variables is stationary in the panel, which in turn means that the variables cointegrate with (1.0, −1.0) as the cointegrating vector. It should be noted that the variables cointegrate because their stochastic trend cancels each other out. In another words, the panel variables have a common stochastic trend. This is the case in the hidden panel cointegration analysis also. In order to have hidden panel cointegration, there must be at least one common stochastic trend between the cumulative components of the positive or negative shocks in the underlying panel.

Transforming data with deterministic trend parts

It is widely agreed that many economic and financial variables contain deterministic trend in addition to the stochastic trend. In such cases, the following approach can be utilized in order to transform the data into partial cumulative sums for positive and negative components. For example, assume that the data generating process is the following:

$$y_{it} = a_i + b_i t + y_{it-1} + u_{it}, \tag{A8}$$

where a is the drift and t is the deterministic trend component. By applying the recursive method, the solution to Eq. (A8) is given as the following:

$$y_{ti} = a_i t + \frac{t(t+1)}{2} b_i + y_{0i} + \sum_{j=1}^{t} u_{ij}, \tag{A9}$$

The positive and negative shocks for this panel variable are defined as $u^{+}_{i,t} := Max(u, 0)$ and $u^{-}_{i,t} := Min(u_{i,t}, 0)$ and $e^{-}_{i2,t} := Min(e_{i2,t}, 0)$. It follows that

$$y_{it} = a_i + b_i t + y_{it-1} + u_{it}$$
$$= a_i t + \frac{t(t+1)}{2} b_i + y_{0i} + \sum_{j=1}^{t} u^{+}_{ij} + \sum_{j=1}^{t} u^{-}_{ij}, \tag{A10}$$

Hence, the positive and negative components can be defined as the following:

$$y^{+}_{it} = \frac{a_i t + \frac{t(t+1)}{2} b_i + y_{0i}}{2} + \sum_{j=1}^{t} u^{+}_{ij}, \tag{A11}$$

and

$$y^{-}_{it} = \frac{a_i t + \frac{t(t+1)}{2} b_i + y_{0i}}{2} + \sum_{j=1}^{t} u^{-}_{ij}. \tag{A12}$$

Thus, $y_{it} = y^{+}_{it} + y^{-}_{it}$.. These results can be proved by a proposition provided by Hatemi-J and El-Khatib (2016).

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