Economic Modelling 61 (2017) 181–192

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/econmod

A panel stationarity test with gradual structural shifts: Re-investigate the international commodity price shocks☆

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A R T I C L E I N F O

JEL codes:
C12
C23
Q02

Keywords:
Gradual shifts
Fourier approximation
Stationarity test
Panel data
Commodity prices

A B S T R A C T

This paper proposes a simple panel stationarity test which takes into account structural shifts and cross-section dependency. Structural shifts are modelled as gradual/smooth process with a Fourier approximation. The so-called Fourier panel stationarity test has a standard normal distribution. The Monte Carlo simulations indicate that (i) if the error terms are *i.i.d*, the test shows good size and power properties even in small samples; and (ii) if the error terms are serially correlated, the test has reasonable size and high power. We re-examine the behavior of the international commodity prices and find out an evidence on the persistence of shocks.

1. Introduction

The panel unit root tests during the last two decades have triggered interest because incorporating time dimension with cross-sectional dimension leads to increase in power of the tests. The early attempts go back to Levin et al. (2002), Im et al. (2003), Maddala and Wu (1999), and Choi (2001) in which cross-sections in a panel data are assumed to be independent. Since the independency assumption is not likely to hold in practice, the literature is extended by the second generation unit root tests which account for cross-section dependency (among others, Breuer et al., 2002; Smith et al., 2004; Bai and Ng, 2004, Pesaran, 2007).

Given the importance of structural breaks in the behavior of macroeconomic series, a special attention in the unit root analysis has been paid to allow the existence of structural shifts. One important question in the literature is how to account for breaks. The traditional approach is to use dummy variables in which structural shifts are assumed to occur instantaneously (for example, Perron, 1989; Zivot and Andrews, 1992; Lee and Strazicich, 2003; Im et al., 2005). In addition to the dummy variable approach, the smooth transition approach is also used since structural changes in macroeconomic time series are likely to be gradual (*inter alia* Leybourne at al., 1998; Kapetanios et al., 2003). Both the dummy variables and the smooth transition modelling assume *a priori* one or two structural shifts and require to know dates, number, and functional form of breaks. Even though the recent studies have focused on multiple structural breaks (*inter alia* Carrion-i-Silvestre et al., 2009; Westerlund, 2012), the unit root tests with many endogenous breaks are subject to determining maximum number of breaks, estimating location of breaks, over parametrization, and loss of power (Enders and Lee, 2012a; Rodrigues and Taylor, 2012). To deal with these problems, Becker et al. (2006), Enders and Lee (2012a, 2012b) and Rodrigues and Taylor (2012) propose the testing procedures with a Fourier approximation based on the variant of Flexible Fourier Form by Gallant (1981). The Fourier approximation does not require to know *a priori* dates, number, and/or form of breaks. This approach captures structural break(s) by using frequency components. The specification problem of selecting dates, number, and form of breaks is thereby transformed into incorporating the appropriate Fourier frequency (Enders and Lee, 2012b). Since the developments in time-series analysis can easily be extended to the panel framework, the unit root tests based on the Fourier approximation in time series context have led to a new direction in the panel unit root literature. Lee et al. (2015) in that respect develop the panel version on the Fourier DF-type test by

☆ We would like to thank Joakim Westerlund (associate editor), Junsoo Lee, Eiji Kurozumi, Ron Smith and two anonymous referees for the constructive comments and suggestions which help us to improve the paper. Authors also would like to thank the participants of the 2nd Annual Conference of the International Association for Applied Econometrics (IAAE-2015) and of the 1st International Conference on New Trends in Econometrics and Finance (1st ICNTEF'15) for their helpful suggestions.Saban Nazlioglu gratefully acknowledges that this study is carried out under the Outstanding Young Scientists Award Program-2015 of the Turkish Academy of Sciences (TÜBA-GEBİP 2015).

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http://dx.doi.org/10.1016/j.econmod.2016.12.003
Received 30 December 2015; Received in revised form 22 November 2016; Accepted 3 December 2016
Available online 27 December 2016
0264-9993/

Enders and Lee (2012b) in order to allow for smoothing structural changes in deterministic terms.

Developing testing procedures with the null hypothesis of stationarity[1] has witnessed ongoing research in both the time series and the panel data literature. The stationarity test developed by Kwiatkowski et al. (1992) (the KPSS test) has attracted interest by practitioners and widely used in the empirical studies. Lee et al. (1997) analyze the effect a structural break on the KPSS test and show that it diverges from the distribution under the null hypothesis if a structural break is ignored. Their Monte Carlo analysis indicates that the KPSS test rejects the null hypothesis too often in the case of a structural shift. In the panel data literature, Hadri (2000) develops the panel stationarity test based on the univariate KPSS statistics. Hadri and Kurozumi (2011, 2012) propose the panel stationarity tests that allow for cross-section dependency based on a factor structure. Since the presence of structural breaks affects the limiting distribution of the individual statistics under the null hypothesis, it is crucial to control for structural breaks in the stationarity tests to deal with the size distortion problem. The more recent panel data studies have focused on accounting for structural breaks (*inter alia*, Carrion-i-Silvestre et al., 2005; Hadri and Rao, 2008; Hadri et al., 2012). It is worthwhile emphasizing that all these studies benefit from the dummy variable approach for modelling structural shifts.

This paper proposes a simple panel stationarity test with gradual structural shifts and cross-section dependency. The test also permits the heterogeneity across cross-sections in a panel. The testing procedure is a combination of the time series stationarity test developed by Becker et al. (2006) in which structural shifts are modeled with a Fourier approximation and the panel stationarity test proposed by Hadri and Kurozumi (2011, 2012) in which cross-section dependency is accounted with a common factor structure[2]. The distribution of the individual statistic only depends on the Fourier frequency and the panel statistic has a standard normal distribution. The small sample properties of the panel stationarity test are investigated by Monte Carlo simulations for the different data generating processes. We find that for the independent and identically distributed errors the empirical size of the test is close to the 5 percent nominal size irrespective of time (T) and cross-section (N) dimensions. Besides there is a substantial increase in the power as T or N or both increase[3]. The size and power analysis for the serially correlated errors shows that the test has good power as T increases and reasonable size properties.

The recent dynamics of international commodity prices have attracted more interest in investigating the behavior of commodity markets. Understanding the behavior of commodity prices has a long theoretical and empirical debate. The Prebisch-Singer hypothesis on the one side postulates a long term tendency with declining trends (Prebisch, 1950 and Singer, 1950). The classical view on the other hand argues that the real commodity prices show a positive trend in the long term (Sarkar, 1986). The equilibrium price theory suggests that the supply and demand forces will push commodity prices towards stable equilibrium in the long-run. A serious research effort has been exerted and the evidence on whether the shocks to international commodity prices are transitory or permanent is not still clear cut. We re-analyze whether international commodity prices are stationary by using the Fourier panel stationarity test proposed in this paper. The results support the evidence on that the null hypothesis of joint stationarity is rejected and many of the real commodity prices follow the unit root process, implying that the shocks to international commodity prices are permanent. This finding contrasts with the results from the previous panel data studies in which the structural breaks are taken into account as sharp process. The new panel stationarity test hence provides a fresh information regarding the nature of shocks to international commodity prices.

The paper is organized as follows: the next section is devoted to develop the Fourier panel stationarity test and to simply show its asymptotic distribution. In Section 3, we conduct the Monte Carlo analysis for the small sample properties. In Section 4, the nature of shocks to international commodity prices is examined. Finally, Section 5 includes the conclusion.

2. Model, test statistic and asymptotic distribution

We consider the following data generating process (DGP):

$$y_{it} = \alpha_i(t) + r_{it} + \lambda_i F_t + \varepsilon_{it} \quad (1)$$

$$r_{it} = r_{it-1} + u_{it} \quad (2)$$

where $i = 1, \ldots, N$ cross-section dimension, $t = 1, \ldots, T$ time dimension, r_{it} is random walk process with initial values r_{i0}=0 for all *i*, without loss of generality as heterogeneous constant terms are included[4]. ε_{it} and u_{it} are mutually independent and identically distributed (*i.i.d*) across *i* and over *t* with $E(\varepsilon_{it}) = 0,\ E(\varepsilon_{it}^2) = \sigma_{\varepsilon i}^2 > 0,\ E(u_{it}) = 0,\ E(u_{it}^2) = \sigma_{ui}^2 \geq 0$, and a finite fourth-order moment. F_t is unobserved common factor and λ_i are the loading weights. F_t is stationary and serially uncorrelated with $E(F_t)$=0 and $E(F_t^2) = \sigma_F^2$>0. ε_{it}, F_t, and λ_i are independently distributed for all *i*. Finally, F_t is assumed to be known[5].

The Eq. (1) describes the deterministic term as a time-dependent function denoted by $\alpha_i(t)$. Any structural breaks or nonlinearity in the deterministic term can be captured by a Fourier approximation which mimics a variety of shifts regardless of date, number, and form of breaks (Becker et al., 2006). If the intercept terms include any structural shifts with unknown forms, the Fourier expansion with a single frequency component[6] is described as

$$\alpha_i(t) = a_i + \gamma_{1i} sin\left(\frac{2\pi kt}{T}\right) + \gamma_{2i} cos\left(\frac{2\pi kt}{T}\right) \quad (3)$$

where γ_{1i} and γ_{2i} respectively measure the amplitude and displacement of shifts and *k* denotes the Fourier frequency. The Eq. (3) allows one to obtain time-varying intercept term by nonzero values of γ_{1i} and γ_{2i} to capture smooth changes in the intercept. More generally both the intercept and the slope of time trend may fluctuate over time. If the trend function is nonlinear (either with breaks or other types of nonlinearity), it can be approximated by the Fourier expansion (Jones and Enders, 2014)

$$\alpha_i(t) = a_i + b_i t + \gamma_{1i} sin\left(\frac{2\pi kt}{T}\right) + \gamma_{2i} cos\left(\frac{2\pi kt}{T}\right). \quad (4)$$

Introducing a time trend in a Fourier approximation removes the restriction of same starting and ending values of the sinusoidal function. The Eq. (4) thereby can capture any changes in the intercept and the slope of deterministic trend by nonzero values of γ_{1i} and γ_{2i} which bring out smoothly curving trend functions (Lee et al., 2015: 4). It is worthwhile noting that the trend functions with sudden breaks are not nested within a single frequency Fourier approximation. If y_{it} has the linear trend with

[1] The null hypothesis of stationarity would be more natural than the null of unit root for many macroeconomic series (Carrion-i-Silvestre et al., 2005) and useful to confirm results from the tests with the null hypothesis of unit root (Hadri, 2000; Becker et al., 2006).

[2] The econometric contribution of this paper hence is simple because the proposed test is based on the existing procedures in the time series and panel data literature. However, the testing procedure would be useful to better understand the nature of shocks by comparing results with those from the panel stationarity tests in which structural shifts are modelled as sharp process.

[3] This result is consistent with the generally invoked powerfulness of the panel unit root and stationarity tests (see Hadri, 2000).

[4] For the importance of initial values in autoregressive models, see Abadir (1993) and Abadir and Hadri (2006).

[5] In practice the common factor is replaced by its estimates. We discuss this point in Section 4.

[6] We refer Becker et al. (2006) for a detailed discussion on using a single frequency instead of cumulative frequencies.

Table 1
Asymptotic moments.

k	Constant		Constant and trend	
	$\xi(k)$	$\zeta^2(k)$	$\xi(k)$	$\zeta^2(k)$
1	0.0658	0.0029	0.0295	0.00017
2	0.1410	0.0176	0.0523	0.00150
3	0.1550	0.0202	0.0601	0.00169
4	0.1600	0.0214	0.0633	0.00180
5	0.1630	0.0219	0.0642	0.00179

The DGP is given by $y_t=\alpha(t)+\lambda F_t+\varepsilon_t$ with $F_t \sim N(0,1)$ and $\varepsilon_t \sim N(0,1)$.$\alpha(t)$ is generated by (3) for the constant and (4) for the constant and trend model with a, b,γ_1, γ_2,λ~U[0,1] that $U[\bullet]$ denotes the uniform distribution.

sharp breaks, then a Fourier approximation cannot capture the breaking trends as accurately as the dummy variable approach (King and Ramlogan-Dobson, 2014). A Fourier approximation also does not permit us to analyze the changes in slope of time trend before and after breaks (Tsong et al., 2016) because it accounts for structural shifts as a gradual/smooth process. If structural shifts are assumed to be sharp, then one can examine the behavior of y_{it} by using the panel stationarity test developed by Hadri and Rao (2008) or by Carrion-i-Silvestre et al. (2005). In practice, it is a strict presupposition that all the cross-sections in a panel data have deterministic trend with sharp changes. Even though a Fourier approximation is not completely flexible to accommodate structural breaks, it provides a flexibility to mimic a variety of breaks with unknown forms that this flexibility appears to be useful for panel data analysis.

We are interested in testing the null hypothesis of stationarity against the alternative hypothesis of unit root.[7] The hypotheses are given by for all i.

The alternative hypothesis allows σ_{ui}^2 to differ across cross-sections and also permits some of cross-sections to be stationary. The individual statistic which is based on the KPSS test allowing the Fourier frequency developed by Becker et al. (2006) is defined as

$$\eta_i(k) = \frac{1}{T^2}\frac{\sum_{t=1}^{T}\widetilde{S}_{it}(k)^2}{\widetilde{\sigma}_{\varepsilon i}^2} \tag{5}$$

where $\widetilde{S}_{it}(k) = \sum_{j=1}^{t}\widetilde{\varepsilon}_{ij}$ is the partial sum process by using the OLS residuals from Eq. (1), and $\widetilde{\sigma}_{\varepsilon i}^2$ is an estimate of the long-run variance of ε_{it} that is defined as

$$\sigma_{\varepsilon i}^2 = \lim_{T\to\infty} T^{-1}E(S_{it}^2). \tag{6}$$

The panel statistic can be developed by the average of individual statistics. The Fourier panel statistic $FP(k)$ is thus obtained as

$$FP(k) = \frac{1}{N}\sum_{i=1}^{N}\eta_i(k). \tag{7}$$

Following Becker et al. (2006), we show that the asymptotic distribution of $\eta_i(k)$ as $T \to \infty$ only depends on k and is invariant to other parameters in the DGP.[8] Only difference between our model and that of Becker at al. (2006) is the common factor. As shown by Hadri and Kurozumi (2011, 2012), the common factor would not permanently accumulate in y_{it} if it is assumed to be stationary under the null hypothesis. The asymptotic distribution of the panel statistic can be obtained as the average of limiting distributions of individual statistics (Carrion-i-Silvestre et al., 2005; Westerlund, 2012) when the common factor does not affect the individual limiting distribution (Bai and Ng, 2004). It is easily seen by the Lindberg-Levy central limit theorem under the null hypothesis as first $T \to \infty$ and then $N \to \infty$, $FP(k)$ converges to the standard normal distribution with the mean $\xi(k)$ and the variance $\zeta^2(k)$:

$$FZ(k) = \frac{\sqrt{N}(FP(k) - \xi(k))}{\zeta(k)} \sim N(0,\,1) \tag{8}$$

Note that the second order moment of $FP(k)$ is finite for sufficiently large T since ε_{it} is assumed to have a finite fourth-order moment. The application of the Lindberg-Levy central limit theorem also requires that T and k are the same for all cross-section units. If T and k differ across cross-sections, it is required to carry out more simulations to get critical values. The limiting distribution of the panel statistic is obtained sequentially with $T \to \infty$ followed by $N \to \infty$.[9] Under the alternative hypothesis, as $T, N \to \infty, \frac{N}{T} \to 0$ and $\frac{N_1}{N} \to \varphi > 0$ the panel stationarity test $FZ(k)$ diverges infinity and hence is consistent if the fraction of cross-sections having a unit root is different from zero.[10]

In order to calculate the test statistic in Eq. (8), one needs to know the numerical values of the mean $\xi(k)$ and the variance $\zeta^2(k)$. One standard way to obtain these values is to benefit from Monte Carlo simulation of the limiting distribution of test statistic if no closed form expression exists (Westerlund, 2012). Table 1 reports the simulated asymptotic moments for T=1000 with 100,000 Monte Carlo replications[11] for different values of k because the limiting distribution of test statistic depends on the number of frequency. The moments are simulated for the constant model and for the constant and trend model since the Wiener process differs with the deterministic term specification as shown in the supplement. It appears that the moments converge as the Fourier frequency increases while they differ for small number of frequency components.

Remark 1. Since the asymptotic distribution of the individual statistic only depends on the frequency k, one can use the simulated critical values by Becker et al. (2006) to draw inferences for each cross-section in the panel.

Remark 2. We assume the homogenous Fourier frequency k across cross-sections in order to obtain the asymptotic distribution of panel statistic because an application of unit root or stationarity tests with the standard limiting distribution is much easier than those with non-conventional distributions (Hadri and Rao, 2008). Nevertheless, the homogeneity assumption of k does not necessarily imply an identical number and form of breaks for each individual (Lee et al., 2015). Becker et al. (2006) illustrate that a series with various kind of breaks can often be captured using a selected frequency component of a Fourier approximation. Enders and Lee (2012a) further show the ability of Fourier approximation in capturing a logistic smooth transition or an exponential smooth transition autoregressive break.

Remark 3. The errors ε_{it} may not have the *i.i.d.* assumption in practice and can have serial dependence and/or heteroscedasticity. In order to allow quite general form of temporal dependence and heteroscedasticity

[7] We are grateful to an anonymous referee for pointing out that under the null hypothesis it in fact would be more appropriate to use "stable" instead of "stationary" because of time-varying mean in the model specifications. Nonetheless, we use the stationary process with this caution in order to be consistent with Becker et al. (2006).

[8] See the supplement for the asymptotic distribution of the test statistic in Eq. (5). It is important to note that our proofs closely follow Becker et al. (2006) and only include a few new propositions related to the common factor.

[9] Phillips and Moon (1999) provide the joint asymptotic analysis of pooled estimators and show that the sequential asymptotic results would be equivalent to the joint results under rate condition $N/T \to 0$. Shin and Snell (2006) more formally prove this result for the panel stationarity test based on mean group estimates. It appears that one can use the results in theorem 1 in Shin and Snell (2006: 127) to also establish joint convergence results of our panel stationarity test. However, such proofs are beyond the scope of the current research and is left for future work.

[10] In order to show the consistency of the test statistic in Eq. (8), we benefit from the results in Shin and Snell (2006) who show the proof for the consistency of mean group stationarity tests. Note that their model does not include any structural shift, however, it can be extended to the model with Fourier frequency components. See the supplement for the proofs. The Monte Carlo simulations also show that the power of the panel statistic increases with the increase of the fraction of the cross-sections possessing a unit root under the alternative hypothesis. The results are reported in the supplement (see Table S1).

[11] The simulations are conducted with GAUSS 15.

over t, one may assume that ε_{it}satisfy the strong mixing regularity conditions defined by Phillips and Perron (1988).[12] In this case it is required to calculate $\eta_i(k)$ by the consistent long-run variance.

$$\tilde{\sigma}_{\varepsilon i}^2 = \frac{1}{T}\sum_{t=1}^{T}\tilde{\varepsilon}_{it}^2 + \frac{2}{T}\sum_{s=1}^{l} w(s,\, l)\sum_{t=s+1}^{T}\tilde{\varepsilon}_{it}\tilde{\varepsilon}_{it-s} \tag{9}$$

where $w(s, l)$ denotes the spectral window which can be estimated through a non-parametric kernel approach such as Bartlett (Kwiatkowski et al. 1992; Becker et al., 2006) or quadratic spectral (Hobijn et al., 2004).[13] Even though the choice of kernel does not play a significant role and depends on the preference of practitioners (Carrion-i-Silvestre and Sansó, 2006), the determination of truncating lag or bandwidth/requires a careful treatment for size and power properties of the stationarity tests (Lee, 1996). The different bandwidth selection methods are proposed. Schwert (1989) uses a fixed value based on sample size; Andrews (1991) conducts the data-driven selection; and Andrews and Monahan (1992) propose the pre-whitening procedure. The Monte Carlo simulations carried out by Lee (1996) for the small sample properties of the KPSS test in the presence of AR(1) errors support that while the fixed lags lead to serious size distortion, the data-driven and the pre-whitening procedures provide less size distortion at the expense of poor power. Moreover, the data-driven selection and the pre-whitening procedure conduce toward the inconsistency of the stationarity tests (Sul et al., 2005). In order to avoid inconsistency and improve size and power properties, some boundary rules are proposed (see Kurozumi, 2002; Sul et al., 2005).[14]

Kurozumi (2002) uses a simple data dependent bandwidth parameter for Bartlett kernel which is defined as

$$\hat{l}_i = \min\left(1.1447\left\{\frac{4\hat{\rho}_i^2 T}{(1+\hat{\rho}_i)^2(1-\hat{\rho}_i)^2}\right\}^{\frac{1}{3}},\, 1.1447\left\{\frac{c^2 T}{(1+c)^2(1-c)^2}\right\}^{\frac{1}{3}}\right) \tag{10}$$

where $\hat{\rho}_i$ is the estimate for autoregressive parameter from $\tilde{\varepsilon}_{it} = \rho_i\tilde{\varepsilon}_{it-1} + v_{it}$ and $c = 0.7$ as in Carrion-i-Silvestre and Sansó (2006). Sul et al. (2005) propose the pre-whitened heteroscedasticity and autocorrelation consistent estimator for the long-run variance. An autoregressive (AR) model defined as $\tilde{\varepsilon}_{it} = \rho_{1i}\tilde{\varepsilon}_{it-1} + \ldots + \rho_{pi}\tilde{\varepsilon}_{it-p} + v_{it}$ is estimated in order to obtain the consistent long-run variance $\tilde{\sigma}_{\varepsilon i}^2 = \tilde{\sigma}_{vi}^2/\tilde{\rho}_i(1)^2$ where $\tilde{\rho}_i(1)$ is the autoregressive polynomial $\tilde{\rho}_i(L) = 1 - \tilde{\rho}_{1i}L - \ldots - \tilde{\rho}_{pi}L^p$ and $\tilde{\sigma}_{vi}^2$ denotes the long-run variance of the residuals v_{it} through using Bartlett kernel. Sul et al. (2005) suggest the following boundary rule

$$\tilde{\sigma}_{\varepsilon i}^2 = min\{T\tilde{\sigma}_{vi}^2,\quad \tilde{\sigma}_{vi}^2/\tilde{\rho}_i(1)^2\}. \tag{11}$$

This rule ensures that the long-run variance is bounded above by $T\tilde{\sigma}_{vi}^2$ and hence the individual statistics under the alternative hypothesis are now consistent (Carrion-i-Silvestre and Sansó, 2006).

3. Small sample properties

Monte Carlo simulations are carried out with 5000 replications at the 5 percent level of significance (i.e., the critical value is 1.645) for the joint hypothesis of stationarity. Following the time series (Becker et al., 2006; Enders and Lee, 2012a, 2012b; Rodrigues and Taylor 2012) and the panel data (Lee et al., 2015) studies in which Fourier approximation is used to capture structural shifts, we consider the DGP with the trigonometric shifts. The DGP is $y_{it} = a_i + \gamma_{1i}sin(2\pi kt/T) + \gamma_{2i}cos(2\pi kt/T) + \lambda_i F_t + \varepsilon_{it}$ for the constant model and $y_{it} = a_i + b_i t + \gamma_{1i}sin(2\pi kt/T) + \gamma_{2i}cos(2\pi kt/T) + \lambda_i F_t + \varepsilon_{it}$ for the constant and trend model with $F_t \sim N(0,1)$, $\varepsilon_{it} \sim N(0,1)$, and the parameters a_i, b_i, γ_{1i}, γ_{2i}, $\lambda_i \sim U[0,1]$ that $U[\bullet]$ denotes the uniform distribution. We examine the small sample properties of $FZ(k)$for different cases. In case 1, $FZ(k)$test is conducted with k frequency which is equal to k in the DGP. In case 2, $\gamma_{1i} = \gamma_{2i}$=0 in the DGP and this case hence investigates the small sample properties of $FZ(k)$ test when there are no structural shifts in the DGP. In cases 3–5, the DGP is generated as in case 1. In case 3, we employ the panel stationarity test developed by Hadri and Kurozumi (2012) and thereby examine whether there is a size distortion and/or loss of power when the existing breaks in the DGP are ignored. Cases 4 and 5 focus on the testing with wrong number of Fourier frequency. As we discussed, our test uses the homogenous Fourier frequency across cross-sections and thereby it is important to examine the small sample properties if one employs the frequency which is more or less than the correct one. In both cases the DGP is generated with k frequency but $FZ(k)$ uses $k+1$ frequency in Case 4 and $k-1$ frequency in Case 5.

We first concentrate on the case of *i.i.d* errors. Table 2 summarizes the empirical size under the different values of cross-section dimension (N), time dimension (T), and Fourier frequency (k). In Case 1, it appears that the empirical size of the test is close to the nominal size in both the constant and the constant and trend models irrespective of whether T(N) is larger than N(T). This implies that the Fourier panel statistic has good size properties even in small samples. The test also seems to have correct size regardless of the number of Fourier frequency. In Case 2 where the DGP does not include Fourier terms but the test is applied with Fourier terms, the size properties are similar to those in Case 1. The results from Case 2 hence imply that the rejection rate of the null hypothesis would be close to the nominal significance level if one employs the Fourier panel stationarity test even though the DGP does not include any Fourier terms. In Case 3, however, the test has considerable size distortions and these distortions do not disappear neither T nor N increases when the Fourier frequency k is one. When the Fourier frequency increases (i.e, $k=2$ or $k=3$) the test has less size distortion but it is not possible to say that the test has good size properties. These results thereby indicate that ignoring Fourier terms leads to size distortions. Finally, let us discuss the size properties in the case of using the wrong number of Fourier frequency. On the one hand, in Case 4, while the DGP has k Fourier frequency the test is applied with one more ($k+1$) Fourier frequency. On the other hand, in Case 5, while the DGP has k Fourier frequency the test is applied with one less ($k-1$) Fourier frequency. In a nutshell, although the test is undersized with small number of T given N and k, the empirical size tends to increase and close to the nominal size as T grows.

Before proceeding with interpreting the results for power analysis, it is important to clarify that the power of the test varies with different values of σ_u^2 where σ_u^2=0 means stationary and $\sigma_u^2=\infty$ implies a random walk process (Becker et al., 2006). In order to save space, we only report the empirical power for σ_u^2=0.01 by assuming all the cross-section possessing a unit root process. The results presented in Table 3 indicate in general that the power of the test increases as T or N or both get larger for a given value of k in all cases but Case 3. In Case 3, we indeed expect that the test would be less powerful because the omission of Fourier components in the estimation would cause to power reduction in small samples. Nonetheless, larger T leads to increase in the empirical power of test when N and k are fixed.

It is known that the KPSS-type tests can suffer from considerable size distortions in finite samples if there is a serial correlation in the series (Caner and Kilian, 2001; Kurozumi and Tanaka, 2010). We hence investigate the small sample properties of the Fourier panel statistic with the serially correlated errors. In particular, y_{it} is generated as in Case 1 but the error process is defined as the AR(1) process by

[12] The strong mixing regularity conditions in Phillips and Perron (1988) are generally assumed in the literature (see among others Hadri, 2000; Carrion-i-Silvestre et al., 2005; Hadri and Rao, 2008; Becker et al., 2006).

[13] An interested reader is referred to Carrion-i-Silvestre and Sansó (2006) for a detailed discussion on the consistent estimation methods of the long-run variance and their comparisons for small samples.

[14] We refer an interested reader to Carrion-i-Silvestre and Sansó (2006) for a detailed survey and further discussion.

Table 2
Size analysis for *i.i.d.* errors.

		Constant						Constant and trend					
k	*N/T*	20	30	50	100	150	200	20	30	50	100	150	200
		Case 1: DGP with Fourier terms and Test with Fourier terms											
1	10	0.047	0.047	0.051	0.044	0.049	0.049	0.043	0.052	0.050	0.054	0.054	0.048
	20	0.052	0.050	0.048	0.052	0.058	0.051	0.046	0.054	0.050	0.049	0.046	0.057
	30	0.047	0.052	0.043	0.044	0.046	0.046	0.047	0.049	0.047	0.050	0.051	0.049
	50	0.055	0.054	0.050	0.047	0.050	0.053	0.047	0.049	0.050	0.051	0.048	0.052
	100	0.053	0.048	0.050	0.047	0.048	0.054	0.049	0.047	0.050	0.052	0.047	0.054
2	10	0.047	0.054	0.052	0.042	0.050	0.051	0.051	0.052	0.045	0.052	0.046	0.051
	20	0.044	0.041	0.052	0.049	0.047	0.044	0.051	0.050	0.048	0.055	0.054	0.049
	30	0.052	0.048	0.052	0.048	0.051	0.049	0.049	0.052	0.048	0.050	0.050	0.049
	50	0.058	0.043	0.050	0.046	0.049	0.053	0.051	0.052	0.046	0.052	0.054	0.046
	100	0.050	0.049	0.048	0.050	0.050	0.051	0.049	0.050	0.054	0.044	0.048	0.054
3	10	0.047	0.052	0.051	0.047	0.051	0.050	0.053	0.051	0.045	0.055	0.044	0.051
	20	0.054	0.053	0.051	0.049	0.055	0.052	0.048	0.047	0.051	0.053	0.052	0.044
	30	0.054	0.046	0.057	0.050	0.052	0.047	0.049	0.052	0.051	0.051	0.054	0.053
	50	0.053	0.048	0.048	0.049	0.053	0.049	0.047	0.054	0.053	0.054	0.052	0.049
	100	0.056	0.049	0.051	0.051	0.053	0.054	0.055	0.045	0.049	0.047	0.044	0.045
		Case 2: DGP without Fourier terms and Test with Fourier terms											
1	10	0.047	0.048	0.056	0.051	0.050	0.049	0.054	0.045	0.052	0.048	0.053	0.046
	20	0.053	0.054	0.050	0.051	0.047	0.050	0.050	0.045	0.054	0.047	0.046	0.050
	30	0.053	0.052	0.051	0.048	0.049	0.049	0.052	0.049	0.049	0.048	0.048	0.050
	50	0.053	0.053	0.049	0.048	0.048	0.049	0.054	0.055	0.046	0.044	0.054	0.051
	100	0.047	0.049	0.051	0.051	0.048	0.047	0.044	0.055	0.050	0.046	0.047	0.051
2	10	0.051	0.048	0.057	0.048	0.049	0.049	0.053	0.052	0.047	0.055	0.047	0.050
	20	0.050	0.050	0.049	0.052	0.050	0.051	0.048	0.048	0.048	0.051	0.054	0.052
	30	0.049	0.049	0.048	0.052	0.052	0.053	0.052	0.050	0.050	0.050	0.048	0.044
	50	0.047	0.050	0.047	0.055	0.049	0.048	0.051	0.053	0.053	0.050	0.056	0.054
	100	0.051	0.045	0.051	0.052	0.047	0.048	0.052	0.047	0.049	0.055	0.052	0.051
3	10	0.050	0.052	0.052	0.047	0.048	0.049	0.051	0.049	0.052	0.049	0.049	0.048
	20	0.050	0.051	0.050	0.048	0.042	0.049	0.046	0.051	0.050	0.048	0.051	0.055
	30	0.055	0.046	0.047	0.051	0.047	0.047	0.047	0.045	0.053	0.043	0.049	0.054
	50	0.053	0.048	0.044	0.049	0.049	0.047	0.043	0.050	0.049	0.053	0.059	0.053
	100	0.054	0.043	0.045	0.048	0.048	0.046	0.048	0.053	0.048	0.053	0.048	0.047
		Case 3: DGP with Fourier terms and Test without Fourier terms											
1	10	0.017	0.021	0.006	0.001	0.002	0.000	0.090	0.044	0.037	0.083	0.737	0.014
	20	0.081	0.072	0.275	0.061	0.008	0.065	0.052	0.018	0.026	0.015	0.002	0.000
	30	0.039	0.052	0.086	0.002	0.000	0.034	0.035	0.004	0.003	0.025	0.000	0.009
	50	0.050	0.074	0.125	0.004	0.011	0.000	0.087	0.091	0.033	0.003	0.133	0.213
	100	0.106	0.029	0.044	0.000	0.051	0.020	0.051	0.069	0.020	0.010	0.366	0.000
2	10	0.050	0.070	0.060	0.023	0.069	0.086	0.053	0.045	0.032	0.055	0.006	0.063
	20	0.046	0.038	0.058	0.064	0.005	0.010	0.041	0.038	0.050	0.041	0.014	0.182
	30	0.047	0.053	0.048	0.037	0.032	0.040	0.066	0.060	0.040	0.013	0.016	0.029
	50	0.066	0.053	0.071	0.048	0.101	0.020	0.053	0.036	0.025	0.007	0.005	0.001
	100	0.056	0.050	0.062	0.097	0.058	0.132	0.055	0.050	0.074	0.066	0.031	0.114
3	10	0.050	0.054	0.051	0.046	0.045	0.037	0.055	0.048	0.043	0.043	0.024	0.010
	20	0.049	0.052	0.050	0.079	0.050	0.045	0.050	0.048	0.048	0.036	0.032	0.027
	30	0.048	0.050	0.046	0.035	0.083	0.050	0.049	0.047	0.043	0.040	0.035	0.027
	50	0.045	0.048	0.052	0.072	0.091	0.086	0.048	0.047	0.056	0.034	0.021	0.017
	100	0.047	0.049	0.052	0.039	0.047	0.030	0.053	0.051	0.041	0.032	0.051	0.111
		Case 4: wrong number of Fourier term (k+1)											
1	10	0.012	0.022	0.032	0.047	0.044	0.049	0.000	0.007	0.021	0.037	0.039	0.044
	20	0.006	0.019	0.033	0.039	0.047	0.050	0.000	0.001	0.010	0.026	0.034	0.034
	30	0.006	0.016	0.023	0.036	0.046	0.040	0.000	0.000	0.005	0.025	0.029	0.039
	50	0.002	0.007	0.028	0.038	0.039	0.035	0.000	0.000	0.002	0.016	0.023	0.030
	100	0.001	0.003	0.017	0.029	0.038	0.043	0.000	0.000	0.000	0.009	0.012	0.019
2	10	0.015	0.031	0.036	0.043	0.043	0.045	0.010	0.016	0.031	0.037	0.035	0.045
	20	0.009	0.023	0.029	0.041	0.043	0.046	0.004	0.013	0.029	0.036	0.036	0.041
	30	0.010	0.024	0.037	0.042	0.046	0.051	0.002	0.010	0.024	0.037	0.031	0.046
	50	0.007	0.016	0.026	0.040	0.051	0.050	0.001	0.006	0.020	0.032	0.032	0.039

(continued on next page)

Table 2 *(continued)*

k	N/T	Constant 20	30	50	100	150	200	Constant and trend 20	30	50	100	150	200
	100	0.003	0.010	0.026	0.032	0.050	0.049	0.000	0.003	0.015	0.031	0.037	0.038
3	10	0.013	0.023	0.031	0.045	0.044	0.053	0.004	0.013	0.026	0.032	0.033	0.038
	20	0.013	0.020	0.027	0.033	0.042	0.044	0.002	0.009	0.019	0.036	0.034	0.040
	30	0.005	0.019	0.024	0.039	0.043	0.047	0.000	0.008	0.014	0.034	0.029	0.031
	50	0.005	0.014	0.026	0.037	0.045	0.041	0.000	0.003	0.013	0.027	0.035	0.032
	100	0.001	0.012	0.017	0.038	0.039	0.039	0.000	0.001	0.011	0.022	0.030	0.026
		Case 5: wrong number of Fourier term (k−1)											
2	10	0.014	0.021	0.037	0.037	0.042	0.044	0.004	0.014	0.020	0.037	0.039	0.038
	20	0.008	0.015	0.027	0.036	0.034	0.039	0.002	0.014	0.033	0.037	0.037	0.040
	30	0.007	0.023	0.028	0.037	0.034	0.040	0.004	0.009	0.028	0.034	0.038	0.032
	50	0.003	0.010	0.028	0.033	0.037	0.040	0.003	0.015	0.028	0.037	0.037	0.050
	100	0.001	0.006	0.016	0.026	0.032	0.031	0.001	0.019	0.034	0.049	0.045	0.054
3	10	0.018	0.029	0.033	0.045	0.042	0.053	0.006	0.017	0.030	0.045	0.047	0.047
	20	0.010	0.019	0.032	0.040	0.042	0.035	0.002	0.008	0.023	0.035	0.048	0.038
	30	0.005	0.016	0.040	0.044	0.049	0.047	0.000	0.006	0.020	0.032	0.040	0.044
	50	0.005	0.017	0.031	0.037	0.044	0.050	0.000	0.004	0.015	0.030	0.029	0.039
	100	0.001	0.008	0.020	0.041	0.039	0.040	0.000	0.001	0.010	0.027	0.027	0.039

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + v_{it} \qquad (12)$$

with $v_{it} \sim i.\ i.\ dN(0,\ 1)$, and $\rho_i \sim U[0.1,0.9]$. We assume that the autoregressive parameter ρ_i differs across cross-sections from low persistence to high persistence both under the null and alternative hypotheses. As discussed in the Remark 3, the test statistic now requires the estimation of the consistent long-run variance. The long-run variance is estimated with Bartlett kernel under the boundary rule of Sul et al. (2005) and Kurozumi (2002).[15] As shown in Sul et al. (2005) and also emphasized in Hadri and Rao (2008), the time dimension should be sufficiently large to obtain precise estimation of the long-run variance. We therefore conduct the Monte Carlo simulations for T=100, 150, and 200.

Table 4 reports the empirical size and size-adjusted power of the test statistic for serially correlated errors. The test statistic based on Sul et al. (2005) boundary rule appears to have substantial size distortions. The model with constant and trend is more undersized than the model with constant when k is one and T is 100. The size distortion in the constant and trend model increases monotonically as T grows when the frequency is one. The substantial size distortion fortunately appears to be eliminated when the Kurozumi (2002) rule is applied in Eq. (10) which provides good size properties. As expected the power of the test increases when time dimension grows. It also improves with larger N when the number of frequency holds fixed. This property in fact can be easily attributed to the main advantage of panel data framework that adding cross-section dimension to time dimension leads to power increases.

4. Empirical application

There is a huge and growing empirical literature on the trend dynamics of commodity prices.[16] The majority of empirical studies conduct univariate unit root tests and there is no consensus about whether the commodity prices are mean reverting or not.[17] The use of panel data approach during the recent years has attracted interest in the commodity price literature, but this literature still appears to be scant. Yang et al. (2012) and Nazlioglu (2014) employs the panel stationarity test developed by Carrion-i-Silvestre et al. (2005); and Iregui and Otero (2013) and Arezki et al. (2014) use the panel stationarity test proposed by Hadri and Rao (2008).[18] In all these papers, the structural shifts in the commodity prices are modelled with dummy variables and the common evidence is supported on the stationarity of the commodity prices.

Using panel data framework not only increases the power of tests but also allows incorporating the information contained in the cross sectional dependence. The cross-section dependence arises from positive and significant correlations between the commodity prices (Arezki et al., 2014).[19] The strong correlation between commodities is referred to as “excess co- movement” (Pindyck and Rotemberg, 1990). Otero and Iregui (2011) provide an alternative interpretation of using the panel stationarity tests in order to examine an existence of the excess co-movement. If the joint null hypothesis of stationarity cannot be rejected, then commodity prices are jointly stationary which implies that primary commodity and manufactured goods prices are linked by a long-run equilibrium relationship and hence there is an evidence on the definition of commodity price co-movement.

We re-investigate whether the international commodity prices are stationary by applying the Fourier panel stationarity test in order to examine whether modelling structural shifts with the Fourier approximation instead of with dummy variables makes sense to better understand the behavior of commodity prices. We employ the updated Grilli and Yang (1988) data for 24 real international commodity prices during the 1900–2011 period.[20] Fig. 1 depicts the log of real commodity prices. The behavior of the commodity prices does not appear to be similar to each other and the prices have different trend dynamics in different time spans. The nature of shifts is generally unknown and there is no specific guide regarding number and date of

[15] The estimation of the long-run variance either with Bartlett or with quadratic spectral window does not considerably change the results. In order to save space, Table 4 does not report the results with quadratic spectral window which are available in the supplement (see Table S2).

[16] The commodity prices mean the real prices which are defined as primary commodity prices relative to manufactured goods prices.

[17] An interested reader is referred to Ghoshray (2011) and Nazlioglu (2014) for the detailed literature reviews.

[18] In order to save space, we do not pay attention to discuss the differences between the panel stationarity tests proposed by Carrion-i-Silvestre et al. (2005) and Hadri and Rao (2008). An interested reader is referred to Hadri and Rao (2008: 246) for a detailed discussion.

[19] The correlation matrix supports the evidence on the positive and high cross-sectional correlations between the commodity prices. To save space, the correlation coefficients are reported in the supplement (see Table S3).

[20] See Pfaffenzeller et al. (2007) for a detailed description of the series. The data is available at http://www.stephan-pfaffenzeller.com/cpi.html.

Table 3
Power analysis for *i.i.d* errors.

		Constant						Constant and trend					
k	*N/T*	20	30	50	100	150	200	20	30	50	100	150	200
		Case 1: DGP with Fourier terms and Test with Fourier terms											
1	10	0.158	0.234	0.593	0.848	1.000	1.000	0.207	0.258	0.267	0.748	0.931	0.985
	20	0.303	0.196	0.598	0.997	1.000	1.000	0.378	0.394	0.303	0.689	0.984	1.000
	30	0.323	0.368	0.830	1.000	1.000	1.000	0.431	0.520	0.420	0.793	1.000	1.000
	50	0.443	0.482	0.929	0.999	1.000	1.000	0.766	0.747	0.597	0.954	1.000	1.000
	100	0.703	0.883	0.996	1.000	1.000	1.000	0.996	0.955	0.865	0.999	1.000	1.000
2	10	0.427	0.277	0.918	1.000	1.000	1.000	0.166	0.167	0.293	0.960	1.000	1.000
	20	0.351	0.667	0.969	1.000	1.000	1.000	0.217	0.282	0.545	0.916	1.000	1.000
	30	0.692	0.771	0.988	1.000	1.000	1.000	0.350	0.473	0.602	0.998	1.000	1.000
	50	0.699	0.824	0.994	1.000	1.000	1.000	0.527	0.604	0.804	1.000	1.000	1.000
	100	0.873	0.937	1.000	1.000	1.000	1.000	0.897	0.886	0.956	1.000	1.000	1.000
3	10	0.320	0.505	0.721	0.997	1.000	1.000	0.218	0.246	0.313	0.724	0.997	1.000
	20	0.333	0.769	0.988	1.000	1.000	1.000	0.282	0.353	0.549	0.994	1.000	1.000
	30	0.544	0.853	1.000	1.000	1.000	1.000	0.439	0.467	0.725	1.000	1.000	1.000
	50	0.749	0.966	1.000	1.000	1.000	1.000	0.586	0.645	0.934	1.000	1.000	1.000
	100	0.914	0.988	1.000	1.000	1.000	1.000	0.835	0.893	0.995	1.000	1.000	1.000
		Case 2: DGP without Fourier terms and Test with Fourier terms											
1	10	0.353	0.439	0.505	1.000	0.999	1.000	0.405	0.561	0.280	0.552	0.719	0.996
	20	0.511	0.407	0.625	0.987	1.000	1.000	0.594	0.793	0.515	0.639	0.986	1.000
	30	0.655	0.525	0.921	1.000	1.000	1.000	0.899	0.914	0.665	0.903	1.000	1.000
	50	0.788	0.782	0.979	1.000	1.000	1.000	0.949	0.984	0.836	0.977	1.000	1.000
	100	0.947	0.932	0.988	1.000	1.000	1.000	1.000	1.000	0.972	1.000	1.000	1.000
2	10	0.463	0.598	0.575	1.000	1.000	1.000	0.326	0.411	0.311	0.991	0.998	1.000
	20	0.696	0.560	0.979	1.000	1.000	1.000	0.438	0.435	0.705	0.919	1.000	1.000
	30	0.748	0.775	0.955	1.000	1.000	1.000	0.650	0.701	0.763	1.000	1.000	1.000
	50	0.866	0.933	0.999	1.000	1.000	1.000	0.838	0.848	0.883	1.000	1.000	1.000
	100	0.907	0.944	1.000	1.000	1.000	1.000	0.889	0.951	0.996	1.000	1.000	1.000
3	10	0.416	0.342	0.850	1.000	1.000	1.000	0.350	0.358	0.700	0.978	1.000	1.000
	20	0.703	0.665	0.894	1.000	1.000	1.000	0.585	0.641	0.859	0.999	1.000	1.000
	30	0.732	0.823	0.999	1.000	1.000	1.000	0.668	0.690	0.831	1.000	1.000	1.000
	50	0.806	0.983	0.999	1.000	1.000	1.000	0.876	0.908	0.962	1.000	1.000	1.000
	100	0.979	0.997	1.000	1.000	1.000	1.000	0.897	0.987	0.995	1.000	1.000	1.000
		Case 3: DGP with Fourier terms and Test without Fourier terms											
1	10	0.060	0.013	0.624	1.000	1.000	1.000	0.017	0.006	0.011	0.437	0.980	1.000
	20	0.008	0.013	0.144	1.000	1.000	1.000	0.008	0.002	0.002	0.983	0.956	1.000
	30	0.033	0.037	0.576	1.000	1.000	1.000	0.010	0.000	0.066	0.195	1.000	1.000
	50	0.000	0.075	0.540	1.000	1.000	1.000	0.002	0.000	0.000	0.910	1.000	1.000
	100	0.000	0.010	0.999	1.000	1.000	1.000	0.000	0.000	0.000	0.867	1.000	1.000
2	10	0.105	0.161	0.599	1.000	1.000	1.000	0.298	0.100	0.167	0.425	1.000	1.000
	20	0.204	0.243	0.946	1.000	1.000	1.000	0.557	0.179	0.280	0.996	1.000	1.000
	30	0.150	0.195	0.982	1.000	1.000	1.000	0.690	0.265	0.273	1.000	1.000	1.000
	50	0.362	0.666	0.999	1.000	1.000	1.000	0.889	0.315	0.587	0.999	1.000	1.000
	100	0.483	0.769	1.000	1.000	1.000	1.000	0.998	0.454	0.662	1.000	1.000	1.000
3	10	0.096	0.155	0.317	1.000	1.000	1.000	0.419	0.180	0.148	0.939	0.999	1.000
	20	0.269	0.265	0.904	1.000	1.000	1.000	0.758	0.295	0.529	0.911	1.000	1.000
	30	0.377	0.271	0.929	1.000	1.000	1.000	0.945	0.475	0.427	0.994	1.000	1.000
	50	0.489	0.563	0.995	1.000	1.000	1.000	0.998	0.705	0.735	1.000	1.000	1.000
	100	0.869	0.939	1.000	1.000	1.000	1.000	1.000	0.979	0.795	1.000	1.000	1.000
		Case 4: wrong number of Fourier term (k+1)											
1	10	0.068	0.704	0.367	0.982	1.000	1.000	0.011	0.186	0.034	0.859	1.000	1.000
	20	0.374	0.723	1.000	1.000	1.000	1.000	0.008	0.028	0.090	0.072	1.000	1.000
	30	0.599	0.598	0.999	1.000	1.000	1.000	0.002	0.024	0.006	0.831	1.000	1.000
	50	0.873	0.660	1.000	1.000	1.000	1.000	0.000	0.000	0.002	0.330	0.987	1.000
	100	0.577	0.969	1.000	1.000	1.000	1.000	0.000	0.000	0.000	0.091	1.000	1.000
2	10	0.497	0.365	0.821	1.000	1.000	1.000	0.307	0.408	0.518	1.000	0.981	1.000
	20	0.549	0.725	0.996	1.000	1.000	1.000	0.432	0.536	0.791	1.000	1.000	1.000
	30	0.607	0.900	0.997	1.000	1.000	1.000	0.559	0.394	0.666	1.000	1.000	1.000
	50	0.766	0.976	1.000	1.000	1.000	1.000	0.792	0.633	0.963	1.000	1.000	1.000

(continued on next page)

Table 3 *(continued)*

		Constant						Constant and trend					
k	*N/T*	20	30	50	100	150	200	20	30	50	100	150	200
	100	0.964	0.997	1.000	1.000	1.000	1.000	0.963	0.874	0.999	1.000	1.000	1.000
3	10	0.455	0.394	0.934	1.000	1.000	1.000	0.345	0.328	0.386	0.996	1.000	1.000
	20	0.431	0.743	0.888	1.000	1.000	1.000	0.523	0.431	0.773	1.000	1.000	1.000
	30	0.630	0.838	1.000	1.000	1.000	1.000	0.662	0.517	0.700	1.000	1.000	1.000
	50	0.786	0.994	1.000	1.000	1.000	1.000	0.877	0.763	0.979	1.000	1.000	1.000
	100	0.981	1.000	1.000	1.000	1.000	1.000	0.990	0.938	0.998	1.000	1.000	1.000
		Case 5: wrong number of Fourier term (k−1)											
2	10	0.287	0.456	0.900	0.854	1.000	1.000	0.284	0.286	0.415	0.884	0.943	1.000
	20	0.384	0.469	0.979	0.994	1.000	1.000	0.193	0.105	0.760	0.550	1.000	1.000
	30	0.339	0.659	0.854	1.000	1.000	1.000	0.155	0.084	0.664	0.951	1.000	1.000
	50	0.606	0.743	1.000	1.000	1.000	1.000	0.261	0.447	0.422	0.998	1.000	1.000
	100	0.860	0.980	0.999	1.000	1.000	1.000	0.402	0.134	0.955	1.000	1.000	1.000
3	10	0.251	0.305	0.740	1.000	1.000	1.000	0.281	0.372	0.323	0.977	0.914	1.000
	20	0.552	0.706	0.966	1.000	1.000	1.000	0.451	0.394	0.618	0.999	1.000	1.000
	30	0.503	0.862	0.994	1.000	1.000	1.000	0.604	0.481	0.723	1.000	1.000	1.000
	50	0.793	0.967	1.000	1.000	1.000	1.000	0.805	0.679	0.992	1.000	1.000	1.000
	100	0.960	0.997	1.000	1.000	1.000	1.000	0.964	0.936	0.999	1.000	1.000	1.000

Table 4
Size and power analysis for serially correlated errors.

		Size						Size-adjusted power					
		Constant			Constant and trend			Constant			Constant and trend		
k	*N/T*	100	150	200	100	150	200	100	150	200	100	150	200
		Sul et al. (2005)											
1	10	0.128	0.102	0.133	0.081	0.098	0.244	0.261	0.799	0.855	0.162	0.121	0.451
	20	0.111	0.177	0.167	0.019	0.104	0.377	0.890	0.977	1.000	0.119	0.619	0.667
	30	0.082	0.132	0.176	0.014	0.083	0.079	0.916	0.995	1.000	0.216	0.700	0.970
	50	0.103	0.311	0.173	0.039	0.147	0.380	0.853	0.999	1.000	0.190	0.715	0.975
	100	0.141	0.229	0.468	0.046	0.093	0.626	0.976	1.000	1.000	0.192	0.995	0.998
2	10	0.158	0.198	0.096	0.378	0.093	0.113	0.595	0.998	1.000	0.696	0.810	0.857
	20	0.170	0.446	0.238	0.175	0.285	0.190	0.979	0.999	1.000	0.618	0.998	1.000
	30	0.304	0.334	0.419	0.331	0.307	0.270	0.999	1.000	1.000	0.919	0.988	1.000
	50	0.384	0.328	0.252	0.401	0.220	0.587	0.997	1.000	1.000	0.779	1.000	1.000
	100	0.627	0.510	0.584	0.586	0.536	0.634	1.000	1.000	1.000	0.983	0.999	1.000
3	10	0.102	0.240	0.205	0.301	0.102	0.134	0.757	0.915	1.000	0.587	0.722	0.999
	20	0.201	0.217	0.307	0.147	0.232	0.493	0.996	1.000	1.000	0.819	0.991	0.915
	30	0.299	0.152	0.259	0.311	0.237	0.342	0.992	1.000	1.000	0.791	1.000	1.000
	50	0.291	0.278	0.454	0.392	0.578	0.558	0.997	1.000	1.000	0.961	0.999	1.000
	100	0.527	0.657	0.549	0.585	0.669	0.609	0.997	1.000	1.000	0.987	1.000	1.000
		Kurozumi (2002)											
1	10	0.058	0.049	0.054	0.039	0.040	0.049	0.385	0.967	0.906	0.819	0.881	0.996
	20	0.049	0.046	0.055	0.036	0.047	0.062	0.997	0.999	1.000	0.937	0.991	1.000
	30	0.041	0.046	0.061	0.060	0.047	0.055	0.953	1.000	1.000	0.997	0.995	1.000
	50	0.060	0.053	0.053	0.058	0.045	0.056	0.999	1.000	1.000	1.000	1.000	1.000
	100	0.057	0.047	0.044	0.038	0.040	0.052	1.000	0.999	1.000	1.000	1.000	1.000
2	10	0.046	0.056	0.043	0.037	0.041	0.053	0.928	0.993	1.000	0.825	0.893	0.999
	20	0.038	0.042	0.060	0.039	0.059	0.043	0.912	1.000	1.000	0.916	0.987	1.000
	30	0.060	0.047	0.048	0.056	0.044	0.044	1.000	1.000	1.000	0.994	1.000	1.000
	50	0.062	0.048	0.053	0.050	0.041	0.047	0.999	1.000	1.000	0.998	1.000	1.000
	100	0.035	0.046	0.063	0.052	0.056	0.060	1.000	1.000	1.000	1.000	1.000	1.000
3	10	0.042	0.053	0.043	0.050	0.044	0.060	0.941	0.988	1.000	0.711	0.933	0.986
	20	0.050	0.046	0.062	0.043	0.036	0.051	1.000	1.000	1.000	0.981	1.000	1.000
	30	0.060	0.040	0.062	0.051	0.046	0.047	1.000	1.000	1.000	0.998	1.000	1.000
	50	0.059	0.054	0.051	0.055	0.039	0.044	1.000	1.000	1.000	1.000	1.000	1.000
	100	0.041	0.038	0.060	0.056	0.043	0.042	1.000	1.000	1.000	1.000	1.000	1.000

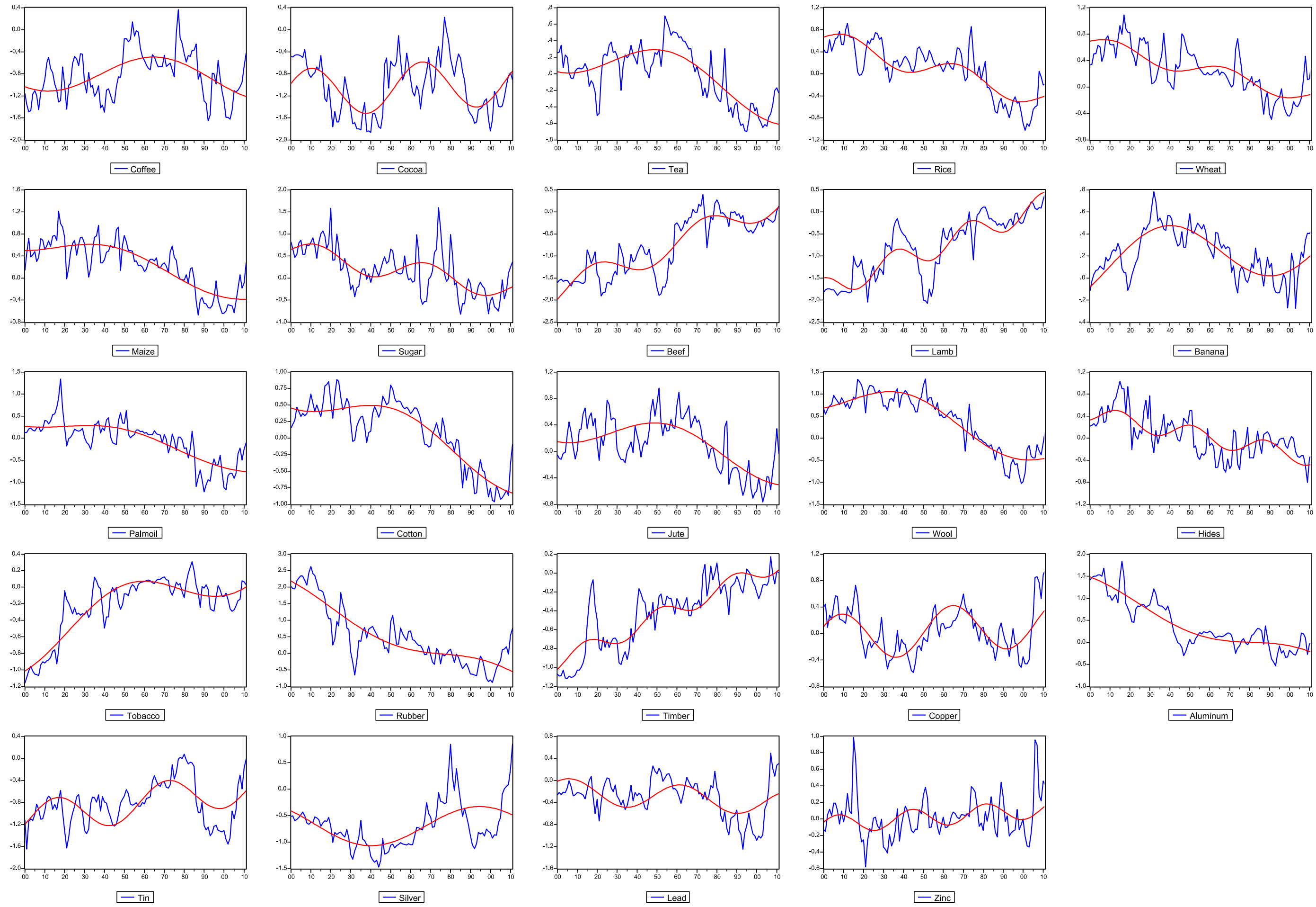

Fig. 1. The dynamics of real commodity prices and their Fourier approximations.

Table 5
Results from the cross-section dependency tests.

	Constant		Constant and trend	
Test	Statistic	p-value	Statistic	p-value
LM	5976.802***	0.000	4138.296***	0.000
LM_{adj}	122.793***	0.000	122.990***	0.000

*** Denotes the statistical significance at 1 percent level.

breaks. The Fig. 1 also shows the Fourier approximations of the series which signal the long swings in real commodity prices.

Before proceed to the implementation of the Fourier panel stationarity test, a preliminary analysis is required. One assumption to be tested is whether there is a cross-section dependency among the commodity prices. We employ two tests proposed by Breusch and Pagan (1980) and Pesaran et al. (2008) to test for the null hypothesis of no cross-sectional dependence - $H_0{:}Cov(\varepsilon_{it}, \varepsilon_{jt})=0$ for all t *and* $i \neq j$ - against the alternative of dependency - $H_1{:}Cov(\varepsilon_{it}, \varepsilon_{jt})\neq 0$ - for at least one pair of $i \neq j$. We first estimate the models with one frequency for the sake of simplicity and obtain the residuals. Then the pair-wise correlations $(\hat{\rho}_{ij}, i \neq j)$ among the residuals are calculated. The LM statistic by Breusch and Pagan (1980) is defined as

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \sim \chi^2_{N(N-1)/2} \quad (13)$$

Pesaran et al. (2008) propose a modified version of the LM test by using the exact mean and variance. The bias-adjusted LM test is

$$LM_{adj} = \sqrt{\left(\frac{2}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{(T-m)\hat{\rho}_{ij}^2-\mu_{Tij}}{\sqrt{v_{Tij}^2}} \sim N(0,1) \quad (14)$$

where m is the number of explanatory variables, and μ_{Tij} and v_{Tij}^2 are respectively the mean and the variance (Pesaran et al., 2008: 108). The results in Table 5 indicate that the null hypothesis is strongly rejected, supporting the evidence on cross-section dependency. The dependence among commodity markets can be explained by the stylized facts. Adams and Glück (2015) show that the commodity markets financialization has led to change the behavior and dependence structure between commodities. Kagraoka (2016) find that the commodity prices during the last two decades are driven by the common factors which are the U.S. inflation rate, the word industrial production index, the world stock index, and the crude oil prices. The dependence also can be attributed to the high degree of integration of the commodity futures and spot markets. Narayan et al. (2013) find out that commodity futures play a crucial role in predicting commodity spot prices.

Even though we find out the existence of cross-section dependency, the common factor F_t is unknown in practice and thereby to be replaced by an estimate.[21] Pesaran (2007) proposes a simple approach by taking a cross-sectional average of the model. Let $Z_t=[1, sin(2\pi kt/T), cos(2\pi kt/T)]'$ or $Z_t=[1, t, sin(2\pi kt/T), cos(2\pi kt/T)]'$ for the notational simplicity, the cross-sectional average of y_{it} is

$$\bar{y}_t = Z_t'\bar{\delta} + \bar{r}_t + \bar{\lambda}F_t + \bar{\varepsilon}_t \quad (15)$$

[21] We refer to Breitung and Pesaran (2008) and Pesaran (2007) for a detailed review of the methods to estimate common factor.

Table 6
Results from the panel stationarity tests.

Commodity	Constant				Constant and trend			
	Sharpshifts	Gradual/smooth shifts			Sharp shifts	Gradual/smooth shifts		
		k=1	k=2	k=3		k=1	k=2	k=3
Coffee	**0.050**	**0.067**	0.477	0.518	**0.046**	**0.036**	0.128	0.138
Cocoa	**0.075**	**0.122**	**0.268**	**0.305**	**0.038**	**0.041**	**0.086**	0.120
Tea	**0.080**	**0.126**	0.333	**0.298**	**0.023**	0.053	0.200	0.189
Rice	**0.033**	0.310	0.807	0.845	**0.036**	**0.032**	**0.100**	**0.099**
Wheat	**0.050**	0.136	0.691	0.691	**0.040**	**0.034**	**0.093**	**0.109**
Maize	**0.056**	0.229	0.823	0.673	**0.096**	**0.032**	0.151	0.197
Sugar	**0.088**	0.160	0.427	0.423	**0.070**	**0.028**	**0.066**	**0.088**
Beef	**0.119**	0.207	0.836	0.756	**0.027**	**0.045**	**0.050**	**0.089**
Lamb	**0.151**	0.268	0.775	0.845	**0.042**	**0.045**	**0.039**	**0.050**
Banana	**0.127**	0.183	**0.183**	**0.190**	**0.040**	**0.035**	0.146	0.168
Palm oil	**0.160**	0.178	0.746	0.671	**0.078**	**0.032**	0.107	0.134
Cotton	**0.056**	0.280	0.688	0.738	**0.048**	**0.037**	0.196	0.236
Jute	**0.085**	**0.059**	**0.219**	**0.268**	**0.056**	**0.044**	0.190	0.237
Wool	**0.073**	0.392	0.844	0.731	**0.056**	**0.031**	0.181	0.194
Hides	**0.083**	0.149	0.573	0.583	**0.058**	0.054	0.154	0.184
Tobacco	**0.073**	0.346	0.619	0.592	**0.030**	0.062	0.250	0.245
Rubber	**0.089**	0.273	0.678	0.623	**0.053**	0.065	0.246	0.220
Timber	**0.056**	0.351	0.856	0.886	**0.036**	**0.039**	**0.052**	**0.072**
Copper	**0.080**	**0.110**	0.481	**0.332**	**0.043**	0.058	0.229	0.203
Aluminum	**0.053**	0.326	0.723	0.725	**0.034**	**0.035**	0.195	0.202
Tin	**0.113**	0.206	0.785	0.779	**0.074**	0.056	**0.073**	**0.110**
Silver	**0.060**	0.162	0.574	0.484	**0.026**	0.050	0.220	0.213
Lead	**0.116**	0.178	**0.141**	**0.125**	**0.030**	0.063	**0.068**	**0.088**
Zinc	**0.188**	0.255	0.613	0.671	**0.058**	**0.047**	0.207	0.218
Panel statistic	**2.098**	13.224	16.582	14.405	**4.217**	5.420	12.188	10.034
p-value		0.000	0.000	0.000		0.000	0.000	0.000

Sharp shift: Panel stationarity test with sharp breaks (dummy variables) by Carrion-i-Silvestre et al. (2005).
Gradual/smoot shift: Fourier panel stationarity test developed in this paper.
Bold numbers: The null hypothesis of stationarity cannot be rejected at least at the 10 percent level of significance.
The statistics are constructed using the Bartlett kernel with the Kurozumi (2002) rule. The p-values are for a one-sided test based on the normal distribution. The constant model critical values for individual statistics are 0.1318 (10%), 0.1720 (5%), 0.2699 (1%) for k=1; 0.3150 (10%), 0.4152 (5%), 0.6671 (1%) for k=2; 0.3393 (10%), 0.4480 (5%), 0.7182 (1%) for k=3. The constant and trend model critical values for individual statistics are 0.0471 (10%), 0.0546 (5%), 0.0716 (1%) for k=1; 0.1034 (10%), 0.1321 (5%), 0.2022 (1%) for k=2; 0.1141 (10%), 0.1423 (5%), 0.2103 (1%) for k=3. (see, Becker et al. (2006, p.389)).

where $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, $\bar{\delta} = N^{-1}\sum_{i=1}^{N}\delta_i$ that $\delta_i = (a_i, \gamma_{1i}, \gamma_{2i})'$ or $\delta_i=(a_i, b_i, \gamma_{1i}, \gamma_{2i})'$, $\bar{r}_t = N^{-1}\sum_{i=1}^{N} r_{it}$, $\bar{\lambda} = N^{-1}\sum_{i=1}^{N}\lambda_i$, and $\bar{\varepsilon}_t=N^{-1}\sum_{i=1}^{N}\varepsilon_{it}$. By assuming $\bar{\lambda}\neq 0$ for a fixed N as $N\to\infty$, solving Eq. (15) for F_t gives $F_t=(\bar{y}_t - Z_t'\bar{\delta} - \bar{r}_t - \bar{\varepsilon}_t)/\bar{\lambda}$. By using this solution, we obtain

$$y_{it} = Z_t'\tilde{\delta}_i + \tilde{\lambda}_i\bar{y}_t + e_{it} \tag{16}$$

where $\tilde{\delta}_i = \delta_i - \bar{\delta}\tilde{\lambda}_i, \tilde{\lambda}_i = \lambda_i/\bar{\lambda}$, and $e_{it} = r_{it} - \tilde{\lambda}_i\bar{r}_t + \varepsilon_{it} - \tilde{\lambda}_i\bar{\varepsilon}_t$ that $\bar{r}_t$ and $\bar{\varepsilon}_t$ tend to zero under the null hypothesis. This solution hence shows that common factor F_t can be replaced by the cross-section averages of $y_{it}(\bar{y}_t)$ and allows us to regress y_{it} on Z_t and $\bar{y}_t$ for each cross-section.

Given the long-time period which covers the twentieth century, we apply the test up to three frequencies in order to capture long-swings and more cycles in the commodity prices. The commodity prices are likely to contain a substantial amount of persistence because of ability to carry inventories through time (Tomek, 2000). We find an evidence on the first order serial correlation in $\tilde{e}_{it}$ and use Bartlett kernel based on Kurozumi (2002) rule to account for the serial dependence.[22] We also conduct the panel stationarity test by Carrion-i-Silvestre et al. (2005) which assumes sharp shifts that are modelled with the dummy variables and uses bootstrapping distribution to account for cross-section dependency. Therefore, the Fourier panel stationarity test has differences for modelling both structural shifts and cross-section dependency. The results are reported in Table 6.

The panel stationarity test with sharp breaks shows that the null hypothesis cannot be rejected for none of the commodity prices irrespective of whether the commodity prices include the level or trend breaks.[23] Because all the commodity prices are found to be stationary, the panel statistic indicates that the null hypothesis of joint stationarity cannot be rejected. The panel stationarity testing procedure with sharp breaks supports the evidence on that the shocks to international commodity prices are temporary. This finding is line with the results from the previous studies (Yang et al., 2012; Iregui and Otero, 2013; Arezki et al., 2014, Nazlioglu, 2014) which accounts the structural shifts in the commodity prices as sharp process by the use of dummy variables. The eye looks at the dynamics of commodity prices in Fig. 1 clearly shows that finding all the commodity prices as stationary may be misleading because the commodity prices are likely to be characterized with stochastic trend behavior (Myers, 1994).

The results from the Fourier panel stationarity test indicate that the null hypothesis of joint stationarity is rejected at the 1 percent level of significance. The rejection of the null hypothesis does not mean that all commodity prices are characterized by a unit process because some of the cross-sections are allowed to be stationary under the alternative hypothesis. Therefore, it would be insightful to look at the individual results to better understand the fraction of stationary and non-stationary cross-sections. For the level stationary (constant) model, five out of twenty-four commodities (coffee, cacao, tea, jute, and copper) are stationary when the Fourier frequency is one. When the frequency is two, two out of these five commodities (cacao, and jute) and banana and lead are found to be stationary. Six commodities (cacao, tea, banana, jute, copper, and lead) are stationary when the frequency is three. For the trend stationary (constant

[22] The results from the serial correlation test are reported in the supplement (see Table S4).

[23] See Table A1 in the appendix for the detailed results from the panel stationarity test by Carrion-i-Silvestre et al. (2005).

and trend) model, the null hypothesis of stationarity is rejected for eight commodity prices if the frequency is one. When we use two (three) frequencies, fifteen (sixteen) commodity prices are found to be non-stationary. The individual analysis thereby shows that the dynamics of many of the international commodity prices are not consistent with the equilibrium price theory as observed in Fig. 1. This finding is contrast with the previous evidence in the literature. The new testing procedure proposed in this paper provides fresh information regarding the nature of shocks to international commodity prices which enables us to discuss policy inferences from a different perspective. If the shocks to commodity prices are temporary, then there is no need to put into effect price stabilization policies. On the other hand, if the shocks to commodity prices are permanent then there would be a room for policy makers to implement stabilization policies. While the previous panel data studies support the evidence in favor of the first policy implication, this study supports the evidence in favor of the second policy implication for many of the international commodity prices.

5. Conclusion

This paper proposes a simple panel stationarity test with gradual/smooth structural shifts, cross-section dependency, and cross-sectional heterogeneity. To account for structural shifts, we employ a Fourier approximation which does not require *a priori* knowledge on date, number, and form of breaks. The asymptotic distribution of the individual statistics under the null hypothesis only depends on the Fourier frequency and the panel statistic has a standard normal distribution after the standardization with the asymptotic moments.

We investigate the small sample properties by Monte Carlo simulations for the different data generating processes. The findings for the size and power properties can be summarized as: (i) if the error terms are *i.i.d.* and the number of Fourier frequency is correctly specified then the Fourier panel statistic shows good size and power even when N is larger than T irrespective of the number of Fourier terms, (ii) if the error terms are *i.i.d.* but the number of Fourier frequency is wrongly specified in testing procedure, even though there is a size distortion and power reduction in the panel data sets where T is equal to or smaller than 50, fortunately the size distortions disappear as T increase and the power increases with larger T or N or both, (iii) if the error terms are serially correlated, the Fourier panel stationarity test has reasonable size and keeps its good power properties.

Understanding the behavior of commodity prices has the long theoretical and empirical debate. In the literature, the panel studies which assume sharp structural changes support the evidence on that the shocks to commodity prices are temporary. We re-investigate whether the shock to international commodity prices are temporary or permanent by means of the Fourier panel stationarity test. The empirical results indicate that the null hypothesis of joint stationarity is rejected. This finding does not coincide with the previous evidence from the panel data studies. The new testing procedure provides fresh information regarding the nature of shocks to international commodity prices.

Acknowledgements

The financial support from Pamukkale University Scientific Research Projects Unit under the grant number 2781 and Faculty of Economics and Administrative Sciences are gratefully acknowledged for the previous versions of this paper presented at the 2nd Annual Conference of the International Association for Applied Econometrics and of the 1st International Conference on New Trends in Econometrics and Finance.

Appendix. A

See Table A1.

Table A1
Results from panel stationarity test with sharp breaks.

	Breaks in constant					Breaks in constant and trend				
		Bootstrap critical values					Bootstrap critical values			
Commodity	KPSStest	0.9	0.95	0.99	# ofbreaks	KPSStest	0.9	0.95	0.99	# ofbreaks
Coffee	0.050	0.559	0.591	0.675	2	0.046	0.057	0.064	0.079	1
Cocoa	0.075	0.244	0.258	0.286	3	0.038	0.037	0.042	0.051	3
Tea	0.080	1.342	1.380	1.452	3	0.023	0.034	0.038	0.046	3
Rice	0.033	1.944	1.972	2.024	2	0.036	0.076	0.091	0.120	1
Wheat	0.050	2.031	2.063	2.111	2	0.040	0.081	0.097	0.130	1
Maize	0.056	1.973	1.999	2.046	2	0.096	0.080	0.095	0.127	1
Sugar	0.088	1.880	1.921	1.994	2	0.070	0.082	0.099	0.134	0
Beef	0.119	1.958	1.983	2.031	1	0.027	0.046	0.051	0.061	2
Lamb	0.151	1.827	1.858	1.908	3	0.042	0.046	0.052	0.066	2
Banana	0.127	0.706	0.743	0.830	2	0.040	0.049	0.056	0.074	3
Palm oil	0.160	1.753	1.790	1.852	2	0.078	0.055	0.065	0.082	2
Cotton	0.056	1.907	1.929	1.970	2	0.048	0.051	0.061	0.076	2
Jute	0.085	1.125	1.182	1.286	2	0.056	0.064	0.075	0.096	1
Wool	0.073	2.051	2.071	2.103	2	0.056	0.043	0.048	0.058	2
Hides	0.083	1.955	1.984	2.042	2	0.058	0.050	0.057	0.071	2
Tobacco	0.073	1.428	1.454	1.503	3	0.030	0.059	0.068	0.087	2
Rubber	0.089	1.851	1.878	1.927	2	0.053	0.071	0.084	0.110	2
Timber	0.056	2.120	2.139	2.168	3	0.036	0.066	0.079	0.101	2
Copper	0.080	0.351	0.383	0.467	2	0.043	0.046	0.052	0.063	2
Aluminum	0.053	2.051	2.069	2.094	3	0.034	0.042	0.047	0.057	2
Tin	0.113	0.437	0.475	0.575	2	0.074	0.070	0.083	0.109	2
Silver	0.060	1.046	1.104	1.212	2	0.026	0.036	0.039	0.047	3
Lead	0.116	1.422	1.489	1.602	1	0.030	0.044	0.049	0.059	2
Zinc	0.188	0.346	0.447	0.649	0	0.058	0.091	0.108	0.147	1
Panel test	2.098	124.03	124.98	126.549		4.217	3.294	3.783	4.948	

The maximum number of breaks is set to 3 and the number of breaks is selected using the LWZ information criterion. Panel test is computed under the heterogeneity assumption of long run variance. The long-run variance was estimated using Bartlett kernel with the bandwidth of $4(T/100)^{2/9}$. Bootstrap critical values are based on 5000 replications.

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.econmod.2016.12.003.

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