The long-run behaviour of the terms of trade between primary commodities and manufactures: A panel data approach

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Abstract

This paper examines the Prebisch and Singer hypothesis using a panel of twenty-four commodity prices from 1900 to 2010. The modelling approach stems from the need to meet two key concerns: i.) the presence of cross-sectional dependence among commodity prices; and ii.) the identification of potential structural breaks. To address these concerns, the Hadri and Rao (2008) test is employed. The findings suggest that all commodity prices exhibit a structural break whose location differs across series, and that support for the Prebisch and Singer hypothesis is mixed. Once the breaks are removed from the underlying series, the persistence of commodity price shocks is shorter than that obtained in other studies using alternative methodologies.

Keywords Prebisch and Singer Hypothesis, Panel Stationarity, Structural Change, Cross Section Dependence

JEL code Agriculture; Natural Resources; Energy; Environment; Other Primary Products O13, Models with Panel Data; Longitudinal Data; Spatial Time Series C33

1 Introduction

Ever since Prebisch (1950) and Singer (1950) put forward the hypothesis that there is a secular deterioration in the price of primary commodities relative to that of manufactures, the study of the long-run behaviour of the terms of trade of developing countries has received a great deal of attention. Certainly, this is because the Prebisch and Singer (PS) hypothesis challenges the conventional classical view, according to which rapid technical progress in the production of manufactures, the operation of the law of diminishing returns in the production of primary goods, and a growing population would actually cause a long-run increase in the relative price of primary commodities.

PS attribute the secular deterioration of the terms of trade of developing countries to two main factors. First, in developed countries technical progress results in higher wages and improvements in the standard of living of the workers, due to the enhanced market power of trade unions, but not in lower prices of their products, some of which are exported to developing countries. By contrast, in developing countries technical progress does not result in higher wages, because of the presence of a Lewis (1954) type excess supply of labour, but in lower prices of their products. Thus, the benefits from technical progress are transferred from developing to developed countries or, in the terminology of Prebisch, from the periphery to the centre. Second, there is the combination of low price and income elasticities of demand for primary commodities relative to those of manufactures. Indeed, primary commodities (and most especially some agricultural products) can be regarded as necessities rather than luxuries, so that their income elasticity of demand is less than one. Thus, other things being equal, if increases in income shift the demand curve for primary commodities to the right by less than the corresponding shift in the demand curve for manufactures, the price of primary commodities relative to manufactures would tend to decline as time passes. Clearly, the importance of the PS hypothesis relies on its main policy recommendation, that developing countries should avoid specialisation according to their Ricardian comparative-advantage.

Being the validity of the PS hypothesis an empirical question, early criticisms focused on the inappropriateness and quality of the data. Then, attention turned to the fact that tests of the hypothesis were not based on a formal statistical procedure, but rather on informal approaches, such as visual inspection of the time-series data, and year-to-year comparisons. During the last three decades or so, however, these shortcomings have been addressed in two main ways. On the one hand, a significant amount of effort has been put on the creation of a consistent data set for a relatively large number of commodity prices. An important contribution in this area is Grilli and Yang (1988), who construct a US dollar commodity price index from 1900 to 1986, which consists of twenty-four internationally traded non-fuel commodities. Generally speaking, studies on the PS hypothesis can be classified into those that have analysed aggregate price indices of commodities, those that have looked at major commodity groupings, and those that have focused on individual commodities. On the other hand, tests of the hypothesis are now based on the application of recent developments of modern time-series econometrics. These developments include fitting regressions against time, estimating structural (also referred to as unobserved-components) time-series models, and applying unit root tests (also allowing for structural breaks at known and unknown dates).

This paper aims to further our understanding of the PS hypothesis by analysing commodity prices within a panel data framework. Panel data not only allow us to examine the potential effect of cross-sectional dependence among commodity price indices, which may arise from common shocks or innovations (e.g. an increased demand for raw materials due to growth in developed countries), but also offers the advantage that, by combining information from the time-series and the cross-section dimensions, fewer time series observations are required for statistical tests to have power. In sharp contrast to most of the literature on the PS hypothesis, we apply statistical tests that take stationarity as the null hypothesis. Testing for stationarity, rather than for non-stationarity (i.e. the existence of a unit root), appears more suitable to assess the PS hypothesis because this hypothesis, as originally postulated, implies the existence of a long-run declining deterministic trend in the price of primary commodities relative to that of manufactures. For this purpose, we employ the residual-based Lagrange multiplier (LM) panel stationarity tests put forward by Hadri and Rao (2008), who extend the Hadri (2000) tests to accommodate one-time structural breaks and cross section dependence. In a recent paper, Hadri (2010) applied the Hadri and Rao (2008) panel stationarity tests to investigate the validity of the PS hypothesis. However, this study leaves scope for further research and analysis. First, Hadri (2010) examined only nine commodities over the period 1960–2007. By contrast, we consider the twenty-four primary commodities that make up the Grilli and Yang (1988) index over the period 1900–2010. Second, and more importantly, Hadri (2010) studied commodity prices relative to the US consumer price index, but this deflator cannot be regarded as an appropriate variable to validate the PS hypothesis, since it does not provide a measure of the export price of manufactures of industrial countries to developing countries.

The paper is organised as follows. Section 2 briefly reviews the empirical literature on the PS hypothesis. Section 3 outlines the Hadri-based approaches to test for stationarity in panels of data, allowing for the presence of one-time structural breaks at unknown dates and cross section dependence. Section 4 describes the data, presents the results of the empirical analysis, and examines the validity of the PS hypothesis. Section 5 discusses policy considerations. Section 6 concludes.

2 Brief literature review

Prebisch (1950) and Singer (1950) analyse average price indices of British imports and exports, which are used as proxy for the world prices of primary commodities and manufactured products, respectively, for the period 1876–80 to 1946–47. They find evidence that from the 1870's to the Second World War the trend of prices has moved against producers of primary commodities and in favour of producers of manufactures. However, Spraos (1980) observes that early critics of Prebisch and Singer focused on the inappropriateness and quality of the price data used in their analyses. Then, attention turned to the fact that formal statistical testing procedures were not considered in the original writings of PS. Thus, for instance, Spraos (1980) and Sapsford (1985) revisit the deterioration hypothesis by estimating semi-logarithmic regressions of (some measure of) developing countries terms of trade against a constant and a time trend, and testing for the statistical significance of the estimated trend coefficient. Sapsford (1985) also tests for structural instability in the underlying trend coefficient.

Grilli and Yang (1988) construct a US dollar commodity price index spanning from 1900 to 1986, consisting of twenty-four internationally traded non-fuel commodities. The Grilly and Yang (GY) data set has become the most widely used data source in the literature related to the PS hypothesis; see e.g. Cuddington and Urzúa (1989), von Hagen (1989), Perron (1990), Powell (1991), Helg (1991), Ardeni and Wright (1992), Bleaney and Greenaway (1993), Newbold and Vougas (1996), León and Soto (1997), Kim et al. (2003), Zanias (2005), Kellard and Wohar (2006) and Ghoshray (2011). However, it is worth mentioning that the work of GY is not only important because they construct a consistent data set over a long period of time, but also because it is perhaps the first study that tests whether commodity prices can be viewed as trend-stationary (TS) or difference-stationary (DS) processes, based on the ADF unit root test of Dickey and Fuller (1979). Subsequently, the ADF test has also been employed by Bleaney and Greenaway (1993), Reinhart and Wickham (1994), and Kim et al. (2003), who analyse major commodity groupings, and by Cuddington (1992), who uses price data for individual commodities.[1]

Further extending the line of work based on unit-root tests, Cuddington and Urzúa (1989), Perron (1990), Helg (1991), Reinhart and Wickham (1994) and Newbold and Vougas (1996) apply the ADF test allowing for the presence of a known structural break.[2] León and Soto (1997) use the Zivot and Andrews (1992) unit root

[1]Reinhart and Wickham (1994) do not use the GY dataset, but quarterly data (1957q1 to 1993q2) for major commodity groupings: all non-oil commodities, beverages, food and metals.

[2]In our literature review, Newbold and Vougas (1996) is the only paper that also tested the null hypothesis of stationarity, which is the testing strategy adopted in our paper. However, they do not study individual commodity price indices, nor account for structural breaks.

test in the presence of an endogenously determined structural break, while Zanias (2005) and Kellard and Wohar (2006) apply the Lumsdaine and Papell (1997) unit root test that allows for the presence of up to two endogenously determined structural breaks. Ghoshray (2011) re-examines the PS hypothesis by employing the Lee and Strazicich (2003) unit root test with two endogenous breaks, which offers better size and power properties than both the Zivot and Andrews (1992) and Lumsdaine and Papell (1997) tests.

Among alternative approaches to unit-root tests that have been implemented, von Hagen (1989) tests for cointegration between prices of commodities and manufactures using the two-step ordinary least squares (OLS) procedure of Engle and Granger (1987), while Powell (1991) tests for cointegration using the Engle-Granger procedure as well as the maximum likelihood estimator of cointegrated vector autoregressive (VAR) models of Johansen (1988), also allowing for the presence of known structural breaks.[3] Ardeni and Wright (1992) and Reinhart and Wickham (1994) employ the structural time series approach advocated by Harvey (1989), according to which models are formulated directly in terms of three unobserved components of interest, namely trend, seasonal and irregular components.

In a recent contribution to the literature, Harvey et al. (2010) test the PS hypothesis using an entirely new and much longer data set of twenty-five relative commodity price series (the specific commodity list, which includes twenty commodities already found in the GY data set, is presented in Section 4). After consulting several historical sources, these authors manage to create an unbalanced panel of prices that goes back to 1650 for eight out of the twenty-five commodities under consideration. Then, they apply the Harvey et al. (2007, 2009) trend hypothesis tests, also allowing for one-time breaks, which involve the computation of a data-dependent weighted average of two trend statistics: one that is appropriate when the underlying series is stationary, and the other one when it is nonstationary. According to their results, there is evidence of a long-run negative trend in the relative

[3]Powell (1991) refers to the effects of breaks on the critical values of the Engle-Granger test, but there is no mention of their effect for the Johansen test.

price of eleven commodities, while no positive and significant trends were detected over all or part of the sample period for the remaining fourteen commodities. It is worth mentioning that, similar to the other studies existing in the literature, the results in Harvey et al. (2010) are based on a univariate analysis of the time-series properties of the commodity prices.

To the best of our knowledge, the only work that has investigated the PS hypothesis within a panel context is Hadri (2010), who use price data on nine primary commodities observed over the period 1960–2007. Hadri finds that, once allowance is made for the presence of structural breaks and cross-sectional dependence, real commodity prices can be best described as mean reverting and declining over time. However, caution should be exercised when interpreting these findings, because they do not constitute a formal test of the PS hypothesis. Indeed, Hadri deflates primary commodity prices with the US consumer price index, while PS where more interested on the dynamic behaviour of the price of commodities relative to that of the manufactures exported from developed to developing countries.

Perhaps it is no surprise that the results of the studies listed above provide mixed support for the PS hypothesis. Broadly speaking, these studies can be classified into three main groups. First, Spraos (1980), Sapsford (1985), Grilli and Yang (1988), Ardeni and Wright (1992), Bleaney and Greenaway (1993), Reinhart and Wickham (1994), León and Soto (1997) and Hadri (2010) confirm the negative sign (but not the magnitude) of the trend implicit in the works of PS. Second, Cuddington and Urzúa (1989), Perron (1990), Helg (1991), Powell (1991) and Zanias (2005) find that the relative price of primary commodities can be best characterised as a trendless process that exhibits a one-time negative shift. According to Cuddington and Urzúa (1989), this finding, strictly speaking, does not support the views of PS, because the latter refer to a secular terms of trade deterioration.[4] Third, von Hagen (1989), Cuddington (1992), Newbold and Vougas (1996), Kim et al. (2003), Kellard and

[4]Singer (1999), however, argues that " ... it does not matter very much whether the data are interpreted as a persistent decline trend or as essentially stationary with intermittent downward breaks. " (p. 911).

Wohar (2006), Harvey et al. (2010) and Ghoshray (2011) do not find strong support for the PS hypothesis.

3 Testing for panel stationarity

In recent years, testing for unit roots in panel data has received a great deal of attention, as it is one possible way to achieve power gains over unit root tests applied to a single time series; see e.g. Breitung and Pesaran (2008) for a literature review. Among the tests available in the literature, that of Im et al. (2003) (IPS) has proved to be one of the most commonly applied. The IPS test is based on averaging individual ADF statistics, and so it permits for all of the individual series in the panel to have a unit root under the null hypothesis. Within this framework, failure to reject the null hypothesis implies that all of the individual series can be characterised as DS (as opposed to TS) processes. However, given that the PS hypothesis implies that commodity prices exhibit a long-run declining deterministic trend, it appears that a more appropriate approach would be one that tests the null of stationarity around a level or around a (broken) trend.

Hadri (2000) develops a residual-based LM procedure to test the null hypothesis of stationarity for all the individual series in the panel, against the alternative that some (but not all) of the individual series have a unit root. As can be seen, this approach offers the key advantage that if the null hypothesis is not rejected, then one may conclude that all the commodity price indices in the panel are stationary. In particular, Hadri considers the following model specifications:

$$y_{it} = \alpha_i + r_{it} + \varepsilon_{it}, \tag{1}$$

$$y_{it} = \alpha_i + r_{it} + \beta_i t + \varepsilon_{it}. \tag{2}$$

where y_{it} denotes the observed series of commodity price index i at time t, $i = 1, ..., N$, $t = 1, ..., T$, r_{it} is a random walk, $r_{it} = r_{it-1} + u_{it}$, and ε_{it} and u_{it} are mutually independent normal distributions. In addition, ε_{it} and u_{it} are independent and identically distributed (i.i.d.) across i and over t, with $E\left[\varepsilon_{it}\right] = 0$, $E\left[\varepsilon_{it}^2\right] = \sigma_{\varepsilon,i}^2 > 0$,

$E[u_{it}] = 0$ and $E[u_{it}^2] = \sigma_{u,i}^2 \geq 0$. Within this framework, the null hypothesis that all the individual series in the panel are stationary is $H_0 : \sigma_{u,i}^2 = 0$, where $i = 1, ..., N$. The alternative hypothesis that some (but not all) of the individual series have a unit root is $H_1 : \sigma_{u,i}^2 > 0$, where $i = 1, ..., N_1$; and $\sigma_{u,i}^2 = 0$, where $i = N_1 + 1, ..., N$.

The models given in Eqs. (1) and (2) are used to test for level and trend stationarity, respectively. In a recent paper, Hadri and Rao (2008) extend the previous setup to allow for the presence of one-time structural breaks. More specifically, they postulate the following models of structural break under the null hypothesis:

$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \varepsilon_{it}, \tag{3}$$

$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \beta_i t + \varepsilon_{it}, \tag{4}$$

$$y_{it} = \alpha_i + r_{it} + \beta_i t + \gamma_i DT_{it} + \varepsilon_{it}, \tag{5}$$

$$y_{it} = \alpha_i + r_{it} + \delta_i D_{it} + \beta_i t + \gamma_i DT_{it} + \varepsilon_{it}, \tag{6}$$

where, in addition to the terms already defined, D_{it} and DT_{it} are dummy variables to specify the type of structural break, which are defined as:

$$D_{it} = \begin{cases} 1, & \text{if } t > T_{B,i} \\ 0 & \text{otherwise} \end{cases}, \tag{7}$$

and

$$DT_{it} = \begin{cases} t - T_{B,i}, & \text{if } t > T_{B,i} \\ 0, & \text{otherwise} \end{cases}, \tag{8}$$

where $T_{B,i}$ denotes the time of occurrence of the structural break for individual i. Also, $T_{B,i} = \omega_i T$, where $\omega_i \in (0, 1)$ indicates the fraction of the break point relative to the whole sample period for individual i. The parameters δ_i and γ_i measure the extent (or magnitude) of the structural break, and allow for the possibility of different breaking dates across the individuals in the panel. The models in Eqs. (3) to (6) comprise the following characteristics. Eq. (3) consists of an intercept term and allows for a shift in the level of the series. Eq. (4) has intercept and linear trend terms, and admits a shift in the former (but not in the latter). Eq. (5) includes intercept and linear trend terms, and permits a change in the latter (but not in the former). Lastly, Eq. (6) also incorporates intercept and linear trend terms, and allows for a change in both the level and the slope of the series.[5]

Hadri and Rao (2008) use a systematic approach to find the appropriate model for each series y_{it}; it should be noticed that in implementing this approach, the models postulated in Eqs. (1) and (2) are also taken into account to allow for the possibility that there is no break in the underlying series y_{it}. Specifically, Hadri and Rao start off by determining the time of the break point endogenously, which involves estimating for each cross section unit in the panel and for each model the break date, $\hat{T}_{B,i,k}$. This can be accomplished by minimising, with respect to $0 < \omega_i < 1$, the residual sum of squares (RSS) from the relevant model under the null hypothesis, where $i = 1, ..., N$ denotes the commodity prices in the panel, and $k = 1, 2, ..., 6$ refers to the models postulated in Eqs. (1) to (6). Then, given $\hat{T}_{B,i,k}$, for each individual in the panel, i, the preferred model, k, is chosen by minimising the Schwarz information criterion.[6]

Let $\hat{\varepsilon}_{it}$ be the residuals that result from estimating the chosen model (with or without a break). The individual univariate Kwiatkowski et al. (1992) (KPSS) stationarity test is given by:

$$\eta_{i,T,k}\left(\hat{\omega}_i\right) = \frac{\sum_{t=1}^{T} S_{it}^2}{T^2 \hat{\sigma}_{\varepsilon_i}^2}, \tag{9}$$

where $S_{it} = \sum_{j=1}^{t} \hat{\varepsilon}_{ij}$ denotes the partial sum process of the residuals, and $\hat{\sigma}_{\varepsilon_i}^2$ is a consistent estimator of the long-run variance of $\hat{\varepsilon}_{it}$ from the appropriate regression. To obtain $\hat{\sigma}_{\varepsilon_i}^2$ we employ the new boundary condition rule derived by Sul et al. (2005), which is implemented as follows: First, an autoregressive (AR) model for the residuals is estimated, that is:

[5] Carrión-i-Silvestre et al. (2005) study the case of testing for panel stationarity with multiple structural breaks. However, they only consider the models formulated in Eqs. (3) and (6).

[6] Notice that in practice the models in Eqs. (1) and (2) are estimated only once, since they do not include the dummy variables D_{it} and DT_{it}.

$$\hat{\varepsilon}_{it} = \rho_{i,1}\hat{\varepsilon}_{i,t-1} + ... + \rho_{i,p_i}\hat{\varepsilon}_{i,t-p_i} + \upsilon_{it}, \tag{10}$$

where the lag length of the autoregression, p_i, can be determined for example using the general to specific (GTS) algorithm proposed by Hall (1994) and Campbell and Perron (1991). The idea in the GTS algorithm is to start with some upper bound on p_i, denoted $p_i^{\max}$, then estimate Eq. (10) with $p_i = p_i^{\max}$, and test the statistical significance of $\rho_{i,p_i^{\max}}$. If this coefficient is statistically significant, using for instance a significance level of 10%, one selects $p_i = p_i^{\max}$. Otherwise, the order of the estimated autoregression in (10) is reduced by one until the coefficient on the last included lag is found to be statistically significant. Second, $\hat{\sigma}^2_{\varepsilon_i}$ is obtained after applying the boundary condition rule:

$$\hat{\sigma}^2_{\varepsilon_i} = \min\left\{T\hat{\sigma}^2_{\upsilon_i}, \frac{\hat{\sigma}^2_{\upsilon_i}}{\left(1-\hat{\rho}_i\left(1\right)\right)^2}\right\}, \tag{11}$$

where $\hat{\rho}_i\left(1\right) = \hat{\rho}_{i,1}\left(1\right) + ... + \hat{\rho}_{i,p_i}\left(1\right)$ denotes the autoregressive polynomial evaluated at $L = 1$. Third, the long-run variance estimate of the residuals in Eq. (10), $\hat{\sigma}^2_{\upsilon_i}$, is obtained using a quadratic spectral window Heteroskedastic and Autocorrelation Consistent (HAC) estimator. Sul et al. report Monte Carlo simulation results that reveal that the new boundary condition rule to estimate $\hat{\sigma}^2_{\varepsilon_i}$ improves the size and power properties of the KPSS tests; see also Carrión-i-Silvestre and Sansó (2006).

Having consistently estimated $\hat{\sigma}^2_{\varepsilon_i}$, the panel stationarity test is calculated as the simple average of the individual univariate KPSS stationarity tests:

$$\widehat{LM}_{T,N,k}\left(\hat{\omega}_i\right) = \frac{1}{N}\sum_{i=1}^{N}\eta_{i,T,k}\left(\hat{\omega}_i\right), \tag{12}$$

which after a suitable standardisation, using appropriate moments of the statistics associated to the models postulated in Eqs. (1) to (6), follows a standard normal limiting distribution:

$$Z_k\left(\hat{\omega}_i\right) = \frac{\sqrt{N}\left(\widehat{LM}_{T,N,k}\left(\hat{\omega}_i\right) - \bar{\xi}_k\right)}{\bar{\zeta}_k} \Rightarrow N\left(0,1\right), \tag{13}$$

where $\bar{\xi}_k = \frac{1}{N}\sum_{i=1}^{N}\xi_{i,k}$ and $\bar{\zeta}_k^2 = \frac{1}{N}\sum_{i=1}^{N}\zeta_{i,k}^2$ denote the mean and variance required for standardisation, respectively. The proof of the previous result can be found in Hadri (2000). Furthermore, Hadri and Rao (2008), in Theorem 3, show that in the presence of breaks, that is for the models in Eqs. (3) to (6), the individual means, $\xi_{i,k}$, and variances, $\zeta_{i,k}^2$, depend upon the relative position of the break in the sample or, in other words, $\xi_{i,k}$ and $\zeta_{i,k}^2$ are functions of $\hat{\omega}_i$.

The Hadri and Rao (2008) test critically relies on the assumption that the individual time series in the panel are independent from each other. To allow for cross section dependence, Hadri and Rao (2008) recommend employing an AR-based bootstrap which consists of the following steps: First, to account for serial correlation Eq. (10) is estimated, and the resulting residuals (centred around zero) are denoted $\hat{\upsilon}_{it}$. Second, following Maddala and Wu (1999), the residuals $\hat{\upsilon}_{it}$ are resampled with replacement with the cross-section index fixed, so that their cross-correlation structure is preserved; the resulting bootstrap innovations are denoted $\hat{\upsilon}_{it}^*$. Third, $\hat{\varepsilon}_{it}^*$ is generated using the following mechanism:

$$\hat{\varepsilon}_{it}^* = \hat{\rho}_{i,1}\hat{\varepsilon}_{i,t-1}^* + ... + \hat{\rho}_{i,p_i}\hat{\varepsilon}_{i,t-p_i}^* + \upsilon_t^*, \tag{14}$$

where $\hat{\rho}_{i,1}, ..., \hat{\rho}_{i,p_i}$ are the corresponding OLS coefficient estimates from the fitted AR model in (10). To ensure that the bootstrap samples, $\hat{\varepsilon}_{it}^*$, generated by (14) are stationary processes, we generate a larger number of $\hat{\varepsilon}_{it}^*$, let us say $T + Q$ values, and then discard the first Q values. This strategy also offers the advantage that the method used to obtain the initial values of $\hat{\varepsilon}_{it}^*$ becomes unimportant, and so one might as well use zeros for the initial values; see Chang (2004), footnote 6. For our purposes, we choose $Q = 40$. Fourth, the bootstrap samples of y_{it}, denoted y_{it}^*, are calculated by adding $\hat{\varepsilon}_{it}^*$ to the deterministic component of the corresponding chosen model, and the Hadri and Rao LM test statistic is calculated for each y_{it}^*. The four steps described earlier are repeated several times to derive the empirical distribution of the LM statistic, and then bootstrap p-values (or alternatively bootstrap critical values) may be obtained.

4 Empirical results

4.1 Data

We employ the commodity price index data set constructed by Grilli and Yang (1988) for the period 1900–1986, and extended to 2010 by Stephan Pfaffenzeller, for a total of 111 time observations; the sample period is thus seven years longer than that recently analysed by Ghoshray (2011).[7] The data set consists of price information on twenty-four commodities that account for (approximately) 54% of all nonfuel commodities traded in the world in the period 1977–1979; see Grilli and Yang (1988), footnote 2. These commodities are: Aluminium, Banana, Beef, Cocoa, Coffee, Copper, Cotton, Hides, Jute, Lamb, Lead, Maize, Palm Oil, Rice, Rubber, Silver, Sugar, Tea, Timber, Tin, Tobacco, Wheat, Wool and Zinc. We use these commodities to conform four balanced panels of data: i.) Food commodities, which comprises Banana, Beef, Cocoa, Coffee, Lamb, Maize, Palm Oil, Rice, Sugar, Tea and Wheat; ii.) Nonfood commodities, which consists of Cotton, Hides, Jute, Rubber, Timber, Tobacco and Wool; iii.) Metals, which includes Aluminium, Copper, Lead, Silver, Tin and Zinc; and iv.) All commodities, which contains all twenty-four commodity price indices. Following the tradition of studies that have used the GY data set, the price indices of the twenty-four commodities are deflated using a trade-weighted unit value index of the exports of manufactured commodities of five major industrial countries (France, Germany, Japan, United Kingdom and United States) to developing countries; see Pfaffenzeller et al. (2007). The resulting deflated series of commodity price indices are considered in logarithms.

As indicated in Section 2, in a recent contribution to the literature, Harvey et al. (2010) construct an entirely new data set with commodity price information predating 1900 up until 2005. The data set is unbalanced because the commodity price series do not start in the same year. More specifically, the data set consists of time-series observations for Beef, Coal, Gold, Lamb, Lead, Sugar, Wheat and

[7] See Pfaffenzeller et al. (2007) for practical advice on how to update the GY commodity price indices, as well as for a full description of the data series and their sources.

Wool that start in 1650; Cotton in 1670; Tea in 1673; Rice and Silver in 1687; Coffee in 1709; Tobacco in 1741; Pig Iron in 1782; Cocoa, Copper and Hide in 1800; Tin in 1808; Nickel in 1840; Zinc in 1853; Oil in 1859; Aluminium in 1872; and Banana and Jute in 1900. Thus, there are twenty commodities that are already included in the GY data set. An important distinction between the GY data set and the one collected by Harvey et al. (2010) relates to the construction of the price of manufactures. Indeed, while the former use manufacturing export unit value indexes for selected industrial countries, the latter employ value-added price deflators for manufacturing products; see Harvey et al. (2010) and the references therein for a discussion of the advantages and disadvantages of both measures.

It is interesting to observe that if we attempt to balance the Harvey et al. (2010) data set, a requirement that is needed to apply the panel stationarity tests, then the relative commodity price series in the resulting balanced panel would begin in 1900, which is the same year when the GY data set starts (since Banana and Jute prices are only available starting in that year).

4.2 Testing for cross-section dependence

We begin our empirical investigation with an analysis of cross-sectional independence of innovations (shocks) in commodity price indices. To do this, we calculate the Pesaran (2004) general diagnostic test for cross section independence in panels, denoted CD statistic. This author presents analytical and Monte Carlo simulation results that indicate that the CD test can be applied to a wide class of panel data models, including heterogeneous dynamic models with normal and non-normal errors, structural breaks and unit roots. Results not reported here indicate that the the null hypothesis that commodity price innovations are cross sectionally independent is strongly rejected for the four commodity groupings that are considered, which provides a justification for analysing the commodity prices jointly within a panel data framework, rather than as individual time series. These findings are consistent with those reported in the study by Pindyck and Rotemberg (1990), who observed "excess comovement" in the prices of unrelated commodities. Excess comovement refers to the idea that the strong correlations that are observed in the prices of unrelated commodities cannot be fully explained by changes in current or expected future values of common macroeconomic variables or fundamentals, such as aggregate demand, industrial production, inflation, exchange rates and interest rates, among others; see also Hadri (2010).

4.3 Testing for structural breaks

Next, we turn our attention to testing for panel stationarity. The analysis starts off by identifying the presence of structural breaks (if any) in the prices of the twenty-four commodities included in the GY study. This issue has been examined by León and Soto (1997), Kellard and Wohar (2006), and Ghoshray (2011) using the sample periods 1900–1992, 1900–1998 and 1900–2003, respectively. Thus, in determining the position of the structural breaks, we carry out our estimations over four sample periods, namely the three that we already mentioned, as well as 1900–2010 (that is, the longest sample period currently available). This approach allows us to examine the effect of extending the sample period on the position of the break date, and also compare our results with those obtained in these three papers.

The results of determining the position of breaks over different sample periods are summarised in Table 1. There are two main aspects worth noticing in this table. First, the results reveal evidence of one structural break in all individual commodity prices. Indeed, notice that the model specifications that do not account for the presence of a structural break, i.e. the models in Eqs. (1) and (2), are never selected. This finding is in sharp contrast with the earlier work by León and Soto (1997), Kellard and Wohar (2006) and Ghoshray (2011), who find that there is no evidence of structural breaks in some commodities. Second, the results suggest that there are ten commodities (namely Coffee, Cocoa, Beef, Lamb, Banana, Palm Oil, Cotton, Rubber, Timber and Aluminium) for which the position of the break does not change as the sample period is extended. More importantly, for the remaining fourteen commodities extending the sample period appears to have an effect on the estimated position of the break date; notice, in particular, the cases of Tea, Sugar, Wool, Tobacco, Copper, Lead and Zinc for which extending the sample period over the years 2004–2010 changes the position of the break date.

In what follows, we use Table 1 to compare our results on the position of break dates with the dates reported by León and Soto (1997), Kellard and Wohar (2006), and Ghoshray (2011). We focus on the commodities for which there is evidence of one structural break, and regard discrepancies of up to two years in the break date (in either direction) as negligible. Thus, in comparison to León and Soto (1997), who based their analysis on the period 1900–1992, we find similar break dates for Cocoa, Beef, Banana, Palm Oil, Wool, Tobacco, Rubber, Copper and Aluminium. With respect to Kellard and Wohar (2006), who extend the sample period to include the years 1993–1998, similar break dates are found for Rice, Palm Oil and Aluminium. Finally, after further extending the sample period to cover the 1999–2003 period, as in Ghoshray (2011), we find similar break dates for Tea, Hides and Zinc.

At this point, it could well be argued that while the Hadri and Rao (2008) procedure accounts for unknown structural breaks, it is limited insofar as only a single break is permitted for each individual in the panel. However, informal visual inspection of the residuals from the chosen models reveals no evidence of further structural breaks, apart from the presence of potential outlier observations.[8]

Overall, it appears that the results on break date determination are dependent on the econometric strategy used to identify the breaks, as well as on how the breaks are characterised, that is on whether we allow for a change in level, a change in slope, or both. Without a doubt, extending the sample period implies that new important events and/or changes in commodity markets are included in the analysis, and these in turn make previously chosen functional forms no longer appropriate.

[8]Bai and Perron (1998) provide a framework for estimating and testing linear regression models with multiple structural breaks that occur at unknown dates. However, the Bai–Perron methodology is not implemented here because it does not permit the use of trending regressors, which is of particular relevance when assessing the validity of the PS hypothesis.

4.4 Testing for panel stationarity

Figure 1 plots the commodity price indices over the 1900–2010 period, along with the chosen broken-trend model that is fitted to each commodity.[9] The residuals of the broken-trend models are then used to construct the univariate KPSS stationarity tests (with breaks) based on Eq. (9). To correct for serial correlation we include $p = 10$ lags in Eq. (10), and then determine the optimal number of lags using the GTS algorithm outlined earlier.

Table 2 summarises the results from the Hadri and Rao panel stationary test under the assumption of cross section dependence, that is where the test statistics are compared with their empirical bootstrap distribution (which is based on 2,000 bootstrap replications). The results indicate that when commodity prices are analysed within a panel data context, and after accounting for the presence of structural breaks and cross sectional dependence, the null hypothesis that they are jointly stationary around a (broken) trend cannot be rejected at traditional significance levels. To illustrate the importance of cross-sectional dependence, notice that if we were to wrongly assume cross-sectional independence among commodity prices, and use the upper tail of the standard normal distribution for the purposes of inference, then the joint stationary null would be rejected at the 5% significance level.

4.5 Testing the Prebisch and Singer hypothesis

Finding that commodity prices are jointly stationary is in agreement with the results reported in Hadri (2010), although it should be recalled that this author used only nine commodities over a much shorter sample period, and deflated commodity prices with the US CPI, which cannot be regarded as a good proxy of the price of the manufactures exported from developed to developing countries. The relevance of the stationarity result is that it is valid to apply standard tools of econometric analysis to examine the PS hypothesis.

[9] León and Soto (1997), Kellard and Wohar (2006), Ghoshray (2011) and Hadri (2010) report plots of the commodity price series, but not of the (broken) trend components that are estimated.

Table 3 reports OLS estimates of the deterministic components of the commodity prices under consideration. As can be seen from this table, the estimated coefficients associated to the variables D_{it} and DT_{it}, that is the dummy variables that help specify the type of structural break as defined in equations (7) and (8), are statistically different from zero for all commodities.

Regarding the validity of the PS hypothesis, the estimated trend components tell very diverse stories indeed. Commodities such as Cocoa, Rice, Sugar, Cotton, Rubber, Copper, Aluminium and Silver offer support for the PS hypothesis by exhibiting a negative trend both before and after the break. Partial support for the PS hypothesis is provided by some commodities where a negative trend is only observed either before the break (Wheat, Maize and Palm Oil) or after the break (Coffee, Tea, Banana, Jute, Wool and Hides). At the other end of the spectrum, Lamb, Tobacco, Timber, Tin and Lead offer no support for the PS hypothesis, as they display a positive trend both before and after the break. Lastly, Beef and Zinc can be viewed as trendless series that show evidence of a one-time positive level shift after the break, which does not corroborate the PS hypothesis either.

5 Policy implications

From a statistical point of view, the finding that commodity prices exhibit TS (as opposed to DS) behaviour is important because the effect of a shock will be transitory (as opposed to permanent). From an economic point of view, as discussed inter alia by Deaton and Miller (1996), the key issue is the choice of the appropriate policy response to commodity price shocks: stabilisation when the shock is transitory, or adjustment when it is permanent. Empirical evidence on the response of developing countries to trade shocks is quite interesting indeed. For instance, Collier and Gunning (1999) compare twenty-three case studies from a sample of countries in Africa, Asia and Latin America that experienced different sorts of commodity shocks, and conclude that, generally speaking, although the countries under investigation did not fail to save a large share of the windfalls (as the permanent income theory of consumption predicts), they did tend to invest these savings badly. However, in practice the implementation of stabilisation policies can be made much more difficult because of uncertainties surrounding the magnitude and (perhaps more importantly) the duration of the price booms or busts. Indeed, as indicated by Deaton and Miller (1996), the high degree of persistence of commodity prices might complicate macroeconomic management. On the one hand, when times are good countries may need to accumulate reserves over prolonged periods of time, and this strategy could turn out to be expensive and possibly not even feasible (or sustainable) from a political point of view. On the other hand, when times are bad countries may face limitations in their ability to borrow to finance their consumption levels.

Taking the above policy issues into consideration, it is of some interest to measure the persistence of commodity price shocks after structural breaks are accommodated in the analysis. For this, we use half-life estimates based on the Pesaran and Shin (1998) generalised impulse response (GIR) functions that result from estimating VAR models.[10] GIR functions, unlike standard impulse response functions based on a Cholesky decomposition, offer the advantage of being invariant to the way shocks in the underlying VAR model are orthogonalised. The empirical analysis starts off by estimating VAR models for each primary commodity group under consideration, namely Food, Nonfood and Metals, where the VAR models themselves consist of the residuals that result from estimating the chosen break-type model. It should be recalled that after accounting for structural breaks (and cross-section dependence), the resulting commodity price series turn out to be jointly stationary and therefore suitable for modelling in a VAR framework.

An important initial stage in the analysis is the selection of the optimal order of the VAR models, which involves selecting an order high enough such that one can be reasonably confident that the optimal order will not exceed it. Bearing in mind that the sample size ($T = 111$ observations) might become small relative to

[10] Seong et al. (2006) recommend using impulse response functions to estimate the half-life of a shock. The traditional formula to estimate the half-life of a shock $-(\ln(2) \div \ln(\delta))$, where δ refers to the value of the autoregressive parameter, is only applicable in the case of simple AR(1) models.

the number of lagged level variables included in each VAR model, we set four lags as the maximum order of the models, and use the Schwarz information criterion to select the optimal order. This criterion selects the optimal number of lags to be equal to one.[11] Then, the underlying VAR(1) models can be used to compute the associated GIR functions, which plot the time profile of the effect of an own unit shock in a commodity price (measured by one standard deviation). Lastly, the resulting statistically significant lag weights are normalised so that they add up to one, and the half-life is calculated as the number of years required for 50 per cent (or the first half) of the adjustment to take place.

The results of the persistence analysis, reported in Table 4, reveal that the estimated half-life to own-price shocks is lower than the typical half-lives estimated in previous studies using other methodologies. For example, the half-life for Food and Nonfood commodities is two years (except for Tea and Hides where it is one year). More persistence is found in the group of Metals where the average half-life is just over three years, varying between two years (for Aluminium and Zinc) and five years (for Silver).[12] It should be noticed that the relatively short-lived persistence of shocks is achieved after removing broken-time deterministic trends from the underlying commodity price series, and that this result is consistent with the findings in the econometrics literature that relate unaccounted structural breaks with spurious non-stationarity, and therefore low rates for mean reversion; see Perron (1989).

The finding that commodity price shocks exhibit low persistence rates, after accommodating structural breaks, suggests that in the short run there appears to be scope for the utilisation of stabilisation mechanisms in order to smooth the path of export revenues in developing countries. Needless to say, the implementation of stabilisation mechanisms to a particular country should be based on a careful examination of the specific products and export markets on which the country is dependent. In the long run, the issue at the core of the discussion is that most devel-

[11]The Akaike information criterion also selects the same optimal lag order.

[12]Collier and Gunning (1999) indicate that in a sample of 19 positive shocks, in two out of three cases the duration is about 3-8 years.

oping countries rely heavily on export revenue from the production of few primary commodities. The evidence reported in this paper indicates that all the twenty-four commodity prices under analysis have exhibited abrupt one-time changes of one form or another. Thus, it is in the interest of developing countries to develop strategies that help them achieve a diversified production structure, so that the impact of future commodity price shocks is cushioned. Related to this point, Singer (1999), among other authors, reiterates the importance for developing countries to diversify their exports by moving into the production of manufactures, in particular of those that are somewhat technologically complex.

6 Concluding remarks

In this paper we have examined the validity of the Prebisch and Singer hypothesis of a long-run negative trend in the terms of trade between primary commodities and manufactures. For this, we use an up-to-date version of the widely used commodity price data set assembled by Grilli and Yang (1988), and employ a panel stationarity testing procedure that addresses both structural breaks and cross-sectional dependence. This modelling approach differs from the one that has been used in the existing literature, which is based on univariate non-stationarity tests applied to individual commodity prices.

The empirical analysis starts off by confirming the presence of cross section dependence of innovations (shocks) in commodity price. This finding supports the view that when dealing with commodity prices it is not appropriate to assume that they are independent from each other, due to the existence of market linkages. Also, it provides a justification for treating commodity prices as a panel of data, which is advantageous since the power of statistical tests increases with the number of cross sections in the panel. The analysis proceeds by revealing that all twenty-four commodity prices exhibit a one-time structural break, which differs across commodities. In fourteen out of twenty-four cases the position of the break varies according to the time span of data that is used, while in the remaining ten cases the estimated position of the break does not change when the sample period is extended by including more recent observations.

The results of the panel stationarity tests suggest that commodity prices are jointly stationarity after accommodating one-time structural breaks and cross section dependence. This implies that standard tools of regression analysis can be used to test the validity of the Prebisch and Singer hypothesis. Broadly speaking, support for the hypothesis is mixed. The strongest evidence in favour is encountered for commodities such as Cocoa, Rice, Sugar, Cotton, Rubber, Copper, Aluminium and Silver, which display a negative trend both before and after the break. The remaining commodities provide either partial support (as some commodity prices exhibit a negative trend only before or after the break) or no support whatsoever for the hypothesis. The results also indicate that once the breaks are removed from the underlying series, the persistence of commodity price shocks (as measured by their half-life) is shorter than that obtained in other studies using alternative methodologies.

From an economic policy standpoint, our results support the adoption of prudent macroeconomic policies. On the one hand, finding that all twenty-four commodity prices exhibit abrupt structural breaks of one form or another, support the view that, in the long run, it is in the interest of developing countries to implement policy measures aimed at diversifying their production structure, so that their dependence on few commodities as a source of foreign exchange is reduced. On the other hand, the relatively low rates of persistence of commodity price shocks suggest that, in the short run, there is scope for developing countries to design and use stabilisation mechanisms in response to trade shocks.

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Table 1. Estimated models and structural breaks

Commodity	1900–1992		1900–1998		1900–2003		1900–2010	
	Model	Date	Model	Date	Model	Date	Model	Date
Coffee	6	1950	6	1950	6	1950	6	1950
Cocoa	6	1947	6	1947	6	1947	6	1947
Tea	6	1954	6	1954	6	1954	6	1968
Rice	6	1973	4	1982	6	1982	4	1982
Wheat	6	1973	6	1921	4	1986	6	1987
Maize	5	1975	4	1986	4	1986	6	1986
Sugar	6	1972	6	1972	6	1972	4	1925
Beef	4	1959	3	1959	3	1959	3	1959
Lamb	4	1947	4	1947	4	1947	4	1947
Banana	6	1926	6	1926	6	1926	6	1926
Palm oil	4	1986	6	1986	4	1986	6	1986
Cotton	6	1946	6	1946	6	1946	6	1946
Jute	6	1947	5	1966	6	1947	6	1973
Wool	5	1952	5	1952	5	1952	5	1942
Hides	6	1921	6	1952	6	1952	6	1921
Tobacco	6	1918	6	1918	6	1918	6	1919
Rubber	4	1918	4	1918	4	1918	4	1918
Timber	6	1921	6	1921	6	1921	6	1921
Copper	4	1953	4	1953	4	1953	4	2006
Aluminium	6	1942	6	1942	6	1942	6	1942
Tin	6	1977	6	1977	6	1986	4	1986
Silver	4	1967	6	1974	6	1974	4	1967
Lead	6	1947	6	1947	6	1947	6	1982
Zinc	6	1918	6	1918	6	1918	3	2006

Notes: The columns labelled "Model" indicate the chosen model specifications, as postulated in Eqs. (1) to (6).

Table 2. Panel stationarity results for relative commodity prices with breaks

Panels	Statistic	p-value
Food	1.658	[0.151]
Nonfood	0.867	[0.136]
Metals	-0.440	[0.769]
All commodities	0.765	[0.364]

Notes: The footnote in Table 1 lists the commodities included in each panel. In constructing the individual KPSS statistics, we set $p_i^{\max} = 10$ in Eq. (10), and select the optimal number using the GTS algorithm with a significance level of 10%. Bootstrap p-values are based on 2000 replications.

Table 3. Estimated long-run trends of commodity prices, 1900–2010

Commodity	Model	Break	Constant	D_{it}	Trend	DT_{it}	R^2
Coffee	6	1950	-1.066	0.861	0.002	-0.020	0.465
			(0.092)	(0.122)	(0.003)	(0.004)	
Cocoa	6	1947	-0.423	1.398	-0.032	0.020	0.526
			(0.102)	(0.132)	(0.004)	(0.004)	
Tea	6	1954	-0.028	-0.428	0.006	-0.019	0.692
			(0.048)	(0.076)	(0.001)	(0.003)	
Rice	4	1973	0.533	-0.602	-0.005		0.749
			(0.052)	(0.079)	(0.001)		
Wheat	6	1973	0.691	-0.500	-0.007	0.024	0.655
			(0.047)	(0.101)	(0.001)	(0.006)	
Maize	6	1975	0.687	-0.730	-0.006	0.016	0.749
			(0.049)	(0.104)	(0.001)	(0.006)	
Sugar	4	1972	0.840	-0.411	-0.006		0.441
			(0.082)	(0.130)	(0.002)		
Beef	3	1959	-1.354	1.194			0.815
			(0.037)	(0.054)			
Lamb	4	1947	-1.923	-0.793	0.028		0.763
			(0.068)	(0.126)	(0.002)		
Banana	6	1926	0.064	0.397	0.004	-0.011	0.556
			(0.060)	(0.065)	(0.004)	(0.004)	
Palm oil	6	1986	0.382	-0.951	-0.005	0.026	0.743
			(0.053)	(0.113)	(0.001)	(0.007)	
Cotton	6	1946	0.498	0.446	-0.004	-0.023	0.848
			(0.059)	(0.076)	(0.002)	(0.003)	
Jute	6	1947	0.107	-0.534	0.006	-0.019	0.579
			(0.063)	(0.108)	(0.001)	(0.004)	
Wool	5	1952	0.786	-0.032	0.006		0.843
			(0.072)	(0.003)	(0.002)		
Hides	6	1921	0.180	-0.697	0.033	-0.039	0.578
			(0.114)	(0.119)	(0.009)	(0.009)	
Tobacco	6	1918	-1.160	0.534	0.024	-0.022	0.827
			(0.072)	(0.074)	(0.006)	(0.006)	
Rubber	4	1918	2.291	-1.141	-0.015		0.829
			(0.090)	(0.126)	(0.001)		
Timber	6	1921	-1.355	-0.355	0.047	-0.038	0.780
			(0.076)	(0.079)	(0.006)	(0.006)	
Copper	4	1953	0.155	0.934	-0.003		0.297
			(0.056)	(0.139)	(0.001)		
Aluminium	6	1942	1.461	-0.491	-0.020	0.016	0.851
			(0.070)	(0.087)	(0.003)	(0.003)	
Tin	4	1977	-1.262	-0.953	0.012		0.527
			(0.059)	(0.091)	(0.001)		
Silver	4	1967	-0.612	0.914	-0.008		0.403
			(0.074)	(0.120)	(0.002)		
Lead	6	1947	-0.255	-0.934	0.002	0.025	0.473
			(0.057)	(0.112)	(0.001)	(0.006)	
Zinc	3	1918	-0.005	0.564			0.213
			(0.022)	(0.104)			

Notes: Standard errors in parentheses.

Table 4. Half-life estimates (in years) from GIR functions

Food	Half-life	Nonfood	Half-life	Metals	Half-life
Coffee	2	Cotton	2	Copper	4
Cocoa	2	Jute	2	Aluminium	2
Tea	1	Wool	2	Tin	3
Rice	2	Hides	1	Silver	5
Wheat	2	Tobacco	2	Lead	3
Maize	2	Rubber	2	Zinc	2
Sugar	2	Timber	2		
Beef	2				
Lamb	2				
Banana	2				
Palm oil	2				

Figure 1: Plots of the commodity price series and fitted broken trend