2010

The Prebisch-Singer Hypothesis: Four Centuries of Evidence

David I. Harvey
University of Nottingham

Neil M. Kellard
University of Essex

Jakob B. Madsen
Monash University

Mark E. Wohar
University of Nebraska at Omaha

Follow this and additional works at: https://digitalcommons.unomaha.edu/econrealestatefacpub

Part of the Economics Commons

Please take our feedback survey at: https://unomaha.az1.qualtrics.com/jfe/form/SV_8cchtFmpDyGfBLE

Recommended Citation

This Article is brought to you for free and open access by the Department of Economics at DigitalCommons@UNO. It has been accepted for inclusion in Economics Faculty Publications by an authorized administrator of DigitalCommons@UNO. For more information, please contact unodigitalcommons@unomaha.edu.
THE PREBISCH-SINGER HYPOTHESIS: FOUR CENTURIES OF EVIDENCE

David I. Harvey, Neil M. Kellard, Jakob B. Madsen, and Mark E. Wohar*

Abstract—We employ a unique data set and new time-series techniques to reexamine the existence of trends in relative primary commodity prices. The data set comprises 25 commodities and provides a new historical perspective, spanning the seventeenth to the twenty-first centuries. New tests for the trend function, robust to the order of integration of the series, are applied to the data. Results show that eleven price series present a significant and downward trend over all or some fraction of the sample period. In the very long run, a secular, deteriorating trend is a relevant phenomenon for a significant proportion of primary commodities.

I. Introduction

This paper reexamines the time-series properties of primary commodity prices relative to manufactures and, in particular, the Prebisch-Singer (PS) hypothesis that such prices present a downward secular trend. This is important because many developing countries rely on a small number of primary commodities to generate the majority of their export earnings. Overall, for the least developed countries, approximately 60% of export earnings are derived from primary commodities. However, for 40 countries, the production of three or fewer commodities explains all export earnings. This level of commodity dependency has profound policy implications conditional on the behavior of prices. Clearly, given strong evidence of a long-run downward trend in its relevant export commodities, a country might explore diversification of its export portfolio to include manufactures or services.1

Theoretical explanations that present, as a corollary, declining relative commodity prices include a low income elasticity of demand for primary commodities, lack of differentiation among commodity producers leading to highly competitive markets, productivity differentials between North (industrial) and South (commodity-producing) countries, and asymmetric market structure (where manufacturing industries capture oligopolistic rents relative to competitive firms earning zero economic profits and producing primary commodities). On the other hand, Lewis (1954) suggests a theoretical account of commodity price determination, which would imply a zero trend in relative prices of some primary commodities (see Deaton, 1999). Briefly, Lewis proposes that real wages will not grow in very poor countries because of unlimited supplies of labor at the subsistence wage. Therefore, the prices of tropical commodities like cocoa cannot, in the long run at least, exceed the costs of production in the lowest real wage region where the crop can be planted. Deaton (1999) subsequently comments, “There is no trend, because the poorest workers in the tropics remain as poor as ever. Prices will always eventually revert to base because, while short-run events can increase prices, sometimes for many years, long-run marginal cost is set by the poverty of the tropics and supply will eventually be forthcoming” (p. 30).

Early empirical evidence on the existence of a downward trend assumed that $y_t$ (the logarithm of the relative commodity price) is generated by a trend-stationary (TS) process:

$$y_t = \alpha + \beta t + u_t, \quad t = 1, \ldots, T,$$

where $t$ is a linear trend and the random variable $u_t$, is stationary with mean 0. The focal point of interest is the slope parameter $\beta$, which the PS hypothesis predicts will be less than 0. Estimations of equation (1) have typically found strong support for the PS hypothesis.2 For example, Grilli and Yang (1988), using a data set of 24 annual commodity prices from 1900 to 1986, found a weighted aggregate index declined by 0.6% per annum, and most of the subsequent literature uses extended versions of the Grilli-Yang data set.

An alternative and commonly assumed generating process is represented by the difference-stationary (DS) model:

$$\Delta y_t = \beta + v_t, \quad t = 2, \ldots, T,$$

where the generating process for $v_t$ is stationary and invertible. Recent empirical studies estimating equation (2) have found evidence against the PS hypothesis. Notably, Kim et al. (2003) suggest that commodity prices exhibit unit root behavior, and modeling the 24 commodities that comprise the Grilli-Yang index as DS processes, it was found that just 5 had the negative trend predicted by the PS hypothesis.3

If $y_t$ is truly generated by equation (2), the series contains a unit root, and standard tests of the null hypothesis $H_0: \beta = 0$ based on equation (1) will suffer from severe size distortions, spuriously rejecting the null when no trend is present.4

Received for publication November 24, 2007. Revision accepted for publication August 7, 2008.

* Harvey: University of Nottingham; Kellard: University of Essex; Madsen: Monash University; Wohar: University of Nebraska at Omaha. Our thanks to two anonymous referees for their helpful comments and to Keeli Hennessy for excellent research assistantship. The opinions expressed in the paper and any remaining errors remain our responsibility.

1 Of course, economic decision making should account for costs as well as prices. For instance, it is quite possible that a long-run decline in prices is compensated by a long-run decline in marginal production costs. On the other hand, even given a positive long-run trend in prices, the substantial volatility of many commodity prices may hinder economic growth with difficulties in economic planning and disincentives to invest (see Blattman, Hwang, & Williamson, 2007).


3 Similarly, Cuddington and Urzua (1989) found no deterioration in the terms of trade, but instead found that commodity prices fluctuated secularly around a stable mean (with a one-time break). For other studies on the long-run trends in commodity prices, see Powell (1991), Bleaney and Greenaway (1993), Labys (1993), Gafar (1995), Bloch and Sapsford (1997), Newbold and Vougas (1996), and Newbold, Rayner, and Kellard (2000). A good summary of this literature can be found in Greenaway and Morgan (1999) and Cuddington, Ludema, and Jayasuriya (2007).
present, even asymptotically. On the other hand, if the generating process is really equation (1), tests based on equation (2) are inefficient, lacking power relative to those based on equation (1). It is clear, therefore, that when the evidence as to the strength of the PS hypothesis is being assessed, the properties of the standard trend tests crucially depend on the integration properties of the commodity price series. Furthermore, if pretests for a unit root are first applied before adopting a trend test based on either equation (1) or (2), inference concerning the PS hypothesis is likely to be highly dependent on the results of the unit root pretests.

The situation is complicated because the true deterministic process underlying either equation (1) or (2) might also contain infrequent structural breaks in trend. For example, it is possible the correct generating process is a trend-stationary model with breaks:

\[ y_t = \alpha + \beta t + \delta DU_t(\tau^*) + \gamma DT_t(\tau^*) + u_t, \tag{3} \]

or, alternatively, a difference-stationary (about breaks) version:

\[ \Delta y_t = \beta + \delta D_t(\tau^*) + \gamma DU_t(\tau^*) + \Delta u_t, \tag{4} \]

where \( DT_t(\tau^*) = 1(t > T^*)(t - T^*) \), \( DU_t(\tau^*) = 1(t > T^*) \) and \( D_t(\tau^*) = 1(t = T^* + 1) \), with \( T^* = \left\lfloor \tau^*T \right\rfloor \) the (potential) break date with associated break fraction \( \tau^* \in (0, 1) \), and where \( 1(.) \) denotes the indicator function and \( \left\lfloor . \right\rfloor \) denotes the integer part of the argument. As in the case of testing for the presence of a linear trend, the properties of tests for the presence of a break in trend are also highly dependent on the order of integration of the series.

With regard to distinguishing between stationary and unit root behavior in a time series, neglecting a break in trend in an otherwise TS process can cause the spurious appearance of unit root behavior (see Perron, 1989), while a neglected trend break in a DS process can lead standard unit root tests to suggest an incorrect inference of stationarity (see Leybourne, Mills, & Newbold, 1998). Accounting for the former possibility, Leon and Soto (1997) and Kellard and Wohar (2006) apply unit root tests to relative commodity price series, allowing structural change under the TS alternative. For the 24 commodities of the Grilli-Yang index, and after allowance for (up to) one break, Leon and Soto classify twenty TS models for the 1900–1992 period, suggesting that shocks to commodity prices, in several cases, do not possess the permanent component suggested by Kim et al. (2003). Moreover, seventeen commodity prices report a negative trend and thus provide evidence in support of the PS hypothesis. Kellard and Wohar allow for (up to) two breaks, and although they find a similar number of TS processes, they point out that the negative trends reported by Leon and Soto often exist only over some segment of the sample period, indicating less support for the PS hypothesis.

This paper contributes to the extant literature by examining evidence for the PS hypothesis using a new and much longer data set and seeks to ameliorate the effect of order of integration issues on the PS hypothesis testing procedure. First, we took the view that it would be both informative and interesting to use annual commodity price data from as far back as is sensibly possible. This resulted in the creation of a new unbalanced panel containing 25 relative commodity price series, 8 of which begin in 1650 (Beef, Coal, Gold, Lamb, Lead, Sugar, Wheat, Wool), 1 in 1670 (Cotton), 1 in 1673 (Tea), 2 in 1687 (Rice, Silver), 1 in 1709 (Coffee), 1 in 1741 (Tobacco), 1 in 1782 (Pig Iron), 3 in 1800 (Cocoa, Copper, and Hide), 1 in 1808 (Tim), 1 in 1840 (Nickel), 1 in 1853 (Zinc), 1 in 1859 (Oil), 1 in 1872 (Aluminum), and 2 in 1900 (Banana and Jute). By contrast, the Grilli-Yang data set commences in 1900. Second, powerful test procedures, robust to whether shocks are generated by an \( I(0) \) or \( I(1) \) process, for the presence of a linear trend (see Harvey, Leybourne, & Taylor, 2007) and a broken trend (see Harvey, Leybourne, & Taylor, 2009) are applied to the new data.

The remainder of the paper is organized as follows. Section II outlines the empirical methodology, and section III describes the new data. The empirical results and associated discussion are presented in section IV, and section V concludes.

II. Empirical Methodology

A. Testing for a Linear Trend

We are interested in testing the PS hypothesis where we have \( H_0 : \beta = 0 \) against a one-sided alternative \( H_1 : \beta < 0 \) but without assuming knowledge of whether \( u_t \) in equation (1) is \( I(0) \) or \( I(1) \). Harvey, Leybourne, and Taylor (2007; hereafter HLT, 2007), propose a relevant statistic based on taking a data-dependent weighted average of two trend statistics: one that is appropriate when the data are generated by an \( I(0) \) process and a second when the data are \( I(1) \). If, for example, it is known that \( u_t \) is \( I(0) \), the appropriate trend statistic is the autocorrelation-robust \( t \)-ratio based on equation (1),

\[
\begin{align*}
z_0 &= \frac{\hat{\beta} - \beta_0}{s_0}, \\
\beta &= s_0 \sqrt{\frac{1}{T} \sum_{t=1}^{T} (t - \bar{t})^2},
\end{align*}
\tag{5}
\]

\footnote{Data are not available for some commodities from 1650 because they were not traded, not extracted, or not produced. Oil, for example, was not extracted for use in production before the mid-nineteenth century.}

\footnote{Another good reason for the use of a longer historical sample is that the behavior of some commodity prices could perhaps be considered atypical over the twentieth century.}
where $\hat{\alpha}$ and $\hat{\beta}$ denote the OLS estimators from equation (1) and $\hat{\sigma}_u^2$ is the long-run variance estimator:

$$\hat{\sigma}_u^2 = \hat{\gamma}_0 + 2 \sum_{j=1}^{T-2} h(j/l) \hat{\gamma}_j = T^{-1} \sum_{t=j+1}^{T} \hat{u}_t \hat{u}_{t-j},$$ (6)

where $\hat{u}_t = y_t - \hat{\alpha} - \hat{\beta} t$, $h(.)$ denotes the kernel function and $l$ the bandwidth. Conversely, if $u_t$ is known to be I(1), the appropriate trend statistic is the autocorrelation-robust $t$-ratio based on equation (2),

$$z_t = \frac{\hat{\beta} - \beta_0}{s_1},$$ (7)

$$s_1 = \sqrt{\hat{\sigma}_u^2/(T-1)},$$

where $\hat{\beta}$ is the OLS estimator of $\beta$ in equation (2) and $\hat{\sigma}_u^2$ is the long-run variance estimator:

$$\hat{\sigma}_u^2 = \hat{\gamma}_0 + 2 \sum_{j=1}^{T-2} h(j/l) \hat{\gamma}_j,$$ (8)

$$\hat{\gamma}_j = (T-1)^{-1} \sum_{t=j+2}^{T} \tilde{u}_t \tilde{u}_{t-j},$$

where $\tilde{u}_t = \Delta y_t - \hat{\beta}$. In both equations (6) and (8), following HLT (2007), we will use the quadratic spectral kernel with the Newey and West (1994) automatic bandwidth selection, adopting a nonstochastic prior bandwidth of $\lfloor 4(T/100)^{2/5} \rfloor$.

When it is not known a priori whether the series is I(0) or I(1), testing for a linear trend can be based on the weighted average of $z_0$ of equation (5) and $z_1$ of equation (7):

$$z_\lambda = \{1 - \lambda\} z_0 + \lambda z_1,$$ (9)

where $\lambda \to 0$ when $u_t$ is I(0), while $\lambda \to 1$ when $u_t$ is I(1). HLT (2007) suggest the following exponential function for $\lambda$:

$$\lambda = \exp \left(-\left(\frac{U}{S}\right)^2\right),$$ (10)

where $U$ is a unit root statistic for testing the I(1) null against the I(0) alternative and $S$ is a stationarity statistic for testing the I(0) null against the I(1) alternative. Given certain restrictions placed on $U$, $S$, and $u_t$, it can be shown that $z_\lambda$ has a standard normal limiting distribution under the null.

With regard to the choices of $U$ and $S$, HLT (2007) employ the local GLS-detrended augmented Dickey-Fuller $t$-test (DF-GLS$^\gamma$) of Elliott, Rothenberg, and Stock (1996), while the KPSS test statistic ($\hat{\eta}_t$) of Kwiatkowski et al. (1992) is chosen for $S$. Specifically, DF-GLS$^\gamma$ is the usual $t$-ratio for testing $\rho = 0$ in the regression equation:

$$\Delta \hat{u}_t = \rho \hat{u}_{t-1} + \sum_{j=1}^{p} \phi_j \Delta \hat{u}_{t-j} + \hat{e}_t,$$ (11)

$$t = p + 2, \ldots, T,$$

where $\hat{u}_t$ are the local GLS detrended residuals obtained from the regression of $y_t = (y_1, y_2 - \hat{\rho} z_1, \ldots, y_T - \hat{\rho} z_{T-1})'$ on $Z_\gamma = (z_1, z_2 - \hat{\rho} z_1, \ldots, z_T - \hat{\rho} z_{T-1})'$, where $z_t = (1, t)'$ and $\hat{\rho} = 1 - \hat{\epsilon}/T$ with $\hat{\epsilon} = -13.5$ (cf. Elliott et al., 1996). The number of lagged difference terms, $p$, included in equation (11) is determined by application of the autocorrelation-robust MAIC procedure of Ng and Perron (2001), setting the maximum lag length at $p_{\text{max}} = \lfloor 12(T/100)^{1/4} \rfloor$. Notice that DF-GLS$^\gamma$ is exact invariant to $\alpha$ and $\beta$. The KPSS statistic can be expressed as

$$\hat{\eta}_t = \sum_{i=1}^{T} \left(\sum_{j=1}^{T} \hat{u}_i \hat{u}_j\right)^2 / T^2 \hat{\sigma}_u^2,$$ (12)

where the long-run variance estimator $\hat{\sigma}_u^2$ is as defined in equation (6). Again, $\hat{\eta}_t$ is exact invariant to $\alpha$ and $\beta$. Finally, given these choices for $U$ and $S$, HLT (2007) found the best finite sample performance was obtained by employing

$$\lambda = \exp \left(-0.00025 \frac{\text{DF-GLS}^\gamma}{\hat{\eta}_t}\right).$$ (13)

Note that the constant 0.00025 does not affect the asymptotic properties of the $z_\lambda$ test but gives rise to improved finite sample behavior.

B. Testing for a Broken Trend

Previous work has suggested that relative commodity prices may not be best represented by a single, secular trend but by some segmented alternative (see Kellard & Wohar, 2006). When examining the case for a breaking trend, this literature has, as in the single-trend context, relied on procedures that require pretesting for a unit root. In particular, Kellard and Wohar (2006) employed the test developed by Lumsdaine and Papell (1997), a procedure that allows shifts in the intercept and trend terms under the TS alternative hypothesis. Specifically, the structural breaks are endogenously chosen, using a search procedure, to maximize the chance of rejecting the unit root with drift null. As such, these unit root tests are not tests for structural change. Additionally, they do not allow the possibility of structural change under the null.

To circumvent the issues surrounding a pretest and to assess directly whether a trend contains a break, we require a test of $H_0 : \gamma = 0$ against a two-sided alternative $H_1 : \gamma \neq 0$ but without assuming knowledge of whether $u_t$ in equation (3) is I(0) or I(1). Harvey et al. (2009; hereafter
I. Denote by $t$ with the associated break-point estimators of $\mu_t$ and $\sigma_t$, the weighted average of two individual statistics, one of which diverges to positive infinity, the weight function $\lambda(\cdot, \cdot)$ converges to unity when $t \to \infty$. For the implicit long-run variance estimators, respectively. For the implicit long-run variance estimators, $\mu_t$ and $\sigma_t$, the Bartlett kernel will be referred to as the trimming parameters, $S_0 = \mu_t$ and $S_1 = \sigma_t$, where the quantities $\mu_t$ and $\sigma_t$ will be referred to as the trimming parameters, and where it is assumed throughout that $\tau^* \in \Lambda$. Defining $\Lambda^* = \{\tau_L T, \ldots, \tau_U T \}$, these statistics are given by

$$I^* = \sup_{j \in \Lambda^*} I_j(sT),$$

and

$$I^*_T = \sup_{j \in \Lambda^*} |I_j(sT)|,$$

with the associated break-point estimators of $\tau^*$ given by

$$\hat{\tau} = \arg \sup_{\tau \in \Lambda} \left| I_0(s/T) \right| \quad \text{and} \quad \tilde{\tau} = \arg \sup_{\tau \in \Lambda} \left| I_1(s/T) \right|,$$

respectively, such that $I^*_0 = |I_0(\hat{\tau})|$ and $I^*_T = |I_1(\tilde{\tau})|$.

Given a lack of knowledge concerning the order of integration of the series, HLT (2009) then propose a test statistic based on the data-dependent weighted average of the supremum statistics for a broken trend under $I(0)$ and $I(1)$ shocks:

$$t_k = \{\lambda(S_0(\hat{\tau}), S_1(\tilde{\tau})) \times I^*_0 \} + m_\ell \left[ \left[ 1 - \lambda(S_0(\hat{\tau}), S_1(\tilde{\tau})) \right] \times I^*_T \},$$

where $m_\ell$ is positive finite constant and $S_0(\hat{\tau})$ and $S_1(\tilde{\tau})$ are auxiliary statistics chosen such that as the sample size diverges to positive infinity, the weight function $\lambda(\cdot, \cdot)$ converges to unity when $u_t$ is $I(0)$ and to 0 when $u_t$ is $I(1)$, such that $t_k$ will collapse to $I^*_0$ when $u_t$ is $I(0)$, and to $I^*_T$ when $u_t$ is $I(1)$. For $S_0(\hat{\tau})$ and $S_1(\tilde{\tau})$, HLT (2009) adopt the stationarity test statistics of KPSS calculated from the relevant residuals of equations (14) and (15), respectively, estimated using the respective break date estimates $\hat{\tau}$ and $\tilde{\tau}$.

The long-run variance estimators employed in the computation of the KPSS statistics again use the Bartlett kernel with bandwidth parameter $\ell = [4(T/100)^{1/4}]$. Finally, HLT (2009) posit a weight function,

$$\lambda(S_0(\hat{\tau}), S_1(\tilde{\tau})) = \exp[-gS_0(\hat{\tau}), S_1(\tilde{\tau})^2],$$

(19)

where $g$ is a positive constant, since this will clearly converge to unity when $u_t$ is $I(0)$ and to 0 when $u_t$ is $I(1)$, as required. HLT (2009) show that the asymptotic null distribution of the weighted statistic $t_k$ of equation (18) differs as to whether $u_t$ is $I(0)$ or $I(1)$; moreover, in neither case is this distribution standard normal. However, the constant $m_\ell$ in equation (18) can be chosen such that for the selected significance level, the asymptotic null critical value of $t_k$ is the same regardless of whether $u_t$ is $I(0)$ or $I(1)$. For the trend break tests to be operational, we also need to specify the constant $g$ in equation (19). After Monte Carlo simulation of the finite sample size and power of the tests for a range of possible settings, HLT (2009) recommend the choice $g = 500$, giving rise to a $\lambda_k$ test with both acceptable size and decent power across the range of simulation experiments considered.

HLT (2009) also consider a second model (model B), which extends model A by allowing for the possibility of a break in the level occurring simultaneously with the break in trend. The $t_k$ test is specified in exactly the same way as for model A, except now the appropriate models on which to base $t_0(\cdot)$ and $t_1(\cdot)$, and also the KPSS statistics, are equations (3) and (4), respectively. Asymptotic critical values for the $t_k$ tests for both models A and B are provided in table 1 of HLT (2009), along with the corresponding values of $m_\ell$. Following HLT (2009), we use 10% trimming, such that $\tau_L = 0.1$ and $\tau_U = 0.9$.

III. Data

The often employed Grilli-Yang (GY) data set comprises 24 internationally traded, nonfuel commodities. Each annual nominal commodity price (in U.S. dollars) series is deflated by the United Nations Manufacturers Unit Value (MUV) index, the MUV series reflecting the unit values of manufacturing exports from a number of industrial countries. As noted in the introduction, the Grilli-Yang data set begins in 1900, primarily because this is the starting date for the MUV series; however, commodity and manufacturing price data can be sampled backward well before this time. Given the extensive interest in modeling and analyzing the

---

6 The null hypothesis $H_0$ must now be restated as $H_0 : \gamma = 0$, in order to obtain a pivotal limiting null distribution for the test statistic.

7 The choice of $g = 500$ also applies to model B.

8 The commodities are Aluminum, Banana, Beef, Cocoa, Coffee, Copper, Cotton, Hide, Jute, Lamb, Lead, Maize, Palm Oil, Rice, Rubber, Silver, Sugar, Tea, Timber, Tin, Tobacco, Wheat, Wool, and Zinc.
long-run trends of relative commodity prices, it would appear important to utilize as many of the existing data as is sensibly possible.

Creating a large and representative data set of relative commodity prices prior to 1900 is not a trivial task. A number of disparate historical sources exist, covering different prices and sample periods. A potential problem associated with construction of commodity price indexes is that movements in commodity import prices are not always synchronized across nations because some of the data include import duties and transport costs that vary across nations and over time. Furthermore, not all commodities are traded in markets for which spot or future price quotations for specified grades and quantities exist. An example is the oil market for which, at least until recently, the free market has been small. The cross-country variations in the growth of tariffs, import quotas, and transport costs were particularly large during World War I. A severe example is oil, for which prices were significantly lower in the United States than Europe due to the risk associated with sea transportation through the Atlantic Ocean and export embargoes.

The seriousness of these problems has been addressed in two papers. Based on very long historical data on commodities for the UK and Netherlands, Froot, Kim, and Rogoff (1995) find that the volatility and persistence of deviations from the law of one price have been stable over time, which suggests, at least for the UK and Netherlands, high comovements of commodity prices across nations. In the more recent study of Pesaran et al. (2006), some evidence of purchasing power parity among OECD countries is found for consumer goods such as meat, bread, tobacco, clothing, footwear, fruits, and other consumables covered in the consumer price index. These observations suggest that commodity prices change at different rates across nations; however, the difference is not significant. To get the most representative price for commodities, the average price for a specified commodity across nations, in common currency, is calculated for most commodities.

Pooling the various sources, a data set of 25 nominal primary commodity prices (in GBP) can be formed, but as a result of employing all available data, the series are of unequal lengths. Specifically, twelve series begin in the seventeenth century (Beef, Coal, Cotton, Gold, Lamb, Lead, Rice, Silver, Sugar, Tea, Wheat, Wool), three series begin in the eighteenth century (Coffee, Tobacco, Pig Iron), eight series begin in the nineteenth century (Aluminum, Cocoa, Copper, Hide, Nickel, Oil, Tin, Zinc), and two start from 1900 (Banana and Jute). Twenty of these commodities are also found in the GY data set, and 23 are nonfuel. Constructing a historical price index of manufactures (HPIM), stretching back to 1650, presented similar challenges to that of building the commodity price series; specifically, numerous sources and definitions of prices exist. For example, while the important studies of Grilli and Yang (1988) and Lewis (1952) use manufacturing export unit indexes for selected industrialized countries and interpolate the data through the world war periods, we use the manufacturing value-added price deflator in the post-1870 period and various deflators for manufacturing products before then. The value-added price deflator has three advantages over export unit values: (a) it omits the influence of intermediate products; (b) it allows compositional changes; and (c) technological progress is to some extent reflected in the deflator. By contrast, export unit values, which are the measured manufacturing export value divided by the weight of export, fail to allow compositional changes in exports and innovation-induced price reductions. A value-preserving shift from exports of heavy manufactured metals to exports of electronics, for example, will artificially increase export unit values, even if prices have remained unaltered. Kravis and Lipsey (1984), for example, have advocated strongly against using export unit indexes because they exaggerate the long-term growth in manufacturing prices. However, manufacturing value-added prices are not free from measurement problems, especially because they do not fully allow for technological progress (see, for example, Griliches, 1979).

Unlike the production of services, manufacturing products are tradable and, as such, manufacturing price data are of relatively good quality (Griliches, 1979). However, the quality of the manufacturing value-added price deflators is likely to deteriorate as we go back in history. For the panel of countries included in the value-added deflator, data were not comprehensively available before 1870. Therefore, for our earliest periods, we use a composite index of prices of the most important manufacturing products. For example, from 1650 to 1784, the Dutch index is an unweighted average of textiles, soap, and paper, while the British index is composed of prices of various items such as leatherbacks, tallow candles, broadcloth (which is used for clothing and upholstering and is sold in large quantities in the world), beverages, linen, bread, oats, and stockings, among other products.

Given the above discussion, our manufacturing value-added price index is therefore spliced from subperiod series over the following periods: 1950–2005, 1870–1950, 1784–1870, and 1650–1784. Major industrialized countries are included in the index, and the data are converted into a common currency. The period 1950–2005 uses an unweighted average of manufacturing value-added price deflators for 22 industrialized countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, 11 Although it is possible to get data for commodity prices from before 1650, we could find no reliable source of manufacturing prices.

9 See the data appendix for a fuller description of the source of each price, available online at http://www.mitpressjournals.org/doi/suppl/10.1162/rest.2010.12184.
10 GBP and not USD is used because the United States did not have its own currency before independence in 1776.
Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and United States. For the period 1870–1950, an unweighted average of manufacturing value-added price deflators for ten countries is used (Australia, Canada, Denmark, Finland, France, Germany, Japan, Sweden, UK, and United States). For the period 1984–1970, we use an unweighted average of various manufacturing price series for five major industrialized countries (France, Germany, Netherlands, UK, and United States). In the period 1650–1784, the index is constructed as an unweighted average of manufacturing prices in the Netherlands and the UK. These two nations were major trading nations during that period. Furthermore, based on recent data, Jurado and Vega (1994) find that the law of one price holds for manufacturing products, which suggests that the potential country selection bias is likely to be small, provided that the recent data are representative of the historical data.

It is of interest to consider how our historical price index of manufactures (HPIM) compares with the MUV index for the period since 1900, over which the MUV index is available. Over the entire twentieth century, our index increased by 3,384% while the MUV index increased 3,310%. In absolute terms, the difference is not large and thus is reflected in a very high correlation coefficient of 0.995. However, in relative terms, there are a few significant differences, most notably during the period 1914–1945, when the MUV index is often 25% below our index. This result suggests that export unit values are potentially biased measures of price movements, particularly when long data series are considered.

Finally, deflating the nominal commodity series with our manufacturing value-added price index resulted in a data set of relative commodity prices covering a 356-year period from 1650 to 2005.12

### IV. Empirical Results

#### A. Trend Function Analysis

Table 1 shows the results of applying the order of integration robust trend tests to the new relative commodity price data set outlined in the previous section. In particular, column 2 gives the one-sided $z_t$ test statistic in equation (9) for each individual series. Notably, for eight commodities (Aluminum, Coffee, Jute, Silver, Sugar, Tea, Wool, and Zinc), the null of no trend is rejected (at least at the 10% level) in favor of the alternative of a negative trend. This seems a remarkable result considering the sample length of the commodities. The tea series, for example, commences in 1673 and has declined at an annual average rate of 1.40% (see column 3).

Of course, previous literature has detected structural breaks in the trend of relative commodity prices. Therefore, table 2 gives the results of applying the order of integration robust trend break tests to all 25 series based on employing model A. Specifically, columns 2, 3, and 4 give the two-sided $t$ test statistic in equation (18) at the 10%, 5%, and 1% significance levels, respectively. For tests that reject using the $t$ test statistic in equation (18), the critical values obtained from the standard normal distribution are reported. These are obtained using equations (8) and (9) of HLT (2007). Testing against a two-sided alternative using $t$ values obtained from the standard normal distribution. None of the series with positive trends have significant coefficients. Two of the series (Jute and Wool) that reject at the 10% level against a one-sided alternative no longer reject when two-sided critical values are used.

<table>
<thead>
<tr>
<th>Commodity</th>
<th>$z_t$</th>
<th>Growth Rate (%)</th>
<th>90% c.i.</th>
<th>95% c.i.</th>
<th>99% c.i.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
<td>-2.133**</td>
<td>-3.908</td>
<td>±3.014</td>
<td>±3.591</td>
<td>±4.720</td>
</tr>
<tr>
<td>Banana</td>
<td>-0.991</td>
<td>1.062</td>
<td>1.110</td>
<td>-0.928</td>
<td>0.069</td>
</tr>
<tr>
<td>Beef</td>
<td>-0.991</td>
<td>1.062</td>
<td>1.110</td>
<td>-0.928</td>
<td>0.069</td>
</tr>
<tr>
<td>Cocoa</td>
<td>-0.928</td>
<td>-0.774</td>
<td>0.652</td>
<td>0.745</td>
<td>0.979</td>
</tr>
<tr>
<td>Coffee</td>
<td>-2.037**</td>
<td>-0.774</td>
<td>0.652</td>
<td>0.745</td>
<td>0.979</td>
</tr>
<tr>
<td>Copper</td>
<td>-0.606</td>
<td>1.195</td>
<td>0.650</td>
<td>0.774</td>
<td>1.018</td>
</tr>
<tr>
<td>Cotton</td>
<td>-0.659</td>
<td>-1.399</td>
<td>0.660</td>
<td>0.787</td>
<td>1.034</td>
</tr>
<tr>
<td>Gold</td>
<td>-0.231</td>
<td>-1.531*</td>
<td>1.479</td>
<td>1.589</td>
<td>1.893</td>
</tr>
<tr>
<td>Hide</td>
<td>-0.659</td>
<td>0.743</td>
<td>0.0493</td>
<td>1.224</td>
<td>1.265</td>
</tr>
<tr>
<td>Jute</td>
<td>-1.531*</td>
<td>-1.479</td>
<td>1.589</td>
<td>1.893</td>
<td>2.488</td>
</tr>
<tr>
<td>Lamb</td>
<td>0.743</td>
<td>1.062</td>
<td>1.062</td>
<td>1.062</td>
<td>1.062</td>
</tr>
<tr>
<td>Lead</td>
<td>-0.571</td>
<td>0.464</td>
<td>0.846</td>
<td>1.265</td>
<td>1.531*</td>
</tr>
<tr>
<td>Nickel</td>
<td>-0.464</td>
<td>0.846</td>
<td>1.265</td>
<td>1.531*</td>
<td>2.037**</td>
</tr>
<tr>
<td>Oil</td>
<td>-0.846</td>
<td>0.846</td>
<td>1.265</td>
<td>1.531*</td>
<td>2.037**</td>
</tr>
<tr>
<td>Pig Iron</td>
<td>-0.493</td>
<td>0.846</td>
<td>1.265</td>
<td>1.531*</td>
<td>2.037**</td>
</tr>
<tr>
<td>Silver</td>
<td>-1.516*</td>
<td>-0.823</td>
<td>0.893</td>
<td>1.065</td>
<td>1.399</td>
</tr>
<tr>
<td>Sugar</td>
<td>-3.024***</td>
<td>-1.195</td>
<td>0.650</td>
<td>0.774</td>
<td>1.018</td>
</tr>
<tr>
<td>Tea</td>
<td>-3.485***</td>
<td>-1.399</td>
<td>0.660</td>
<td>0.787</td>
<td>1.034</td>
</tr>
<tr>
<td>Tin</td>
<td>0.287</td>
<td>0.650</td>
<td>0.774</td>
<td>1.018</td>
<td>1.034</td>
</tr>
<tr>
<td>Tobacco</td>
<td>1.259</td>
<td>1.589</td>
<td>1.893</td>
<td>2.488</td>
<td>3.591***</td>
</tr>
<tr>
<td>Wheat</td>
<td>-1.265</td>
<td>0.774</td>
<td>1.077</td>
<td>1.399</td>
<td>1.479</td>
</tr>
<tr>
<td>Wool</td>
<td>-1.318*</td>
<td>-0.653</td>
<td>0.815</td>
<td>0.972</td>
<td>1.277</td>
</tr>
<tr>
<td>Zinc</td>
<td>-2.463***</td>
<td>-0.922</td>
<td>0.616</td>
<td>0.733</td>
<td>0.964</td>
</tr>
</tbody>
</table>

Notes: *, **, and *** denote rejection at the 10%, 5%, and 1% significance levels, respectively. For tests that reject using the $z_t$ test, growth rates and two-sided confidence intervals are reported. These are obtained using equations (8) and (9) of HLT (2007). Testing against a two-sided alternative using $z_t$ values obtained from the standard normal distribution. None of the series with positive trends have significant coefficients. Two of the series (Jute and Wool) that reject at the 10% level against a one-sided alternative no longer reject when two-sided critical values are used.

12 It is useful to note that we undertake the analysis using data only in GBP since the relative prices are invariant to currency denomination, that is, the conversion factor, is eliminated when we divide one series in GBP by another GBP-denominated series.
increased supply of hides (Mack, 1956). To assess the
Worden, 1989). Finally, the 1905 break in Hide is plausibly
would seem to have its root in competition from petroleum-
(Johnson, 1984). On the other hand, the 1960 break for Jute
1973), Sugar (Swerling & Timoshenko, 1957), and Tobacco
providing downward price pressure on many commodities
perhaps suggest the effect of strong technological progress

difficult to ascertain the causal factors, the preponderance of

In total, six price series now show a break in the trend function over the sample period. Although it is typically
difficult to ascertain the causal factors, the preponderance of
breaks located (close to or) in the twentieth century would
perhaps suggest the effect of strong technological progress
providing downward pressure on many commodities
including Oil (Castaneda, 2003), Wheat (Everson & Kislev,
1973), Sugar (Swerling & Timoshenko, 1957), and Tobacco
(Johnson, 1984). On the other hand, the 1960 break for Jute
would seem to have its root in competition from petroleum-
based synthetics, entering the market, and competing with
jute for practically all of its uses (Grilli, 1975; Heitzman &
Worden, 1989). Finally, the 1905 break in Hide is plausibly
associated with increased meat consumption, leading to an
increased supply of hides (Mack, 1956). To assess the

<table>
<thead>
<tr>
<th>Commodity</th>
<th>$t_1$ 10%</th>
<th>$t_2$ 5%</th>
<th>$t_3$ 1%</th>
<th>Estimated Break Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
<td>1.987</td>
<td>2.030</td>
<td>2.118</td>
<td></td>
</tr>
<tr>
<td>Banana</td>
<td>1.619</td>
<td>1.647</td>
<td>1.704</td>
<td></td>
</tr>
<tr>
<td>Beef</td>
<td>1.202</td>
<td>1.228</td>
<td>1.281</td>
<td></td>
</tr>
<tr>
<td>Coal</td>
<td>1.150</td>
<td>1.174</td>
<td>1.225</td>
<td></td>
</tr>
<tr>
<td>Cocoa</td>
<td>1.291</td>
<td>1.319</td>
<td>1.376</td>
<td></td>
</tr>
<tr>
<td>Coffee</td>
<td>1.357</td>
<td>1.386</td>
<td>1.446</td>
<td></td>
</tr>
<tr>
<td>Copper</td>
<td>1.073</td>
<td>1.096</td>
<td>1.144</td>
<td></td>
</tr>
<tr>
<td>Cotton</td>
<td>2.067</td>
<td>2.112</td>
<td>2.203</td>
<td></td>
</tr>
<tr>
<td>Gold</td>
<td>0.806</td>
<td>0.916</td>
<td>0.955</td>
<td></td>
</tr>
<tr>
<td>Hide</td>
<td>12.805*</td>
<td>12.819**</td>
<td>12.849***</td>
<td>1905</td>
</tr>
<tr>
<td>Jute</td>
<td>2.015</td>
<td>2.040</td>
<td>2.091</td>
<td></td>
</tr>
<tr>
<td>Lamb</td>
<td>1.146</td>
<td>1.171</td>
<td>1.222</td>
<td></td>
</tr>
<tr>
<td>Lead</td>
<td>1.562</td>
<td>1.591</td>
<td>1.650</td>
<td></td>
</tr>
<tr>
<td>Nickel</td>
<td>1.517</td>
<td>1.546</td>
<td>1.605</td>
<td></td>
</tr>
<tr>
<td>Oil</td>
<td>2.356*</td>
<td>2.397</td>
<td>2.481</td>
<td>1875</td>
</tr>
<tr>
<td>Pig Iron</td>
<td>1.233</td>
<td>1.260</td>
<td>1.314</td>
<td></td>
</tr>
<tr>
<td>Rice</td>
<td>1.742</td>
<td>1.763</td>
<td>1.807</td>
<td></td>
</tr>
<tr>
<td>Silver</td>
<td>1.744</td>
<td>1.782</td>
<td>1.859</td>
<td></td>
</tr>
<tr>
<td>Sugar</td>
<td>3.655*</td>
<td>3.682***</td>
<td>3.736***</td>
<td>1951</td>
</tr>
<tr>
<td>Tea</td>
<td>1.323</td>
<td>1.352</td>
<td>1.410</td>
<td></td>
</tr>
<tr>
<td>Tin</td>
<td>1.548</td>
<td>1.581</td>
<td>1.650</td>
<td></td>
</tr>
<tr>
<td>Wheat</td>
<td>5.808*</td>
<td>5.832**</td>
<td>5.883***</td>
<td>1938</td>
</tr>
<tr>
<td>Wool</td>
<td>1.914</td>
<td>1.955</td>
<td>2.040</td>
<td></td>
</tr>
<tr>
<td>Zinc</td>
<td>1.556</td>
<td>1.579</td>
<td>1.627</td>
<td></td>
</tr>
</tbody>
</table>

Notes: * denotes rejection at the 10% significance level.
** denotes rejection at the 5% significance level.
*** denotes rejection at the 1% significance level.

1% levels, respectively. Only five of the series show evi-
dence of a broken trend (Hide in 1905, Oil in 1875, Sugar
in 1951, Tobacco in 1951, and Wheat in 1938). Of course,
while model A allows a possible break in trend, it does not
allow a simultaneous break in the level. To allow this
possibility, the commodities were retested employing model
B; however, a rejection of the no break null was obtained for
only one further commodity (Jute in 1960), as reported in
table 3.

At this point, a useful comparison exercise is to apply the
methodology employed above to the GY data set typically
used in the literature.\(^{13}\) Currently the latest incarnation of
the GY data set contains annual data on real commodity
prices from 1900 to 2003 (see Pfaffenzeller, Newbold, &
Rayner, 2007). Table 5 provides results of application of the
$z_A$ test in equation (9) to individual commodity prices in the
GY data set, alongside those of the new data provided in our
current paper (hereafter referred to as HKMW).\(^{14}\)

Column 2 gives the $z_A$ results for the GY data, and for
only three series (Aluminum, Rice, and Sugar) is the null of
no trend rejected in favor of a negative trend. In contrast,
column 4, which reports the $z_A$ results for the HKMW data,
shows that thirteen commodities (Aluminum, Banana, Cot-
ton, Hide, Jute, Lead, Rice, Silver, Sugar, Tea, Wheat, Wool,
and Zinc) present a zero trend.

On the basis of the results in table 5, it would appear as
if the GY data set is predisposed toward rejection of the PS
hypothesis. To observe if this conclusion is maintained after
allowing structural breaks, we applied the same procedure
as before to the GY and HKMW data over the period
1900–2003: namely testing for a break in trend first using
model A, and then testing based on model B. For series
where breaks in trend were detected, we applied the $z_A$ test
to the postbreak period. The outcome of this procedure was
that negative trends were detected over the latter portion of
the series for four further commodities when using the GY
data (Banana, Coffee, Jute, and Lead) and three further
commodities (Beef, Coffee, and Tin) when using the
HKMW data. Thus, even after allowing the presence of
structural breaks, the GY data reject the null of no trend far
less frequently than does the HKMW data set. Overall, the
GY data suggest that downward trends are present in seven

---

13 We thank an anonymous referee for this helpful suggestion.

14 Note that in this comparison section of the paper, the HKMW data set
is curtailed to run only from 1900 to 2003, so as to be directly comparable
to the GY data set.
Fitzgerald (2003) to decompose metals prices into three employed the asymmetric bandpass filter of Christiano and were posited. More recently, Cuddington and Jerrett (2008) Kondratieff (1935), long waves or cycles of 45 to 60 years

B. Analysis of Cyclical Components

Finally, it is important to note that although this paper is primarily concerned with the issue of long-term trends, the identification of cycles in commodity prices has also been a popular theme in the literature.15 In the seminal work of

| Table 4.—One-Sided Tests for a Negative Trend (Postbreak) |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | \( \bar{z}_k \) | Growth Rate (%) | 90% c.i. | 95% c.i. | 99% c.i. |
| Aluminum       | -1.958**        | -1.654          | -2.517*** | -2.331         |
| Banana         | -0.204          | 0.070           | -1.516*  | -1.276         |
| Beef           | -0.862          | 1.000           | 0.213    | 0.523           |
| Cotton         | -1.028          | -1.492**        | -1.992   | -1.864         |
| Hide           | -0.652          | -6.021***       | -1.991   | -2.193**       |
| Jute           | -0.727          | -1.650**        | -1.659   | -1.846         |
| Lamb           | 3.956           | 1.023           | 1.638    | 1.942**        |
| Lead           | -1.060          | -2.193**        | -1.684   | -2.504**       |
| Rice           | -1.938**        | -1.350          | -2.054** | -1.790         |
| Silver         | -0.181          | -1.790**        | -2.075   | -2.193**       |
| Sugar          | -2.535***       | -1.223          | -2.449   | -3.456         |
| Tea            | -1.111          | -1.859**        | -1.956   | -1.956         |
| Tin            | -0.167          | -1.172          | 0.352    | 1.040          |
| Tobacco        | 1.000           | -2.870***       | -1.813   | -2.524**       |
| Wheat          | -1.191          | -2.165**        | -1.338   | -2.165**       |
| Wool           | -0.806          | -2.524**        | -1.885   | -2.165**       |
| Zinc           | -0.276          | -2.165**        | -1.338   | -2.165**       |

Notes: * and ** denote rejection at the 10% and 5% significance levels, respectively. Testing against a two-sided alternative does not lead to any more or fewer rejections of the no trend null, although, as would be expected, the significance levels are different in some cases.

Relative commodity price series, over either the sample period 1900–2003 or some postbreak subsample of this time span, while the HKMW data give rise to evidence in favor of negative trends for sixteen commodities.

The first step of the Christiano and Fitzgerald filter is to detrend the data under the assumption that a unit root is present in the data; specifically, the estimate of the trend coefficient is the OLS estimate of \( \beta \) in equation (2). For the series where breaks in trend were detected, we modify this first step by including the break in the deterministic component used for the detrending. The estimates of the trend and break parameters are again obtained under an assumption that a unit root is present in the stochastic component of the series—from OLS estimation of either equation (15) for model A or equation (4) for model B.

Table 6 provides some summary measures of the cyclical components when the Christiano and Fitzgerald filter is applied to individual commodity price series of the full (1650–2005) HKMW data set.

Column 2 shows the standard deviation of the long-term cyclical component \( (LC_t) \) and column 3, the ratio of the standard deviations of \( LC_t \) and the total nontrend cyclical component \( (SC_t + LC_t) \). The range of this ratio extends from 0.48 (Wheat) to 0.90 (Aluminum), clearly indicating the primacy of the long-term component in cyclical com-

Note: * and ** denote rejection at the 10% and 5% significance levels, respectively.

\begin{align}
T_t &= CF(70, \infty) \\
LC_t &= CF(20, 70) \\
SC_t &= CF(2, 20).
\end{align}
modernity price movements. Such results strongly underline the
relevance of Kondratieff’s identification of long-term
cycles in commodity prices, although it should be noted that
the mean periodicity of the cycles in $LC_t$ (see Table 6,
column 4) ranges from 23.5 years (Rice) to 43.3 years
(Copper), clearly lower than the 45- to 60-year interval
consonant with Kondratieff cycles. In any case, the exis-
tence of cyclical components lasting longer than 20 years
suggests that common policy initiatives to smooth either
commodity prices themselves or producer or consumer
incomes around a trend may require economic planning
with respect to any cyclical determination. More theoretical
and empirical work in the area of real price commodity
price cycles is encouraged after our long-run data analysis.

From a policymaker perspective, we might posit that the
conventional view of real commodity prices as presenting
(a) a negative or zero trend and (b) relatively high volatility
around that trend, can be augmented by (c) cycles of lower
and higher prices over long horizons. Although short-term
movements in prices can be hedged using options or futures,
no such market-based instruments currently exist for such
longer-term movements. Clearly, during periods of rising
(the recent context) or falling commodity prices, policy-
makers need to be keenly aware that prices may not return
to equilibrium for many years.

V. Conclusion

Primary commodity production contributes a significant
fraction of the export volume of many developing countries.
Given this context, the time-series properties of such prices,
relative to manufactured goods, have important policy
implications. A negative trend, for example, in the relative
price of a country’s main export commodity indicates the
need to consider diversifying the export mix.

The literature presents the consensual position that the
typically large variance of relative commodity prices
makes it difficult to ascertain the existence of a trend (see
Deaton, 1999, and Cashin & McDermott, 2002). How-
ever, this has not inhibited academic study on the issue
and, commencing with the seminal work of Prebisch
(1950) and Singer (1950), debate has raged as to whether
relative commodity prices actually suffer from long-run
secular decline.

Given the subjugation of the trend of prices by the
variance of prices, the empirical results with respect to trend
existence and direction are unsurprisingly mixed. In partic-
ular, the results are often conditional on the assumed order
of integration of the relative price processes. Since the
properties of standard tests for trends are highly dependent
on whether the series in question contains a unit root, it is
difficult to draw unambiguous conclusions regarding the
presence of trends using standard trend tests alone. This
situation is further problematized by the possibility that
structural breaks may occur in the underlying mean or trend
function. If such breaks occur but are not adequately mod-
elled, further errors of inference can arise.

This paper makes a number of new contributions to the
literature while assessing the evidence for a long-run trend
in primary commodity prices. An entirely new data set of 25
major primary commodity prices, relative to manufactures,
is assembled by pooling, for the first time, numerous his-
torical data sources. This can be compared with the com-
monly employed Grilli-Yang data set, which contains 24
commodities, at an annual frequency, stretching back to
1900. After an exhaustive search of the available sources,
the new data set contains data from 1650, providing not only
historical interest but many more degrees of freedom with
which to disentangle any trend component from its variance.
Specifically, twelve series begin in the seventeenth century

---

Table 6.—Summary Measures of Twenty- to Seventy-Year Cyclical
Components ($LC_t$)

<table>
<thead>
<tr>
<th>Commodity</th>
<th>s.d. ($LC_t$)</th>
<th>s.d. ($LC_t$) + s.d. ($SC_t$)</th>
<th>Mean Periodicity</th>
<th>AR(1) Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
<td>0.354</td>
<td>0.900</td>
<td>25.750</td>
<td>0.982</td>
</tr>
<tr>
<td>Banana</td>
<td>0.095</td>
<td>0.684</td>
<td>25.333</td>
<td>0.978</td>
</tr>
<tr>
<td>Beef</td>
<td>0.167</td>
<td>0.759</td>
<td>25.727</td>
<td>0.981</td>
</tr>
<tr>
<td>Coal</td>
<td>0.096</td>
<td>0.670</td>
<td>25.917</td>
<td>0.980</td>
</tr>
<tr>
<td>Cocoa</td>
<td>0.261</td>
<td>0.783</td>
<td>23.714</td>
<td>0.975</td>
</tr>
<tr>
<td>Coffee</td>
<td>0.185</td>
<td>0.680</td>
<td>28.111</td>
<td>0.980</td>
</tr>
<tr>
<td>Copper</td>
<td>0.177</td>
<td>0.749</td>
<td>43.333</td>
<td>0.991</td>
</tr>
<tr>
<td>Cotton</td>
<td>0.195</td>
<td>0.640</td>
<td>26.545</td>
<td>0.978</td>
</tr>
<tr>
<td>Gold</td>
<td>0.172</td>
<td>0.878</td>
<td>27.455</td>
<td>0.986</td>
</tr>
<tr>
<td>Hide</td>
<td>0.121</td>
<td>0.581</td>
<td>30.500</td>
<td>0.983</td>
</tr>
<tr>
<td>Jute</td>
<td>0.135</td>
<td>0.531</td>
<td>25.000</td>
<td>0.985</td>
</tr>
<tr>
<td>Lamb</td>
<td>0.196</td>
<td>0.812</td>
<td>24.500</td>
<td>0.980</td>
</tr>
<tr>
<td>Lead</td>
<td>0.133</td>
<td>0.689</td>
<td>25.417</td>
<td>0.985</td>
</tr>
<tr>
<td>Nickel</td>
<td>0.198</td>
<td>0.711</td>
<td>25.800</td>
<td>0.980</td>
</tr>
<tr>
<td>Oil</td>
<td>0.367</td>
<td>0.726</td>
<td>26.250</td>
<td>0.974</td>
</tr>
<tr>
<td>Pig Iron</td>
<td>0.161</td>
<td>0.749</td>
<td>30.200</td>
<td>0.980</td>
</tr>
<tr>
<td>Rice</td>
<td>0.180</td>
<td>0.676</td>
<td>23.545</td>
<td>0.984</td>
</tr>
<tr>
<td>Silver</td>
<td>0.150</td>
<td>0.730</td>
<td>32.000</td>
<td>0.994</td>
</tr>
<tr>
<td>Sugar</td>
<td>0.146</td>
<td>0.593</td>
<td>26.900</td>
<td>0.980</td>
</tr>
<tr>
<td>Tea</td>
<td>0.137</td>
<td>0.659</td>
<td>25.000</td>
<td>0.986</td>
</tr>
<tr>
<td>Tin</td>
<td>0.188</td>
<td>0.728</td>
<td>28.800</td>
<td>0.988</td>
</tr>
<tr>
<td>Tobacco</td>
<td>0.131</td>
<td>0.709</td>
<td>37.167</td>
<td>0.984</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.103</td>
<td>0.481</td>
<td>29.800</td>
<td>0.986</td>
</tr>
<tr>
<td>Wool</td>
<td>0.106</td>
<td>0.531</td>
<td>26.727</td>
<td>0.982</td>
</tr>
<tr>
<td>Zinc</td>
<td>0.175</td>
<td>0.725</td>
<td>35.667</td>
<td>0.982</td>
</tr>
</tbody>
</table>
tic component of the time series is assumed to be weighted average of the relevant statistics when the stochas-
tical breaks. The tests are based on a data-dependent
time-series techniques by Harvey et al. (2007, 2009) to
and Jute).

In addition to the new data, this paper also applies new
time-series techniques by Harvey et al. (2007, 2009) to
assess the trend function and the existence of any possible
structural breaks. The tests are based on a data-dependent
weighted average of the relevant statistics when the stochas-
tic component of the time series is assumed to be \( I(0) \) and
\( I(1) \), respectively. In this manner, the tests employed are
robust to the order of integration issues that have plagued
the literature. Our empirical methodology thus requires no
unit root pretests and simply tests the trend function directly.
The empirical results are informative. Initially, we exam-
ined the trend function of each commodity price series
without allowing for the possibility of structural breaks. It
was found that eight commodities (Aluminum, Coffee, Jute,
Silver, Sugar, Tea, Wool, and Zinc) present a secular down-
trend. As a specific example, consider that the relative
price of an important commodity like coffee has been
decreasing at an annual rate of 0.77% for approximately 300
years! Second, we tested each price series for a break in the
trend function, and for the series that rejected in favor of a
break, the postbreak period was reanalyzed for the presence
of a downward trend. This resulted in a further three
commodities being found to present a negative trend (Hide,
Tobacco, and Wheat).

Overall, eleven major commodities show new and robust
evidence of a long-run decline in their relative price. In our
opinion, this provides much more robust support that the
Prebisch-Singer hypothesis is relevant for commodity
prices. For the remaining fourteen commodities, no positive
and significant trends could be detected over all or some
fraction of the sample period. These zero-trending commod-
ities suggest that the Lewis hypothesis may also play a part
in explaining the behavior of certain commodity prices;
conversely, however, in the very long run, there is simply no
statistical evidence that relative commodity prices have ever
tended upward.

REFERENCES

Andrews, Donald W. K., “Tests for Parameter Instability and Structural

Band-Pass Filters for Economic Time Series,” this REVIEW 81
(1999), 575–593.

Blattman, C., J. Hwang, and J. G. Williamson, “Winners and Losers in the
Commodity Lottery: The Impact of Terms of Trade Growth and
Volatility in the Periphery 1870–1939,” *Journal of Development

of Primary Commodities and in the Terms of Trade of Developing

Effects on the Terms of Trade between Primary Producers and

Cashin, P., and C. J. McDermott, “The Long-Run Behaviour of Commodity
Prices: Small Trends and Big Variability,” *IMF Staff Papers* 49
(2002), 175–199.

Castaneda, C., “Oil Industry: Technological Change” (pp. 126–129), in J.
Mokyr (Ed.), *The Oxford Encyclopedia of Economic History* (New


Cuddington, J., and D. Jerrett, “Super Cycles in Metals Prices?” *IMF Staff

Cuddington, J., R. Ludema, and S. Jayasuriya, “Prebisch-Singer Redux,”
in D. Lederman and W. Maloney (Eds.), *Natural Resources: Neither
Curse nor Destiny* (Stanford, CA: Stanford University
Press, 2007).

Cuddington, J., and C. Urzua, “Trends and Cycles in the Net Barter Terms
442.

Deaton, A., “Commodity Prices and Growth in Africa,” *Journal of


Evenson, R. E., and Y. Kislev, “Research and Productivity in Wheat and

Fernald, J. G., “Trend Breaks, Long-Run Restrictions, and Contractionary
Technology Improvements,” *Journal of Monetary Economics* 54

Fisher, J. D. M., “The Dynamic Effects of Neutral and Investment-
Specific Technology Shocks,” *Journal of Political Economy* 114

Froot, K., M. Kim, and K. Rogoff, “The Law of One Price over 700 Years,”


Greenaway, D., and C. W. Morgan (Eds.), *The Economics of Commodity

Griliches, Z., “Issues in Assessing the Contribution of Research and
Development to Productivity Growth,” *Bell Journal of Economics*

Grilli, E., *The Future for Hard Fibers and Competition from Synthetics*

Grilli, R. E., and M. C. Yang, “Commodity Prices, Manufactured Goods
Prices, and the Terms of Trade of Developing Countries,” *World

and Powerful Test of the Trend Hypothesis,” *Journal of Eco-

Heitzman, J., and L. Worden, “Bangladesh: A Country Study” (Washing-

Johnson, P., *The Economics of the Tobacco Industry* (New York: Praeger,
1984).

Jurado, M., and J. Vega, “Purchasing Power Parity: An Empirical Analy-

Commodity Prices,” *Journal of Development Economics* 79

Kim, T., S. Pfaffenzeller, A. Rayner, and P. Newbold, “Testing for Linear
Change with Unknown Change Point,” *Econometric Theory*
25 (2009), 995–1029.

Kondratieff, N. D., “The Long Waves in Economic Life,” this REVIEW 17

Kraris, I. B., and R. E. Lipsey, “Prices and Terms of Trade for Developed
Country Exports of Manufactured Goods,” in B. Csikos-Nagy, D.
Hague, and G. Hall (Eds.), *The Economics of Relative Prices*

Null Hypothesis of Stationary against the Alternative of a Unit
