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Trends and cycles in real commodity prices: 1650–2010*

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Abstract

The Prebisch-Singer hypothesis is often popularised as implying a declining long-run trend in primary commodity prices relative to manufactures, and conventional datasets to examine the hypothesis typically commence at the beginning of the 20th century. Theoretical rationales include the juxtaposition of highly competitive primary commodity markets with oligopolistic manufacturing markets, or technological and productivity differentials between core (industrial) and periphery (non-industrial) countries. However, even if such rationales are germane for the 20th century, are they equally so for prior centuries? In particular, the extant literature notes a 19th century terms of trade boom in the primary commodity producing periphery, hardly suggestive of a declining long-run trend in relative commodity prices.

To disentangle trend and cyclical components for relative commodity prices we employ new and ultra-long aggregate time series, covering the period 1650-2010, and apply recent tests robust to the order of integration. Strikingly, results show that relative commodity prices present a significant and downward global trend over almost the entire capitalist age. Moreover, structural break tests suggest the full sample can be segmented into four intertemporal regimes: 1650 to the early 1820s; the early 1820s to the early 1870s; the early 1870s to the mid-1940s; and the mid-1940s to 2010. This identification of changes in the trend function provides new characterisations of historical price behaviour - for example, the 19th century terms of trade boom is captured by a local increase in prices during the second regime, superimposed on a generic long-run downward trend. Finally, Kondratieff-type cycles around this downward trend are shown to have increased in amplitude from the early 1870s onward.

Keywords: Primary commodities; Prebisch-Singer hypothesis; Structural breaks; Cycles.

JEL Classification: O13; C22.

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1 Introduction

The recent "food crisis"' in 2008 starkly demonstrated the importance of global commodities markets. In particular, sharply rising prices for commodities such as wheat, maize, rice and oil pushed many vulnerable groups deeper into poverty (see Ivanic and Martin, 2008).[1] In any case, the behaviour of primary commodity prices is typically important to many developing countries, wherein a significant proportion of national income is often generated by a small number of primary products (see Harvey *et al.*, 2010 [HKMW]).[2] The nature and causes of long-term trends and shorter-term fluctuations in primary commodity prices therefore have significant implications for growth and poverty reduction policies in developing countries.

1.1 Long-run commodity price movements

Analysis of the long-run is dominated by the Prebisch-Singer hypothesis (PSH) which implies a secular, negative trend in commodity prices relative to manufactures.[3] Possible theoretical rationales include low income elasticities of demand for commodities, asymmetric market structures that result from comparatively homogeneous commodity producers generating highly competitive commodity markets whilst facing oligopolistic manufacturing markets, and technological and productivity differentials between core (industrial) and periphery (non-industrial) countries. If a country's export commodities present long-run downward trends in their relative prices, the policy advice is typically to diversify the export mix to include significant proportions of manufactures and/or services.[4]

[1]In 1990-1992, it was estimated that 817 million people, approximately 20% of the global population, were undernourished. In 2005-2007, this was estimated to be 830 million people, around 16%. However, with current estimates at more than one billion undernourished people, this represents a return to approximately 20% of the world population (see Millennium Development Goals Report, 2010).

[2]For example, the World Bank's World Development Indicators suggests that primary commodities contributed 50% of the total merchandise exports of developing countries in 2007. Strikingly, reliance on primary commodities is even higher in Sub-Saharan Africa and the Higher Indebted Poorer Countries, accounting for approximately 66% and 80% of merchandise exports respectively.

[3]See Prebisch (1950) and Singer (1950). 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 the existence of unlimited supplies of labour 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).

[4]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 et al., 2007).

Empirical evidence examining the PSH provides an ambiguous picture. The vast majority of recent studies employ the Grilli and Yang (1988) [GY] dataset of 24 annual non-fuel primary commodity prices which commences in 1900.[5] For example, assuming that logarithms of prices are represented appropriately by a pure trend stationary process, GY find support for the PSH, reporting a weighted aggregate real index decline of 0.6% per annum from 1900-1986.[6] On the other hand, Zanias (2005) employs the same GY index extended to 1998, identifies two structural breaks (1920 and 1984) and shows the 20th century decline in commodity prices is almost exclusively explained by these shifts in the mean as opposed to any gradual trending effect. Moreover, empirical results within the literature are often conditional on the assumed order of integration of the relative price processes (see Kim *et al.*, 2003) and whether structural breaks are allowed in the underlying mean or trend function (see HKMW).

In any case, the relatively large variance of commodity prices (see Deaton, 1999, and HKMW) inhibits statistical determination of any trend magnitude and direction. A possible approach to address this issue is to provide greater degrees of freedom via a backwards extension of the sample. Addressing this issue, Cashin and McDermott (2002) employ "the longest publicly available dataset", the industrial commodity price index of The Economist, covering the period 1862-1999. Their results suggest a downward trend of 1.3% per annum in real commodity prices with no breaks in the trend function. Finally, HKMW employ a unique disaggregated dataset, comprised of 25 separate commodity time series and spanning the 17th to the 21st centuries. To circumvent any order of integration issues, test procedures for the presence of a linear trend and a broken trend which are robust to whether shocks are generated by an I(0) or I(1) process, are applied to the new data. Interestingly, results show that five price series (Aluminum, Banana, Rice, Sugar and Tea) present a significant and downward trend over all or some fraction of the sample period. Of the remainder, nineteen reveal a zero trend (Beef, Coal, Cocoa, Coffee, Copper, Cotton, Gold, Hide, Jute, Lamb, Lead, Nickel, Oil, Pig Iron, Silver, Tin, Wheat, Wool and Zinc), whilst only Tobacco has a significant positive trend over the full sample period.[7]

[5] Earlier work, not employing the GY dataset, includes Spraos (1980), Sapsford (1985) and Thirwall and Bergevin (1985).

[6] The extant literature either employs aggregate or disaggregated data. For example, *inter alios*, Sapsford (1985), GY, Cuddington and Urzúa (1989), Powell (1991), Ardeni and Wright (1992), Sapsford *et al.* (1992), Reinhart and Wickham (1994) and Zanias (2005) examine trends in aggregate commodity price indexes. However, Cuddington (1992), Leon and Soto (1997), Badillo *et al.* (1999), Newbold *et al.* (2000), Kim *et al.* (2003), Kellard and Wohar (2006), Balagtas and Holt (2009), HKMW (2010) and Ghoshray (2011) examine trends in individual commodity prices. Good summaries of this literature can be found in Greenaway and Morgan (1999) and Cuddington *et al.* (2007).

[7] The original HKMW article indicated that eleven commodities presented a downward trend, but the authors subsequently identified data construction errors arising from the incorrect conversion of some US dollar prices to British pound sterling; the corrected results are given in Harvey *et al.* (2012) and the corrected data set is available from www.nottingham.ac.uk/∼lezdih/data.xlsx.

1.2 Shorter-term commodity price movements

Compared to long-run trends, shorter-term fluctuations in commodity prices are relatively under-researched in the literature. This is surprising given that commodity prices are known to be extremely volatile, leading to uncertainty over future revenue and cost streams. This uncertainty may inhibit planning and deter investment by all the relevant agents in the commodity supply chain (i.e., household farmers, cooperatives, larger commercial farmers and governments). The shortfalls in investment subsequently act as a drag on future growth and poverty reduction prospects (see Blattman *et al.*, 2007 and Poelhekke and van der Ploeg, 2009). Additionally, although severe price movements may be temporary in character, permanent and detrimental effects on physical and cognitive development, particularly during early childhood, can arise in commodity dependent communities (see, *inter alia*, Pongou *et al.*, 2006 and Miller and Urdinola, 2010).

Clearly, any form of policy intervention (such as stabilization funds, derivative usage, international market sharing agreements, or increased government borrowing in response to a negative but temporary shock to revenue) to smooth commodity-dependent flows should be grounded in an understanding of the duration and amplitude of price cycles.[8,9] In the seminal work of Kondratieff (1935), long waves or cycles of 45-60 years were suggested. HKMW (and Harvey *et al.*, 2012) show the mean periodicity of commodity price cycles ranges from 23.7 years (Cocoa) to 38.8 years (Copper), clearly lower than the 45-60 year interval consonant with Kondratieff cycles. Cuddington and Urzúa (1989) decomposed the aggregate commodity price index of GY into permanent and temporary or cyclical components using an approach presented by Beveridge and Nelson (1981); for a typical price shock, approximately 61% is shown to be temporary, with these temporary effects lasting only three years. Importantly, Cashin and McDermott (2002) argue that defining cycles as deviations from trend requires the subjective methodological decision of how to de-trend the data. In an attempt to circumvent such subjectivities, they define a cycle in terms of the peaks and troughs of the level of the series, subsequently showing that commodity price volatility is typically large in magnitude and has risen over the 20th century. In particular, the frequency of "large" price cycles[10] has increased since the collapse of the Bretton Woods fixed exchange rate system in the early 1970s.[11] Specifically, prior to 1971, the average duration of a large price cycle was 34 years; after 1971, this dropped to 7 years.

[8]Recent work by Collier *et al.* (2010) suggests that the resource revenue saved by capital scarce developing countries should not be invested primarily in foreign financial assets (i.e., via sovereign wealth funds) but in domestic assets to build up the capital base. Additionally, volatility in revenue can be managed by allowing this investment flow to fluctuate (protected in part by a sovereign liquidity fund) rather than domestic consumption. See also van der Ploeg and Venables (2011).

[9]Frankel (2011) notes that successful counter-cyclical fiscal policy is dependent on isolating the forecasts of key macroeconomic inputs (e.g., future commodity prices and trend output) from the political process; specifically, allowing forecasts to be determined by expert, independent panels.

[10]Cashin and McDermott (2002) posit a "large" price cycle as comprising a large boom and a large slump, defined as a sequence of generally increasing/decreasing prices that have experienced a price movement of at least 25% over the phase.

[11]Cuddington and Liang (2003) report that higher commodity price volatility is associated with flexible as opposed to fixed exchange rate regimes.

Finally, a more historical schematic is recently provided by Jacks *et al.* (2011). Separately examining eleven price datasets that overlap intertemporarily from 1700-2005,[12] results suggest that nominal commodity prices have typically provided greater volatility than manufactures, even prior to the industrial revolution. Notably, volatility itself is shown not to be a function of time *per se*, but to increase in periods of war or autarky and decrease in periods of internationalisation and trade.

1.3 Aims and contribution

As noted above, the PSH is typically examined using data commencing at the beginning of the 20th century. In an attempt to gain greater degrees of freedom, a few studies have extended samples backward. However, even if theoretical rationales for the hypothesis are germane for the 20th century, are they equally so for prior centuries? In particular, it could be argued that some relevant factors were weaker; for example, the relative concentration of manufacturing to primary commodity producing industry has likely risen over the long-run.[13] In any case, Williamson (2008) suggests that a powerful 19th century terms of trade boom in the poor periphery led to commodity specialisation in locations away from the industrial core. The relatively high commodity prices required to induce specialisation are hardly indicative of a declining trend in relative prices over the entirety of the 1800s. Moreover, it is conceivable that specialisation in commodity production and away from manufactures, juxtaposed with the commodity price decline of the 20th century, contributed significantly to the Great Divergence.

To empirically assess the validity of the theoretical notions expressed above, aggregate measures of relative commodity prices are required over a long historical time frame. Therefore, we create new annual series beginning in 1650 and running continuously until 2010. The data set covers several important epochs: the pre-industrial, 1650-1775; revolutions and Napoleonic wars, 1776-1815; the industrial and first globalisation age, 1816-1913; war and autarky[14], 1914-1945; and the second globalisation age, 1946-2010. This historical scope consequently allows examination of a number of questions. For example, firstly, assuming a decline in real commodity prices over the 20th century, how far does this extend backwards into the 19th century? Secondly and relatedly, can the 19th century terms of trade boom in the poor periphery suggested by Williamson (2008) be formally dated? Thirdly, did relative commodity prices also present a secular decline over the 17th and 18th centuries, and, if so, was this at a slower rate as compared with the 20th century? Finally, the continuous nature of the aggregate series allows a reassessment of the length of Kondratieff cycles, whilst additionally asking whether the amplitude and duration of such cycles have increased over the long-run, i.e. a cyclical analog to the PSH.

Given the well known problems of identifying the order of integration of relative

[12]For example, the three datasets collected by Bezanson *et al.* (1936) are employed, covering the dates 1720-1775 (19 commodities), 1770-1790 (25 commodities) and 1784-1861 (133 commodities).

[13]Arguably, the process of globalisation encourages manufacturing firms to tend towards oligopoly at an international level. Conversely, sources of primary commodity supply multiply, partially in response to the structural adjustment policies adopted by indebted developing countries.

[14]Jacks *et al.* (2011) employs an analogous descriptive.

commodity price series, and the pervasive influence of any unit root/stationarity pre-tests on subsequent tests of commodity time series characteristics (see HKMW), we shall apply trend tests, trend break tests and a cyclical decomposition which are robust to the whether or not the series under consideration contains a unit root. The remainder of the paper is organised as follows. Section 2 outlines the empirical methodology, while section 3 describes the new data. The empirical results and associated discussion are presented in section 4, and section 5 concludes.

2 Empirical methodology

2.1 Testing for a linear trend

We initially consider the following data generating process (DGP) for y_t, the logarithm of relative commodity prices:

$$y_t = \alpha + \beta t + u_t, \quad t = 1, ..., T \tag{1}$$

$$u_t = \rho u_{t-1} + \varepsilon_t, \quad t = 2, ..., T \tag{2}$$

with $u_1 = \varepsilon_1$, where ε_t is assumed to follow a stationary process. To permit the errors u_t to be either I(0) or I(1), we assume $-1 < \rho \leq 1$, with the cases $|\rho| < 1$ and $\rho = 1$ corresponding to I(0) and I(1) errors, respectively. Given that we are interested in examining the PSH, the null hypothesis to be tested is $H_0 : \beta = 0$, and we wish to conduct tests on this hypothesis without assuming knowledge of whether the errors u_t are stationary or contain a unit root.

In the context of such a DGP, Harvey *et al.* (2007) and Perron and Yabu (2009a) both propose tests of $H_0 : \beta = 0$ that are robust to the order of integration properties of the underlying errors u_t. The z_λ statistic of Harvey *et al.* (2007) is comprised of a data-dependent weighted average of two trend test statistics, one that is appropriate when the data are generated by an I(0) process and one when the data are I(1). Specifically:

$$z_\lambda = (1 - \lambda)z_0 + \lambda z_1$$

where z_0 and z_1 are autocorrelation-robust t-ratios based on (1), and a first differenced version of (1), respectively, i.e.:

$$z_0 = \frac{\hat{\beta}}{\sqrt{\hat{\omega}_u^2 / \sum_{t=1}^{T}(t - \bar{t})^2}}, \qquad z_1 = \frac{\tilde{\beta}}{\sqrt{\tilde{\omega}_v^2/(T-1)}}$$

with $\hat{\beta}$ the OLS estimator of β in (1), and $\tilde{\beta}$ the OLS estimator of β in

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

and where $\hat{\omega}_u^2$ and $\tilde{\omega}_v^2$ are the corresponding long-run variance estimators.[15] The weight

[15] As in Harvey *et al.* (2007), the long-run variance estimators are computed using the quadratic spectral kernel with Newey and West (1994) automatic bandwidth selection, adopting a non-stochastic prior bandwidth of $\lfloor 4(T/100)^{2/25} \rfloor$.

λ is given by:

$$\lambda = \exp\left(-0.00025\left(\frac{\text{DF-GLS}^{\tau}}{\hat{\eta}_{\tau}}\right)^{2}\right)$$

where DF-GLS$^{\tau}$ denotes the GLS-detrended Dickey-Fuller unit root statistic of Elliott *et al.* (1996), and $\hat{\eta}_{\tau}$ denotes the stationarity test statistic of Kwiatkowski *et al.* (1992).[16] The weight function is constructed so that $\lambda \xrightarrow{p} 0$ when u_t is I(0), and $\lambda \xrightarrow{p} 1$ when u_t is I(1), ensuring that in the limit, the appropriate trend test statistic is chosen in each case. Critical values for z_{λ} are taken from the standard normal distribution.

Perron and Yabu (2009a) propose an alternative strategy based on quasi-feasible GLS estimation of (1)-(2), i.e. a test based on $\hat{\beta}_{QF}$, the OLS estimator of β in the regression:

$$y_t - \tilde{\rho}_{MS} y_{t-1} = (1-\tilde{\rho}_{MS})\alpha + \beta[t - \tilde{\rho}_{MS}(t-1)] + (u_t - \tilde{\rho}_{MS} u_{t-1}), \quad t = 2, ..., T \quad (3)$$

together with $y_1 = \alpha + \beta + u_1$. Here, $\tilde{\rho}_{MS}$ is an estimator of ρ designed to be super-efficient when $\rho = 1$. It is obtained by first constructing a bias-corrected estimator of ρ using the truncated weighted symmetric least squares method of Roy and Fuller (2001); Perron and Yabu consider two such estimators derived under different truncation settings (see their paper for full details), which we denote by $\tilde{\rho}_{MU}$ and $\tilde{\rho}_{UB}$. This bias-corrected estimate is then assigned a value of 1 when it lies within a $T^{-1/2}$ neighbourhood of 1, generating the estimator $\tilde{\rho}_{MS}$, i.e.:

$$\tilde{\rho}_{MS} = \begin{cases} \tilde{\rho}_M & \text{if } |\tilde{\rho}_M - 1| > T^{-1/2} \\ 1 & \text{if } |\tilde{\rho}_M - 1| \leq T^{-1/2} \end{cases}$$

where $\tilde{\rho}_M$ denotes either $\tilde{\rho}_{MU}$ or $\tilde{\rho}_{UB}$. Finally, the robust trend test statistic is given by:

$$t_{\beta}^{RQF} = \frac{\hat{\beta}_{QF}}{\sqrt{\hat{h}_{\varepsilon}(X'X)^{-1}_{22}}}$$

where $(X'X)^{-1}_{22}$ denotes the $(2,2)$ element of $(X'X)^{-1}$ with $X = [x_1, ..., x_T]'$, $x_t' = [1 - \tilde{\rho}_{MS}, t - \tilde{\rho}_{MS}(t-1)]$ for $t = 2, ..., T$ and $x_1' = [1, 1]$, and where $\hat{h}_{\varepsilon}$ denotes the long-run variance estimator detailed in section 3 of Perron and Yabu (2009a), the exact form of which depends on whether $\tilde{\rho}_{MS} = \tilde{\rho}_M$ or $\tilde{\rho}_{MS} = 1$. We denote the two alternative versions by $t_{\beta}^{RQF}(MU)$ and $t_{\beta}^{RQF}(UB)$, according to which of $\tilde{\rho}_{MU}$ and $\tilde{\rho}_{UB}$ is used. Perron and Yabu show that these statistics both follow an asymptotic standard normal distribution under the null $H_0 : \beta = 0$.

2.2 Testing for breaks in trend

The extant literature has shown that relative commodity prices may not be optimally represented by a single, secular trend but by some segmented alternative (see, *inter*

[16]Note that both DF-GLS$^{\tau}$ and $\hat{\eta}_{\tau}$ allow for a constant and linear trend. In constructing DF-GLS$^{\tau}$, lag selection is performed using the MAIC procedure of Ng and Perron (2001), setting the maximum lag length at $\lfloor 12(T/100)^{1/4} \rfloor$. The long-run variance estimator adopted in $\hat{\eta}_{\tau}$ is $\hat{\omega}_u^2$.

alia, Ghoshray, 2011, and Kellard and Wohar, 2006). When assessing the evidence for a broken trend, this literature has typically, as in the unbroken trend context, relied on procedures that require pre-testing for a unit root. To circumvent the issues surrounding the identification of the order of integration, and to examine directly whether commodity prices contain a break in trend, HKMW employ the Harvey *et al.* (2009) test for a single break in trend, which does not assume any *a priori* knowledge as to the order of integration of series. Analogously, Perron and Yabu (2009b) provide a robust test for a single trend break that adopts the same broad approach as the Perron and Yabu (2009a) test for a linear trend.

Of course, it is quite possible that commodity price series contain more than one structural break, particularly given the long historical time series under study in this paper, thus we next consider testing for the presence of multiple breaks in trend. We therefore augment the deterministic component of the DGP to allow for, say, m breaks in level/trend, i.e. we consider replacing (1) with the following specification:

$$y_t = \alpha + \beta t + \sum_{j=1}^{m} \delta_j DU_{jt}(T_j^B) + \sum_{j=1}^{m} \gamma_j DT_{jt}(T_j^B) + u_t, \quad t = 1, ..., T \tag{4}$$

where $DU_{jt}(T_j^B) = 1(t > T_j^B)$ and $DT_{jt}(T_j^B) = 1(t > T_j^B)(t - T_j^B)$, $j = 1, ..., m$, with $1(.)$ denoting the indicator function and T_j^B, $j = 1, ..., m$, denoting the break dates.

In this framework, Kejriwal and Perron (2010) propose a methodology for determining the number of breaks in trend, robust to the order of integration of the errors u_t, based on a sequential application of the Perron and Yabu (2009b) procedure for detecting a single break in trend. The first step is to apply the Perron and Yabu (2009b) test directly to the series, testing the null of no breaks against the alternative of one break in level/trend. As in the linear trend testing context, the Perron-Yabu approach involves a test based on quasi-feasible GLS estimation, i.e. the regression:

$$\begin{aligned} y_t - \tilde{\rho}_{MS} y_{t-1} = (1 - \tilde{\rho}_{MS})\alpha + \beta[t - \tilde{\rho}_{MS}(t-1)] + \delta_1[DU_{1t}(T_1^B) - \tilde{\rho}_{MS} DU_{1,t-1}(T_1^B)] \\ + \gamma_1[DT_{1t}(T_1^B) - \tilde{\rho}_{MS} DT_{1,t-1}(T_1^B)] + (u_t - \tilde{\rho}_{MS} u_{t-1}), \quad t = 2, ..., T \end{aligned}$$

together with $y_1 = \alpha + \beta + u_1$. As before, $\tilde{\rho}_{MS}$ is given by:

$$\tilde{\rho}_{MS} = \begin{cases} \tilde{\rho}_M & \text{if } |\tilde{\rho}_M - 1| > T^{-1/2} \\ 1 & \text{if } |\tilde{\rho}_M - 1| \leq T^{-1/2} \end{cases} \tag{5}$$

now with $\tilde{\rho}_M$ a bias-corrected estimator of ρ based on an OLS Dickey-Fuller regression (allowing for a constant, trend and break in level/trend) and the subsequent correction of Roy and Fuller (2001) (see Perron and Yabu, 2009b, for full details). For a known break date T_1^B, the test statistic is an autocorrelation-corrected Wald-type statistic for testing $H_0 : \delta_1 = \gamma_1 = 0$, the precise form of which depends on whether $\tilde{\rho}_{MS} = \tilde{\rho}_M$ or $\tilde{\rho}_{MS} = 1$ (see their paper for details); we denote this statistic by $W_{RQF}(T_1^B)$. However, given that the timing of any potential break is treated as unknown, the final Perron-Yabu statistic is obtained by taking the following functional of the Wald-type statistics across all candidate break dates:

$$\textit{Exp-W} = \log\{T^{-1} \textstyle\sum_{T_1^B \in [\lfloor \pi T \rfloor, \lfloor (1-\pi)T \rfloor]} \exp[\frac{1}{2} W_{RQF}(T_1^B)]\} \tag{6}$$

where $\lfloor . \rfloor$ denotes the integer part of the argument, and the fraction $0 < \pi < 1$ represents a trimming parameter (set to 0.10 in this paper) excluding breaks at the very beginning or end of the sample. Although the limit null distribution of *Exp-W* differs under I(0) and I(1) errors, Perron and Yabu (2009b) show that the critical values are not dissimilar at typical levels of significance, and recommend using the maximum of the I(0) and I(1) critical values to ensure the resulting test is conservative.[17]

If the null of zero breaks in level/trend is not rejected, the Kejriwal and Perron procedure terminates. Otherwise, the next step is to condition on there being at least one break, and proceed to examine evidence for more than one break. The sequential procedure continues according to the following steps, beginning with $l = 1$:

1. Conditional on l break(s) having been detected, estimate the timing of the break(s) $T_1^B, ..., T_l^B$ by minimising the global sum of squared residuals (SSR) obtained from OLS estimation of (4) across all candidate break points, i.e.:

$$\hat{T}_1^B, ..., \hat{T}_l^B = \arg \min_{T_1^B, ..., T_l^B \in [\lfloor \pi T \rfloor, \lfloor (1-\pi) T \rfloor]} \sum_{t=1}^{T} \hat{u}_t^2(T_1^B, ..., T_l^B) \tag{7}$$

with $\hat{u}_t(T_1^B, ..., T_l^B)$ denoting the residuals in the OLS estimated equation:

$$y_t = \hat{\alpha} + \hat{\beta} t + \sum_{j=1}^{l} \hat{\delta}_j DU_{jt}(T_j^B) + \sum_{j=1}^{l} \hat{\gamma}_j DT_{jt}(T_j^B) + \hat{u}_t(T_1^B, ..., T_l^B), \quad t = 1, ..., T. \tag{8}$$

2. Split the sample into $l + 1$ segments according to the estimated break dates $\hat{T}_1^B, ..., \hat{T}_l^B$. Compute the *Exp-W* test statistic (6) for a single break in trend for each of the $l + 1$ segments, denoting the resulting statistics $Exp\text{-}W_1, ..., Exp\text{-}W_l$.

3. Test the null of l break(s) against the alternative of $l + 1$ breaks using the test statistic

$$F_T(l + 1 \,|\, l) = \max\{Exp\text{-}W_1, ..., Exp\text{-}W_l\} \tag{9}$$

compared with critical values provided by Kejriwal and Perron. As with the Perron and Yabu (2009b) statistic, the limit critical values depend on whether the errors are I(0) or I(1) (but are quite close) and the maximum of the two critical values is used.

4. If no rejection is obtained, terminate the procedure with the inference that l break(s) are present. If the null of l break(s) is rejected, increase l by 1 and repeat from step 1.

Although in principle this sequential procedure can continue until termination where no further breaks are detected, in practice Kejriwal and Perron caution against allowing too many breaks in finite samples, given the potential for size distortions and low power that can arise in the small sub-samples involved in the procedure. In our application, we set the maximal number of breaks to be three.

[17] Note that in the I(1) case, normality of the innovations is assumed when obtaining the null limit distribution, due to the fact that the level change dummy variable in the GLS regression becomes an outlier when $\tilde{\rho}_{MS} = 1$.

2.3 Trend-cycle decomposition

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 extant literature. In the seminal work of Kondratieff (1935), long waves or cycles of 45-60 years were posited. More recently, HKMW and Cuddington and Jerrett (2008) employed the asymmetric band pass filter of Christiano and Fitzgerald (2003) to decompose commodity prices into three components as follows:

$$y_t = T_t + LC_t + SC_t, \quad t = 1, ..., T$$

where T_t is a trend component, LC_t is a long-term cyclical component and SC_t a short-term cyclical component. Christiano and Fitzgerald propose a finite sample approximation for the band pass filter that is nearly optimal for typical economic time series. The filter extends the band pass approach developed by Baxter and King (1999), and allows computation of cyclical components for the full span of the time series without trimming at the end-points. It can be applied to series regardless of whether they contain a unit root or are stationary (around some deterministic component), and has recently been employed by a number of authors: see, for example, Fuhrer and Rudebusch (2004), Fisher (2006) and Fernald (2007).

Following HKMW we define long-term cycles as those lasting from 20-70 years, thus nesting those proposed by Kondratieff (1935). Additionally, the trend is defined as all cyclical components lasting 70 years or longer and short-term cycles as those ranging from 2-20 years. Denoting by $CF(c_1, c_2)$ the Christiano and Fitzgerald band pass filter that passes cycles between c_1 and c_2 in length, we can define T_t, LC_t and SC_t as follows:

$$\begin{aligned} T_t &= CF(70, \infty) \\ LC_t &= CF(20, 70) \\ SC_t &= CF(2, 20). \end{aligned}$$

The initial step of the Christiano and Fitzgerald filter is to de-trend the data under the assumption that a unit root is present in the data. In an unbroken trend framework, the estimate of β in (1)-(2) is therefore obtained by OLS estimation with ρ set to 1, i.e. OLS estimation of the first differenced regression $\Delta y_t = \beta + \varepsilon_t$. If breaks in the trend function are detected, this initial step can be modified by including the breaks in the deterministic component used for the de-trending, now estimating the relevant coefficients using a first differenced version of (4).

3 Data

The often employed GY dataset comprises twenty-four, internationally traded, non-fuel commodities.[18] Each annual nominal commodity price series (in US dollars) is deflated

[18]The commodities are Aluminium, 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.

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. Although a number of papers in the extant literature examine the twenty-four commodities separately, many employ GY's weighted aggregate real index to summarise the behaviour of relative commodity prices as a whole.[19]

As noted in the introduction, the GY dataset begins in 1900, primarily because this is the starting date for the MUV series; however, commodity and manufacturing price data can be sampled backwards well before this time. Given the extensive interest in modeling and analyzing the long-run trends of relative commodity prices, it would appear important to utilize as much of the existing data as is sensibly possible. To do this, HKMW created a large and representative dataset of twenty-five relative commodity price series[20] (nominal prices in British pound sterling[21]) covering a 356 year period from 1650 to 2005.[22] However, as a result of employing all available data, the series are of unequal lengths. Specifically, twelve series begin in the 17th century (Beef, Coal, Cotton, Gold, Lamb, Lead, Rice, Silver, Sugar, Tea, Wheat and Wool), three series begin in the 18th century (Coffee, Tobacco and Pig Iron), eight series begin in the 19th century (Aluminum, Cocoa, Copper, Hide, Nickel, Oil, Tin and Zinc) and two start from 1900 (Banana and Jute). Twenty of these commodities are also found in the GY dataset and twenty-three are non-fuel. Each nominal commodity price was deflated by a historical price index of manufactures (HPIM), stretching back to 1650.[23]

HKMW assess the properties of the twenty-five ultra-long commodity prices separately. However, given the tendency in the literature to also examine aggregate commodity series, it would appear useful to construct an ultra-long aggregate series. Of course, this is not a trivial task, in particular because prices and weights series for all commodities are not available uniformly over the period 1650 to the present day. Let the Commodity Composite Price Index (CCPI) be the weighted average of twenty-three HKMW commodities, where the weights reflect the importance of each commodity in total commodity trade.[24] When constructing the CCPI, the following steps have been followed. First, the commodity price index (CPI) is calculated using $\sum_{i=1}^{N} w_{it}p_{it}$, where w_{it} and p_{it} respectively represent the weight and price of the ith commodity in a particular year t. If prices and weights are available for $N-1$ commodities in the first x years and then for N commodities in next y years, individual CPI series are first constructed for each period x and y using data on $N-1$ and N commodities, respectively. Secondly, using the values in common benchmark years, the later series is spliced upward

[19] The 1977-1979 values of world exports of each commodity are used as weights.

[20] See the appendix of HKMW for a fuller description of the source of each price.

[21] British pound sterling is used because the US did not have its own currency before independence in 1776.

[22] Although it is possible to get data for commodity prices from before 1650, we could find no reliable source of manufacturing prices.

[23] For details on the construction of HPIM see HKMW.

[24] In this paper, we employ the extended HKMW commodity and manufacturing price dataset that runs from 1650 to 2010. Additionally, we removed gold and silver from the original list of twenty-five commodities. There is no clear distinction between monetary gold/silver and commodity gold/silver imports in the US Geological Survey data; this could create a distortion, as, for example, monetary gold and silver were heavily imported during the two world-war eras.

to assemble the CCPI.

Several benchmark years, namely 1830, 1860, 1900, 1912, 1928, 1937, 1950, 1975 and 2006 are chosen to calculate the weights of commodities. Specifically, exports of commodities from the commodity-dependent price-taking economies (the periphery[25]) are used as weights.[26] To be clear, the export value of the ith commodity is divided by the total export value of all selected N commodities in year t to get the weight, w_{it}, of the ith commodity in year t. The periphery consists of Asia (excluding Russia), Africa and South America. The benchmark dates are predominantly dictated by data availability; in particular, data on commodity exports are not available before 1830 on a world scale and it is doubtful that the scant import data that are available for a couple of industrialized countries before 1830 are representative of commodity exports for the periphery. In terms of composition of traded commodities there has been a marked change over time. Sugar, textile fibres, coffee, tea and cocoa were the main export items in 1830 and came predominantly from Asia and South America. Of course, energy and metals have recently become the dominant commodities in world trade.

The benchmark years are subsequently linearly interpolated to get weighted series for each commodity on an annual basis. Specifically, interpolation is applied between the benchmark years from 1830 to 2006; to complete the series, 1830 weights are used before 1830 and 2006 weights are used after 2006. Although weights before 1830 are kept constant due to unavailability of data, the weights of commodities have been calculated such that their sum remains 100 in each year. For years where price data is unavailable for a few commodities, weights for those commodities in those years are set to zero under the assumption that a commodity has no value or weight when the price is zero. This leads to the construction of the CCPI covering a 361 year period from 1650 to 2010.

Finally, note that another comparator index was also created, a non-oil version of the Commodity Composite Price Index (CCPI′). Figure 1 shows the logarithms of CCPI and CCPI′, revealing a close similarity and apparent downward trend in both series over the full sample period. CCPI and CCPI′ will be empirically examined over the full sample; the unbroken trend analysis is applied to a sub-sample of these series (1900-2008), allowing for a more direct comparison with an updated version of the GY non-fuel weighted aggregate real index (GYCPI).[27] Figure 2 plots the logarithms of these indices over 1900 to 2008. Notably (and as might be expected), the logarithms of CCPI, CCPI′ and GYCPI appear to move in a relatively consistent manner over the course of the 20th century. Of course, differences will arise, even between these similar series. For example, while CCPI and CCPI′ are constructed using variable weights and the HPIM deflator, GYCPI uses constant weights from 1977-79 and the MUV

[25]Blattman *et al.* (2007) adopts the distinction between the *periphery* and the *core* (industrial leaders).

[26]The primary source for the weights to 1937 is 'Commodity Structure in Third World Exports 1830-1937', by Paul Bairoch and Bonda Etemad. The sources for subsequent weights are UN International Trade Statistics Yearbooks and UNCTAD.stat commodity trade matrix. For more details and a full list of sources, see the Data Appendix.

[27]The authors thank Stephan Pfaffenzeller for providing the extended GYCPI series from 1900 to 2008.

deflator. In particular, Figure 3 illustrates how HPIM compares with the MUV index for the period since 1900, over which the MUV index is available. In absolute terms the difference is not large and thus is reflected in a very high correlation coefficient of 0.993. However, and as can be observed in Figure 3, in relative terms there are a few significant differences, most notably during the period 1914-1945, where the MUV index is often 25% below our index. As noted by HKMW, this result suggests that export unit values used to construct the MUV index are potentially biased measures of price movements, particularly when long data series are considered.[28]

4 Empirical results

4.1 Trend function analysis

Table 1 shows the results of applying the order of integration robust trend tests z_λ and $t_\beta^{RQF}(MU)$ presented in section 2.1 to the new relative commodity price indices outlined in the previous section.[29] The table also reports estimated growth rates and confidence intervals based on the quasi-feasible GLS approach of Perron and Yabu (2009a), i.e. from estimation of (3). Notably, for both new series CCPI and CCPI′ over the full sample, the null of no trend is rejected in favour of the alternative of a negative trend at the 1% significance level. This is a striking result, particularly when considering the sample length of the new commodity indices. The two series, commencing in 1650, have declined subsequently at an annual average rate of approximately 0.9%.

On the other hand, although the three sub-sample series also display negative growth rates, only the test statistic for the GYCPI series is large enough to reject the null from 1900 onwards. The inability of the CCPI and CCPI′ series to generate rejections of the null of no trend is perhaps reflective of their relatively larger variance over the course of the 20th century, compared with the GYCPI data. Note that testing against a two-sided alternative (allowing for the possibility of positive trends) does not lead to any further rejections of the no trend null.

Focusing now on the two ultra-long series (CCPI and CCPI′), it is important to next consider the possibility that one or more structural breaks have occurred in the deterministic trend function, as discussed in section 2.2. Table 2 reports results for the Kejriwal and Perron (2010) sequential order of integration robust procedure for detecting the number of breaks in level/trend, up to the maximum number permitted of three. For each step of the sequential procedure, the table reports results for the $F_T(l+1\,|l)$ test of (9), and, if a rejection is obtained in favour of $l+1$ break(s), the estimated break date(s) obtained at each stage using (7) are also reported. The end result of the procedure is a finding of evidence (at the 1% significance level) in favour of three breaks in level/trend for both CCPI and CCPI′. The breaks occur at the dates 1820, 1872/3 and 1946, with the corresponding fitted values at these minimum global

[28]HKMW suggest the value-added price deflator used by HPIM has three advantages over export unit values: first, it omits the influence of intermediate products; second, it allows for compositional changes; and third, technological progress is, to some extent, reflected in the deflator.

[29]The $t_\beta^{RQF}(UB)$ test gives analogous results and is therefore not reported.

SSR dates, i.e. the fitted values from (8), given by:

$$\begin{aligned}
\text{CCPI:} \qquad y_t \;=\;& 2.88 - 0.0079t \\
&+0.34DU_{1t}(1820) + 0.0031DT_{1t}(1820) \\
&-0.37DU_{2t}(1872) - 0.0087DT_{2t}(1872) \\
&+0.49DU_{3t}(1946) - 0.0049DT_{3t}(1946) + \hat{u}_t
\end{aligned}$$

$$\begin{aligned}
\text{CCPI}': \qquad y_t \;=\;& 2.88 - 0.0079t \\
&+0.34DU_{1t}(1820) + 0.0027DT_{1t}(1820) \\
&-0.39DU_{2t}(1873) - 0.0074DT_{2t}(1873) \\
&+0.68DU_{3t}(1946) - 0.0059DT_{3t}(1946) + \hat{u}_t
\end{aligned}$$

Graphical representations of these results are given in Figures 4 and 5.

The two commodity price indices can therefore be approximately split into four intertemporal regimes: 1650 to the early 1820s; the early 1820s to the early 1870s; the early 1870s to the mid-1940s; and the mid-1940s to the present day. To ascertain whether the trends in each of these four regimes are significantly negative, we wish to test the following hypotheses (based on the model (4)): $H_0 : \beta = 0$ for the first regime (1650-1820), $H_0 : \beta+\gamma_1 = 0$ for the second regime (1821-1872/3), $H_0 : \beta+\gamma_1+\gamma_2 = 0$ for the third regime (1873/4-1946), and $H_0 : \beta+\gamma_1+\gamma_2+\gamma_3 = 0$ for the fourth regime (1947-2010), in each case against a one-sided (lower-tailed) alternative. In order to conduct tests of these hypotheses that are again robust to the order of integration of the errors, we consider a quasi-feasible GLS-based testing approach consistent with the Perron and Yabu (2009b) approach for testing for a break. Specifically, conditioning on the three dates determined by the Kejriwal and Perron (2010) procedure, we use autocorrelation-corrected t-tests based on quasi-feasible GLS estimation of (4), with quasi-difference parameter $\tilde{\rho}_{MS}$ as defined in (5), but with $\tilde{\rho}_M$ now a bias-corrected estimator of ρ based on an OLS Dickey-Fuller regression that allows for a constant, trend and the three breaks in level/trend. The resulting autocorrelation-corrected t-statistics are then formed in an analogous way to $W_{RQF}(T_1^B)$ of Perron and Yabu (2009b), and, conditional on the break dates, follow asymptotic standard normal distributions under the respective null hypotheses. Table 3 reports the results, and we find strong evidence in favour of a declining trend in all regimes for CCPI′, and for CCPI, all regimes apart from 1821-1872, where the trend estimate is negative but found to be insignificantly different from zero.

In the introduction, we asked "assuming a decline in real commodity prices over the 20th century, how far does this extend backwards into the 19th century?" and whether "relative commodity prices also present a secular decline over the 17th and 18th centuries". Strikingly, results confirm that relative commodity prices present a significant and downward global trend over almost the entire sample period. With the exception of the 1821-1872 period, the growth rates of the commodity price indices were found to decline in the ranges -0.79% to -1.83% per annum for CCPI, and -0.79% to -1.84% per annum for CCPI′, over the different regimes. It is noticeable that the broadly declining trend paths of the price series are punctuated by structural breaks in the level and trend; 1820 shows a sharp rise in the level and trend, 1872/3 sees a sharp fall in level and trend, while 1946 shows a rise in level but further decline in trend[30]. This identification of changing trend behaviour provides new characterisations of historical price behaviour – for example, the 19th century terms of trade boom is captured by a local increase in prices during the second regime (i.e. early 1820s to the early 1870s), superimposed on a generic long-run downward trend. Moreover, the results suggests that the decline in trend has been greater since the early 1870s than at any time previous (albeit offset to some extent by an upward level shift in 1946). The causes behind the modern incarnation of the PSH therefore appear arguably stronger than those that existed in the more distant past – we shall return to this later.

As noted earlier, Williamson (2008) posits that a terms of trade boom occurred during the 19th century and encouraged primary commodity specialisation in the poor periphery. The boom itself can perhaps be attributed to three primary factors noted by Williamson (2008): growing GDP in the industrialising core, liberalisation of trade, and the rapid fall in transport costs via sea (see Jacks and Pendakur, 2010) and rail routes. In particular, the relative technology improvements in manufacturing compared to other economic activities (see Clark *et al.*, 2008), occurring while demand in the core for commodities rose, produced upward pressure on the periphery terms of trade.[31] The resulting specialisation is hypothesised by Williamson (2008) to have caused deindustrialisation[32] via the twin mechanisms of high commodity price levels and the associated volatility[33], and ultimately the Great Divergence, as the income gap between the industrial core and poor periphery widened.

Earlier seminal work by Lewis (1978a, 1978b) proposed the causal factors for the Great Divergence operated primarily between 1870 and 1913. In contrast, Williamson (2008) suggests the relevant period can be dated before and up to 1870. Our results provide new statistical evidence for the latter claim. Given relative commodity prices are an appropriate proxy for periphery terms of trade, the early 1820s to the early 1870s period is clearly a hiatus in the falling terms of trade experienced in the centuries before. Indeed, Figure 1 shows a long boom from around 1820 to the mid-1840s and a local peak during the mid-1860s. If any period could incentivise commodity price specialisation and resulting deindustrialisation, it seems plausible to suggest the globalisation phase in the 19th century prior to 1870.

Returning to the 17th and 18th centuries, our results show the growth rate of the

[30]Sumner (2009) notes that agricultural commodity prices rose sharply through World War II to post-war spikes.

[31]This is perhaps analogous to the situation in the early 21st century, as China and India (in particular) industrialise, demand more primary commodities and increase their relative price.

[32]We suggest an appropriate term in some country cases might be "non-industrialisation".

[33]As noted in the introduction, recent research has established a link between commodity price volatility, lower growth and disincentives to invest in countries with economies dominated by natural resource production (see, *inter alia*, Poelhekke and van der Ploeg, 2009). Additionally, as Jacks *et al.* (2009, p.5) note, "...while greater volatility increases the need for international borrowing to help smooth domestic consumption, Catão and Kapur (2004) have shown recently that volatility constrained the ability to borrow between 1970 and 2001. It seems likely that the same was true between 1870 and 1901, a century earlier, and even more so before 1870 when a global capital market was only just emerging (Obsfelt and Taylor 2004; Mauro *et al.* 2006)".

commodity price indices declining significantly between the 1650 and the early 1800s at approximately 0.79% per annum. It is important to note that traded goods for the three centuries (i.e., 16th, 17th, 18th) following the exploratory voyages of Columbus (1451-1506) and da Gama (1460/1469-1524) were typically non-competing, high priced luxury goods (i.e. spices, sugar and gold), worth transporting over large distances at high cost (see O'Rourke and Williamson, 2002 and 2004). Subsequently, trade in the 19th and 20th century is characterised by increasingly lower priced goods. The trade boom (from the early 1500s to late 1700s) was therefore driven by discovery and growing demand in Europe; however, prices were supported by duties, monopolies and the high cost of sea transportation (including piracy) which did not begin to fall until the 19th century (see O'Rourke and Williamson, 2002).

Perhaps the most important traded commodity in the 17th and 18th centuries was sugar. The great naval powers of the time (i.e. Spain, Portugal and Britain) imported sugar from West Indian and South American colonies, devoting enormous resources to protecting the trade.[34] European consumption grew astonishingly; for example, from 1663 to 1775, consumption in England and Wales increased twenty fold (Robbins, 1999). As the demand for sugar grew, supply was encouraged, and although the price was supported by the factors discussed above, prices fell and sugar consumption became no longer the preserve of the upper classes (see Robbins, 1999). Given the dominant role of sugar in the commodity indices prior to the 19th century, it is plausible to view the gradual decline of the indices as reflecting that of sugar until the occurrence of the commodity supply disruptions brought about by the combined efforts of the American War of Independence, the French Revolution and the Napoleonic Wars from 1776-1812 (see O'Rourke, 2006).

4.2 Analysis of cyclical components

Table 4 provides summary measures of the cyclical components when the Christiano and Fitzgerald (2003) filter is applied to the aggregate commodity prices series over the full sample (1650-2010) and some relevant sub-samples. The sub-samples considered are primarily based around the estimated break dates identified in the earlier part of the empirical results. Additionally, the period 1900-2010 is examined, given that a starting value of 1900 is consonant with the common initial date used in the extant literature. A graphical representation of the full sample cyclical components is given in Figures 6 and 7.

Column 2 of Table 4 shows the standard deviation of the long-term cyclical component LC_t, and column 3 shows the ratio of the standard deviations of LC_t and the total non-trend cyclical component $SC_t + LC_t$. The range of this ratio extends from 0.709 to 0.896 and, analogously to HKMW, indicates the primacy of the long-term component in cyclical commodity price movements. The mean periodicity of the LC_t cycles (see column 4) ranges from 26.571 to 31.500 and appears to get longer as the sample moves into the 20th century. This increasing periodicity, accompanied by an

[34]It should not go without comment that the sugar trade was a major factor in the expansion of the Atlantic slave trade. As Robbins (1999, p.216) notes, "From 1701 to 1810 almost one million slaves were brought to Barbados and Jamaica to work on the sugar plantations".

increasing standard deviation, is further suggestive of the increasing amplitude that can be observed in Figures 6 and 7. Clearly, if long-term cycles are increasing both in amplitude and duration, policy initiatives to directly smooth commodity prices or producer or consumer incomes around a trend will require economic planning over increasingly long time horizons. Conversely, the mean periodicity of the SC_t cycles (see column 5) ranges from 3.529 to 4.255 and appears to get shorter as the sample moves into and through the 20th century. This is suggestive of increasing commodity price volatility, analogous to the results of Cashin and McDermott (2002), but placed in the context of a much longer time period.

5 Conclusions

This paper attempts the non-trivial task of constructing aggregate real commodity price series from 1650 to the present day. Moreover, employing techniques robust to whether or not series present a unit root, it is shown that the trend path of these series can be split into four regimes (i.e. 1650 to the early 1820s, the early 1820s to the early 1870s, the early 1870s to the mid-1940s, and the mid-1940s to 2010). Strikingly, through all but the second regime, a long-run downward trend can be detected, giving new historical support to the Prebisch-Singer hypothesis.

Given the typically large variance of real commodity prices relative to the trend, of great import to both consumers and producers of commodities are cycles about any secular deterioration. The ultra-long aggregate series presented in this paper provide many more observations to assess cycles than previously considered in the literature. Two prominent findings emerge: firstly, long-run cycles (often called "super-cycles" in the contemporary literature) last for approximately twenty seven years, but appear to be increasing in periodicity over the 20th century. By contrast, shorter-run cycles last for approximately four years but appear to be decreasing in periodicity. If this dual pattern continues (i.e. longer super-cycles but higher short-run volatility) it will clearly present new challenges for policy makers in the 21st century and beyond.

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Data Appendix

to do

Table 1. Tests for a negative trend and estimated growth rates.

	z_λ	$t_\beta^{RQF}(MU)$	Growth Rate (%)	90% c.i.	95% c.i.	99% c.i.
Panel A. 1650-2010						
CCPI	−2.40***	−16.67***	−0.90	−0.99, −0.81	−1.01, −0.80	−1.04, −0.76
CCPI′	−3.64***	−17.42***	−0.86	−0.94, −0.78	−0.96, −0.77	−0.99, −0.74
Panel B. 1900-2008						
CCPI	−0.86	−0.25	−0.32	−2.40, +1.77	−2.79, +2.16	−3.56, +2.93
CCPI′	−0.47	−0.37	−0.35	−1.87, +1.18	−2.16, +1.47	−2.73, +2.03
GYCPI	−2.49***	−4.08***	−0.58	−0.81, −0.34	−0.85, −0.30	−0.94, −0.21

Note: *** denotes rejection at the 1% significance level.

Table 2. Sequential tests for multiple breaks in level/trend.

	CCPI		CCPI′	
	$F_T(l+1\,\|\,l)$	Estimated break date(s)	$F_T(l+1\,\|\,l)$	Estimated break date(s)
$F_T(1\,\|\,0)$	7.81***	1820	8.99***	1881
$F_T(2\,\|\,1)$	8.09***	1823, 1946	9.11***	1823, 1946
$F_T(3\,\|\,2)$	15.71***	1820, 1872, 1946	15.64***	1820, 1873, 1946

Note: *** denotes rejection at the 1% significance level.

Table 3. Tests for a negative trend in sub-sample regimes.

		CCPI	CCPI′
1650-1820	$H_0 : \beta = 0$	−9.78***	−13.03***
1821-1872/3	$H_0 : \beta + \gamma_1 = 0$	−0.92	−2.03**
1873/4-1946	$H_0 : \beta + \gamma_1 + \gamma_2 = 0$	−4.37***	−5.59***
1947-2010	$H_0 : \beta + \gamma_1 + \gamma_2 + \gamma_3 = 0$	−2.29**	−4.10***

Note: ** and *** denote rejection at the 5% and 1% significance levels respectively.

Table 4. Summary measures of cyclical components.

Panel A. CCPI					
	$s.d.(LC_t)$	$s.d.(SC_t)$	$\frac{s.d.(LC_t)}{s.d.(SC_t+LC_t)}$	Mean periodicity (LC_t)	Mean periodicity (SC_t)
1650-2010	0.147	0.097	0.832	27.273	4.140
1650-1872	0.098	0.095	0.709	26.571	4.255
1873-2010	0.194	0.099	0.888	31.500	4.094
1900-2010	0.220	0.108	0.895	31.500	3.815
1947-2010	0.229	0.109	0.896	25.000	3.529

Panel B. CCPI′					
	$s.d.(LC_t)$	$s.d.(SC_t)$	$\frac{s.d.(LC_t)}{s.d.(SC_t+LC_t)}$	Mean periodicity (LC_t)	Mean periodicity (SC_t)
1650-2010	0.135	0.096	0.813	27.182	4.140
1650-1873	0.098	0.095	0.710	26.571	4.231
1874-2010	0.168	0.096	0.865	30.500	4.226
1900-2010	0.191	0.104	0.876	31.000	3.962
1947-2010	0.170	0.102	0.841	24.000	3.867