Long-Run Commodity Prices, Economic Growth and Interest Rates: 17th Century to the Present Day

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Abstract

A significant proportion of the trade basket of many developing countries is comprised of primary commodities. This implies relative price movements in commodities may have important consequences for economic growth and poverty reduction. Taking a long-run perspective, we examine the historical relation between a new aggregate index of commodity prices, economic activity and interest rates. Initial empirical tests show that commodity prices present a downward trend with breaks over the entire industrial age, providing clear support for the Prebisch-Singer hypothesis. It would also appear that this trend has declined at a faster rate since the 1870s. Conversely, several GDP series such as World, Chile, China, UK and US, trend upwards with breaks. Such trending behaviour in both commodity prices and economic activity suggests a latent common factor like technological innovation.

To assess the relationships between economic series, we apply a stationary VAR (Vector Autoregression) to model movements around trends. Strikingly, there is evidence that commodity prices Granger cause income and interest rates, whilst interest rates Granger cause commodity prices. From these results and

the related impulse response function analysis, the historical perspective provides some useful information for contemporary policy makers. For example, loose monetary policy has tended to support higher commodity prices. Moreover, commodity price movements have an asymmetric country effect on economic activity; periods of falling commodity prices will support GDP growth for commodity importers like the US but depress growth for commodity exporters such as Chile.

Keywords: Primary commodities; Prebisch-Singer hypothesis; Economic growth; Interest rates; Structural breaks; VAR.

JEL Classification: O13; C22.

1 Introduction

A significant proportion of national income for many developing countries is often generated by a small number of primary commodities (see Harvey *et al.*, 2010), leading to a possible resource curse.[1] The nature and causes of any long-run trends and short-run movements in primary commodity prices therefore have significant implications for growth and poverty reduction policies in developing countries.

Analysis of long-run commodity prices is dominated by the Prebisch-Singer (PS) hypothesis which implies a secular, negative trend in commodity prices relative to manufactures.[2] 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

[1]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.

[2]See Prebisch (1950) and Singer (1950).

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. Additionally, as is noted in Arezki *et al.* (2014a), understanding the trend and other time series characteristics should enable improved forecasting of commodity price movements.

Empirical evidence examining the PS hypothesis provides an ambiguous picture. The vast majority of recent studies employ the Grilli and Yang (1988) dataset of 24 annual non-fuel primary commodity prices which commences in 1900.[3] However, the relatively large variance of commodity prices (see Deaton, 1999) and the possibility of trend structural breaks inhibits statistical determination of any trend magnitude and direction with this sample size. A possible approach to address this issue is to provide greater degrees of freedom via a backwards extension of the sample. Recently, Harvey *et al.* (2010) and Arezki *et al.* (2014b) employ a unique disaggregated dataset, comprised of 25 separate commodity time series and spanning the 17th to the 21st centuries.

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

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

Miller and Urdinola, 2010).

Some studies have attempted to identify the macroeconomic variables that influence the behaviour of commodity prices around any long-run trend. Amongst others, the structural approach of Gilbert (1989) and Chu and Morrison (1986) demonstrated that two demand side variables, the US dollar real exchange rate and industrial production of industrialised countries, adequately explained movements in commodity prices over the early 1980s. After 1984, when industrial countries started to recover from recession, this demand-side framework failed to explain the continuing weakness in prices. In response, Borensztein and Reinhart (1994) extended the traditional framework to include supply side factors, the relative price of oil and a new definition of demand, encompassing output changes from Eastern Europe and the Soviet Union. The model greatly improved empirical explanation of commodity price movements over the 1980s and early 1990s. More recent work, such as Arango et al. (2012), stresses that economic activity and interest rates are the primary determinants of commodity prices.

Papers attempting to explain movements in commodity prices typically use post World War 2 data. For example, the aforementioned Arango *et al.* (2012), employs annual data from 1960 to 2006. Our paper takes a different tack by examining relationships between commodity prices, economic activity and interest rates over the very long-run. To do so, we first create an aggregate index for real commodity prices. This is achieved by collecting a large historical dataset on the export values of 23 individual commodities; not a straightforward task. These new data are then used as weights when combined with updated individual commodity series from Harvey *et al.* (2010) to construct the aggregate annual series beginning in 1650 and running continuously until 2014. Additionally, data for interest rates are obtained from the Bank of England, whilst historical GDP data (i.e., for the World and various individual countries) are obtained from the Maddison Project.

As a precursor to the multivariate approach, our second contribution is to examine

the time series properties, and in particular the trend, of the long-run series. Given the well known problems of identifying the order of integration of commodity price or GDP series, and the pervasive influence of any unit root/stationarity pre-tests on subsequent tests of commodity time series characteristics (see Harvey *et al.*, 2010), we apply trend tests and multiple trend break tests which are robust to whether or not the series under consideration contains a unit root. The results show that the trend path of our new aggregate commodity 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 2014). Through all but the second regime, a long-run downward trend can be clearly detected, giving new historical support to the PS hypothesis. Moreover, although prices present a secular decline over the 17th and 18th centuries, this was at a slower rate as compared with the 20th century. The economic forces behind the PS hypothesis would appear to have intensified during the 1900s.

In terms of economic activity, it is shown that UK GDP presents an upward trend break in the 1820s and World GDP in the 1870s and 1950s. Interestingly, these dates are closely associated with those found for commodity prices. Additionally, the increasing rate of trend growth in GDP as the sample increases, mirrors the decreasing rate of trend growth for commodity prices, suggesting a common latent factor such as technological innovation.

Our third contribution is to model the relationships between our long-run series. The data are first demeaned and detrended according to the breaks found in the prior time series analysis. These detrended series are shown to be stationary and therefore, unlike other recent literature which does not allow for breaks, a cointegration approach is not appropriate. Using a stationary VAR (Vector Autoregression), there is evidence that (detrended) commodity prices Granger cause (detrended) GDP and interest rates, whilst interest rates Granger cause commodity prices. Such results have implications for the resource curse and the effect of monetary policy.

The remainder of the paper is organised as follows. Section 2 outlines the theory and empirical methodology, whilst section 3 describes the new data. The empirical results and associated discussion are presented in section 4, and section 5 concludes.

2 Theory and Empirical Methodology

2.1 Demand and supply in the commodity market

The theory of either long-run trend or cyclical movements about the trend are not well developed or evidenced (see Deaton and Laroque, 2003). As noted in the introduction, rationales for the trend include low income elasticities of demand for commodities, technological and productivity differentials or asymmetric market structures between the oligopolistic, manufacturing core and the competitive, commodity producing south. Additionally, new discoveries of commodities and technological innovation[4] in commodity production will increase supply and reduce costs respectively, also placing downward pressure on the trend in commodity prices. Movements around any trend, and including macroeconomic variables mentioned by the literature such as economic activity (see Borenszstein and Reinhart, 1994) and interest rates (see Frankel, 2006), might be described by the following partial equilibrium model. Using a standard log-linear demand function (see Deaton and Laroque, 2003), it can be written that:

$$d_t = \alpha y_t - \beta p_t + \gamma + \varepsilon_t^d \tag{1}$$

where d_t is demand, y_t represents the logarithm of world income. and p_t is the world price for an internationally traded commodity. Moreover, a complimentary supply function (see Arango *et al.*, 2012) can be stated:

$$p_t = \delta s_{t-1} + \eta r_{t-1} + \theta p_t + \varepsilon_t^s \tag{2}$$

[4]We thank an anonymous reviewer for this point.

where s_t is current supply as a function of last period's supply and r_t represents the interest rate. In equilibrium, supply is equal to demand, and it can be shown that:

$$p_t = (\beta + \delta)^{-1}[\alpha y_t + \gamma - \delta s_{t-1} + \eta r_{t-1} + \varepsilon_t^d - \varepsilon_t^s] \tag{3}$$

where (3) suggests that commodity prices around any trend are related to income, interest rates and supply. Of course, before examining any multivariate association, the time series properties of each individual series requires investigation. Given we will employ very long-run data, breaks in the individual data generating processes (DGP) are likely. Therefore, the following sections will outline our testing procedure for trends and any breaks in trends and levels.

2.2 Testing for a linear trend

We initially consider the following DGP for z_t, the logarithm of a variable of interest:

$$z_t = \alpha + \beta t + u_t, \quad t = 1, ..., T \tag{4}$$

$$u_t = \rho u_{t-1} + \varepsilon_t, \quad t = 2, ..., T \tag{5}$$

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 issues like the PS hypothesis, 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, Perron and Yabu (2009a) propose tests of $H_0 : \beta = 0$ that are robust to the order of integration properties of the underlying errors u_t. We denote the two alternative versions by $t_\beta^{RQF}(MU)$ and $t_\beta^{RQF}(UB)$; Perron and Yabu

show that these statistics both follow an asymptotic standard normal distribution under the null $H_0 : \beta = 0$.

2.3 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 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, Harvey *et al.* (2010) 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 our long historical time series contain more than one structural break, 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 (4) with the following specification:

$$z_t = \alpha + \beta t + \sum_{j=1}^{m} \delta_j DU_{jt}(T_j^B) + \sum_{j=1}^{m} \gamma_j DT_{jt}(T_j^B) + u_t, \quad t = 1, ..., T \tag{6}$$

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. Although the limit null distribution of their *Exp-W* test statistic 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.[5]

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 (i.e., $l = 1$), and proceed to examine evidence for more than one break by estimating the test statistic $F_T(l+1\,|l)$ and comparing with critical values provided by Kejriwal and Perron. 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.

3 Data

3.1 Commodity prices, historical exports and aggregation

The often employed Grilli-Yang dataset comprises twenty-four, internationally traded, non-fuel commodities.[6] Each annual nominal commodity price series (in US dollars) 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

[5] In this paper, π, the trimming parameter, is set to 0.10 to exclude breaks at the very beginning or end of the sample.

[6] 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.

countries. Although a number of papers in the extant literature examine the twenty-four commodities separately, many employ Grilli and Yang's weighted aggregate real index to summarise the behaviour of relative commodity prices as a whole.[7]

As noted in the introduction, the Grilli-Yang 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, Harvey *et al.* (2010) created a large and representative dataset of twenty five relative commodity price series[8] (nominal prices in British pound sterling[9]) covering a 356 year period from 1650 to 2005.[10] 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 Grilli-Yang 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.[11]

Harvey *et al.* (2010) 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 se-

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

[8]See the appendix of Harvey *et al.* (2010) for a fuller description of the source of each price.

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

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

[11]For details on the construction of HPIM see Harvey *et al.* (2010).

ries for all commodities are not available uniformly over the period 1650 to the present day. Let the Composite Commodity Price Index (CCPI) be the weighted average of twenty-three Harvey *et al.* (2010) commodities, where the weights reflect the importance of each commodity in total commodity trade.[12]

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 Grilli-Yang non-fuel weighted aggregate real index (GYCPI).[13] 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 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 Harvey *et al.* (2010), this result suggests that export unit values used to construct the MUV index are potentially biased

[12]In this paper, we employ an extended Harvey *et al.* (2010) commodity and manufacturing price dataset that runs from 1650 to 2014. 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.

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

measures of price movements, particularly when long data series are considered.[14]

3.2 Other historical macroeconomic data

In section 2, it was suggested that macroeconomic variables related to commodity prices include income, interest rates and supply. Although annual data on quantities traded for many commodities is only available post-World War 2, longer-run series are available for income and interest rates. For example, in terms of income, we initially source our income data, similarly to Erten and Ocampo (2013), from Angus Maddison's data, updated recently by the Maddison Project.[15] From here we obtain (i) World GDP[16] for 1820-2009 (ii) USA GDP from 1820-2009 (iii) Chile GDP from 1870-2009 and (iv) China from 1950-2009. Of course, the UK became the world's pre-eminent economy over the course of the 17th to 19th century and by the early 1800s had the highest per capita income in the world (see Bolt and Van Zenden, 2013). However, Maddison's annual data for UK GDP only goes back to 1800. Recently, Broadberry *et al.* (2011) produced a real output series for the UK from 1270 to 1870, and we use these data from 1650.

Finally, sources of historical interest rate data are more difficult to obtain but the Bank of England (see Hills *et al.*, 2010) have recently made available annual data on long-term UK government bonds from 1703 and this is used in our later analysis.

[14]Harvey *et al.* (2010) 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.

[15]See http://www.ggdc.net/maddison/maddison-project/home.htm

[16]Analogously to Erten and Ocampo (2013) we use the annual GDP series for the World with complete data from 1950 onwards and discrete values for 1820, 1870, 1913 and 1940. The missing values are interpolated using data for 16 OECD countries from 1870, and the 7 available OECD countries from 1820.

4 Empirical results and discussion

4.1 Commodity price trend function analysis

Table 1 shows the results of applying the order of integration robust trend test $t_{\beta}^{RQF}(MU)$ presented in section 4.1 to the new relative commodity price indices outlined in section 3.[17] The table also reports estimated growth rates and confidence intervals based on the quasi-feasible GLS (Generalized Least Squares) approach of Perron and Yabu (2009a). 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 just below 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 2.3. 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, and, if a rejection is obtained in favour of $l+1$ break(s), the estimated

[17] The $t_{\beta}^{RQF}(UB)$ test gives analogous results and is therefore not reported. Additionally, the z_{λ} test of Harvey *et al.* (2007) also gives similar results that are available on request from the authors.

break date(s) obtained at each stage 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 SSR dates, i.e. the fitted values from (6), given by:

$$\begin{aligned}
\text{CCPI:} \qquad p_t &= 2.88 - 0.0079t \\
&\quad + 0.34DU_{1t}(1820) + 0.0031DT_{1t}(1820) \\
&\quad - 0.37DU_{2t}(1872) - 0.0087DT_{2t}(1872) \\
&\quad + 0.48DU_{3t}(1946) - 0.0003DT_{3t}(1946) + \hat{u}_t
\end{aligned}$$

$$\begin{aligned}
\text{CCPI}': \qquad p_t &= 2.88 - 0.0079t \\
&\quad + 0.34DU_{1t}(1820) + 0.0032DT_{1t}(1820) \\
&\quad - 0.39DU_{2t}(1873) - 0.0080DT_{2t}(1873) \\
&\quad + 0.69DU_{3t}(1946) - 0.0015DT_{3t}(1946) + \hat{u}_t
\end{aligned}$$

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 (6)): $H_0 : \beta = 0$ 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. 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.

The vast majority of work has examined the PS hypothesis over the post-1900 period but we can now additionally comment on its relevance prior to the 20th century. Strikingly, our 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 -1.38% per annum for CCPI, and -0.79% to -1.42% 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[18]. This identification of changing trend behaviour provides new characterisations of historical price behaviour – for example, the 19th century terms of trade boom (see Williamson, 2008) 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 suggest 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

[18]Sumner (2009) notes that agricultural commodity prices rose sharply through World War II to post-war spikes. Additonally, we acknowledge that if individual commodities have differing trends as suggested by the work of Harvey et al. (2010) and others, reweighting could induce a break in trend even where there are no breaks in the individual commodity series. We thank an anonymous referee for this latter point.

causes behind the modern incarnation of the PS hypothesis therefore appear arguably stronger than those that existed in the more distant past – we shall return to this later.

4.2 Macroeconomic variables trend function analysis

The results of the trend and trend break tests for our macroeconomic series are shown in Tables 4 and 5 respectively.[19] Interestingly, UK GDP (plotted in Figure 6) shows a significant and positive trend growth rate of 1.28% per annum over the 1650 to 1870 sample period. Moreover, a positive break in the trend in 1817, captures the UK's rising industrial production driven by technological advances in manufacturing and growth, and closely matches the first break found in our CCPI series.

The US overtook the UK in terms of GDP in the 1870s (see Broadberry and Klein, 2011) and the rest of the industrial core also grew strongly over much of the 19th and 20th century. This is reflected in the growth of World GDP plotted in Figure 7 for 1820-2009. Table 4 shows the trend presents a growth rate of 2.23% per annum whilst Table 5 shows breaks of a positive sign occur in the trend during the 1870s and 1950s. Again, these breaks closely match those identified for earlier CCPI series. Overall, it would appear that since the 1870s, increasing rates of trend economic growth in World GDP are associated with declining trend rates in relative commodity prices. Both trends may reflect a latent common factor such as increasing technological innovation.

Of course, since the mid-1990s and over most of the first decade of the 21st century, commodity prices rose (see Figures 1 and 2). Academics (see, for example, Cuddington and Jerrett, 2008) and commentators alike asked whether prices were in a positive growth phase of a supercycle; a medium length cyclical movement with a periodicty between 20 and 40 years. Explanations for higher prices include the rapid economic growth delivered by China and other modernising developing economies, and therefore

[19] Given the shorter sample period available for the macroeconomic series, we set the maximal number of breaks to two.

Figure 8 plots the available Maddison GDP data for China from 1950 .[20] Interestingly, China's path of trend growth broke positively around the late 1970s and has since shown particularly high growth rates of 7.5% per annum. If this continued, real commodity prices could remain supported above trend (similar to the mid-19th century) for a number of years. However, recent price falls occurred during 2014 and are associated with falling oil prices and concerns around the future economic growth of countries like China.

Finally, before examining the relationship between commodity prices and macroeconomic variables, we note that the interest rate, as one might expect, presents no trend.

4.3 Stationary VAR analysis

Recent work such as Erten and Ocampo (2013) has tested whether real commodity prices and income are cointegrated. To assess whether this approach is appropriate, we first test each series for a unit root. Table 6 presents results of ADF-type unit root tests that account for the breaks in level/trend that we have previously determined. Specifically, we conduct the additive outlier unit root t-tests of Perron (1989) (incorporating the Perron and Vogelsang (1993) correction), extended appropriately to the multiple break case, with critical values obtained by simulation of the corresponding limit distributions, conditioning on the number and timing of breaks in each case. The lag order is determined using the Schwarz Information Criterion with a maximum of 12 lagged differences. We find evidence in favour of stationarity (around the broken trend function) for all series except the interest rate. A cointegration approach is therefore not appropriate, and we proceed to analyse the relationships between the variables using a stationary VAR analysis, based on the de-trended commodity price and GDP series, i.e. the residuals from estimation of (6), along with the first differences of the

[20] As the China series only contains 61 observations, we set the maximal number of breaks in this series to one.

interest rate. A stationary VAR(p) of the following form is estimated:

$$z_t = v + A_1 z_{t-1} + ... + A_p z_{t-p} + u_t, \quad t = 1, ..., T \tag{7}$$

where $z_t = (z_{1t}, ..., z_{kt})'$. Following Lütkepohl (2005), lag lengths are chosen for pairs of commodity price series[21] and GDP, and where data are available, combinations of commodity prices, GDP and interest rates, by comparing the results of a selection of information criteria (IC)[22]. Table 7 shows the results of Granger causality tests, within the different VAR frameworks. By way of explanation, consider Panel A which refers to a VAR(1) of CCPI and a joint UK-World GDP series that covers the entirety of our sample period. Here the p-value of 0.044 suggests that CCPI Granger causes GDP. Taken as a whole, the other results in Table 7 confirm that commodity prices appear to Granger cause income and interest rates, whilst interest rates[23] tend to Granger cause prices. Interestingly, these implications hold whether we examine combinations of our composite commodity price index and US GDP or individual commodity price series like copper, with GDP from commodity exporting economies like Chile.

Of course, we might expect shocks to composite commodity prices on US GDP, to have a different affect to those shocks to copper prices on Chile GDP. Impulse response functions, show this to be the case, with positive innovations to CCPI leading to a fall in US GDP (see Figure 9), whilst a similar innovation to the copper price sees a rise in Chile GDP (see Figure 10). It is notable that innovations to interest rates cause a fall in commodity prices, whilst innovations to prices lead to a rise in interest rates no matter what combination of prices and interest rate we observe.

[21] We only show results for CCPI in the multivariate analysis, as the results with CCPI′ are similar. China is removed from this section of analysis as its GDP data are only available annually from 1950.

[22] Using a maximum lag length of 8 years, we use the Schwarz, Akaike and Hannan-Quinn Information Criterion. When the ICs agree, that lag length is selected. When they disagree, the IC that shows the most evidence of Granger causality is displayed

[23] Using consumer price level data from 1704 (see Hills *et al.*, 2010), we also formed the real interest rate. However, the constructed variable appears very variable until the second half of the 20th century. Additionally, this variable did not appear at all related to either commodity prices or economic activity.

5 Conclusions

Many developing countries present export earnings that are primary commodity dependent. Therefore, the presence of a secular decline in primary commodity relative prices as implied by the Prebisch-Singer hypothesis, suggests that unless developing countries diversify into manufactures and/or services, they will incur long-run economic stagnation. However, as Deaton and Laroque (2003) note, the literature has a relatively limited understanding of both the causes of the long-run path in relative commodity prices and any movements around that path. Given the recent availability of relevant historical data, we suggest a very long-run approach to examine both issues.

First, we suggest that aggregating relative commodity prices over the very long-run can smooth idiosyncratic effects and provide summary series shaped primarily by common factors. To this end, this paper constructs new aggregate real commodity price series from 1650 to 2014. The series are created by combining a new historical dataset on the export values of 23 commodities, with the individual commodity price dataset from Harvey *et al.* (2010). Subsequently, employing multiple break techniques robust to whether or not each series contains a unit root, it is shown that the trend path of these series can be partitioned 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 2014). A long-run downward trend is estimated in all but the second regime, revealing that the Prebisch-Singer hypothesis has relevance for the 17th, 18th and 20th centuries at least. However, it is also shown that the series declined at a slower rate over the 17th and 18th centuries as compared with the 20th century, suggesting that the economic forces underlying the hypothesis intensified over this recent period.

Secondly, again employing multiple break techniques, we examine the time series behaviour of several macroeconomic series over our long sample period. As might be expected a number of breaks are found and in particular, it is shown that breaks in the trend growth rate of the UK (1650 to 1870) and the World GDP (1820-2010) are

dated analgously to those in the trend of commodity prices. This increasing rate of trend growth in GDP as the sample increases, coupled with the decreasing rate of trend growth for commodity prices, suggests a common latent factor such as technological innovation may be behind both. Certainly, *inter alios*, Sachs and McArthur (2002) stress that technological innovation is a fundamental driver of long-run economic growth.

Thirdly, given recent work has suggested economic activity and interest rates are related to commodity prices, we model the relationships between our long-run series. As a precursor to this, the data are initially demeaned and detrended according to the breaks found. Although income and commodity prices are often modelled as I(1) in the literature, our residual series are typically found to be I(0) and therefore we adopt stationary VAR approach. Strikingly, whether we assess large economy GDP like the US with composite price indices or commodity exporting countries such as Chile and the real price of its copper exports, there is evidence that commodity prices Granger cause GDP and interest rates, whilst interest rates Granger cause commodity prices.

There would appear to be several lessons for the present day. For example, it would appear likely, given our analysis, that the recent loose monetary policy supported higher commodity prices. However, now that such prices are falling, policymakers should note the historical asymmetric effect: a GDP boost for commodity importers but a fall for commodity exporters. The recent slowdown in the growth of BRIC (Brazil, Russia, India, China) countries appears likely to continue whilst commodity prices remain low.

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6 Data Appendix

6.1 Commodity data sources

The weighted average commodity price indices are constructed using export values from developing countries as weights, over the period 1830-2014. The sources used are as follows:

1. 1830-1937. Principle source (for commodities Banana, Beef, Cocoa, Coffee, Cotton, Hides, Jute, Oil, Pig Iron, Sugar, Tea, Tobacco, Wheat and Wool): Commodity Structure of Third World Exports 1830-1937, Paul Bairoch and Bouda Etemad, Centre of International Economic History, University of Geneva.

2. 1830-1937. Secondary sources (for commodities Aluminum, Coal, Copper, Lamb, Lead, Nickel, Rice, Tin and Zinc); imports to developed countries are used as a proxy for exports from developing countries:

   (a) US Geological Survey;

   (b) Statistical Yearbook of Canada, 1899;

   (c) Annuaire Statistique de la France, Vol. 19, 1899;

   (d) Entwicklung und Strukturwandlungen des Englischen Außenhandels von 1700 bis zur Gegenwart, Werner Schlote, Probleme der Weltwirtschaft, Jena Fischer, 1938;

   (e) Statistical Abstract for the United Kingdom in Each of the Last Fifteen Years from 1871 to 1885, HMSO, 1986.

3. 1938-2014. All data from 1962-2014 are obtained from the from the Comtrade database, http://comtrade.un.org/data/. Trade weights between 1938 and 1961 are all linearly interpolated.

6.2 Composite commodity price index construction

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 $t = 1, ..., x$ years and then for N commodities in the next $t = x+1, ..., y$ years, individual CPI series are first constructed for each period $t = 1, ..., x+1$ and $t = x+1, ..., y$ using data on $N-1$ and N commodities, respectively. Next, denote by $w_{i,x+1}^{N-1}$ and $w_{i,x+1}^{N}$ the weights employed in these two schemes for the overlapping year $t = x+1$. Then, using the ratio $\sum_{i=1}^{N} w_{i,x+1}^{N} p_{i,x+1} / \sum_{i=1}^{N-1} w_{i,x+1}^{N-1} p_{i,x+1}$, the aggregate series is created by multiplying the ratio by the individual CPI values for the $t = 1, ..., x$ period and splicing the individual series together to assemble the CCPI.

Several benchmark years, namely 1830, 1860, 1900, 1912, 1928, 1937 and 1962 onwards are used to calculate the weights of commodities. Specifically, exports of commodities from the commodity-dependent price-taking economies (the periphery[24]) are used as weights. 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,

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

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 1962; to complete the series, 1830 weights are used before 1830 and annual weights are used after 1962 until 2014. 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 are 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 365 year period from 1650 to 2014.

Figure 1. Logarithms of CCPI and CCPI′, 1650-2014: — CCPI, $\cdots$ CCPI′

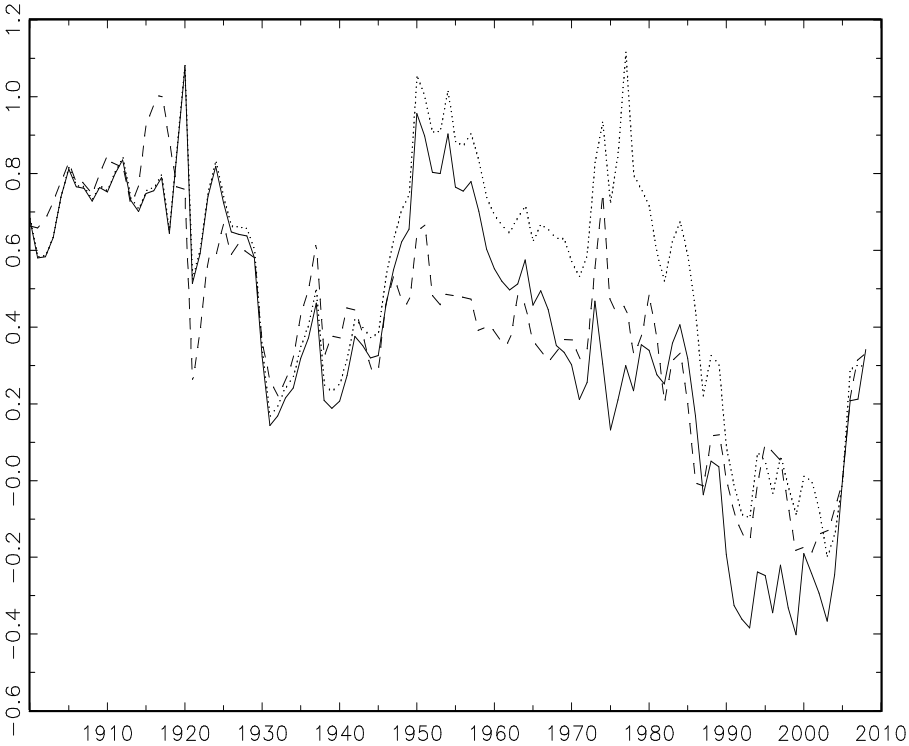

Figure 2. Logarithms of CCPI, CCPI′ and GYCPI, 1900-2008: — CCPI, $\cdots$ CCPI′, - - - GYCPI

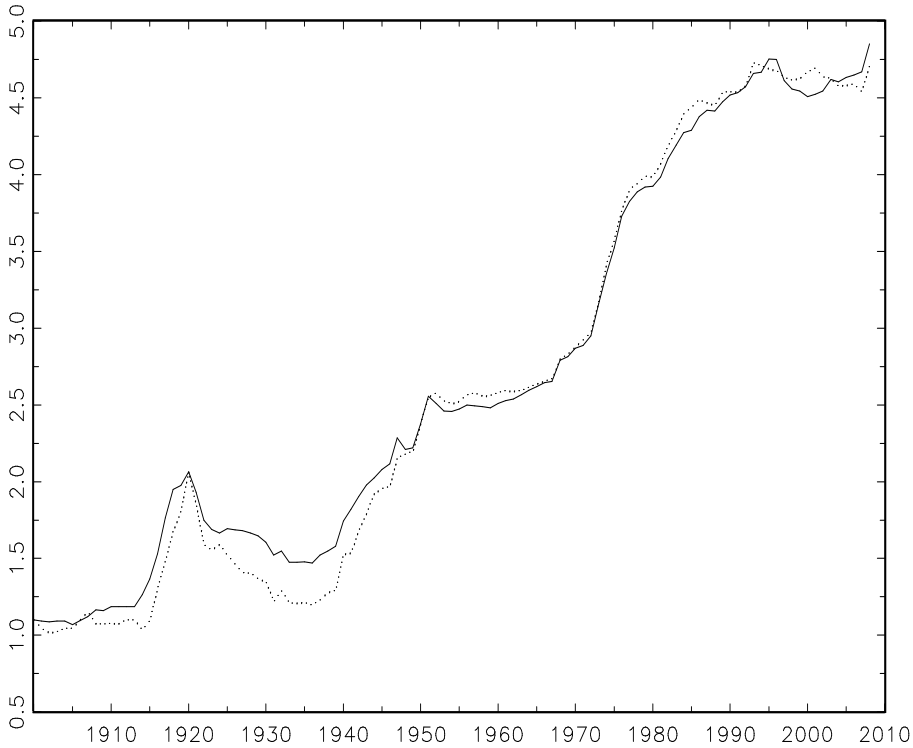

Figure 3. Logarithms of HPIM and MUV deflators, 1900-2008: — HPIM, $\cdots$ MUV

Figure 4. Logarithms of CCPI and fitted broken trend, 1650-2014: — CCPI, - - - fitted values

Figure 5. Logarithms of CCPI′ and fitted broken trend, 1650-2014: — CCPI′, - - - fitted values

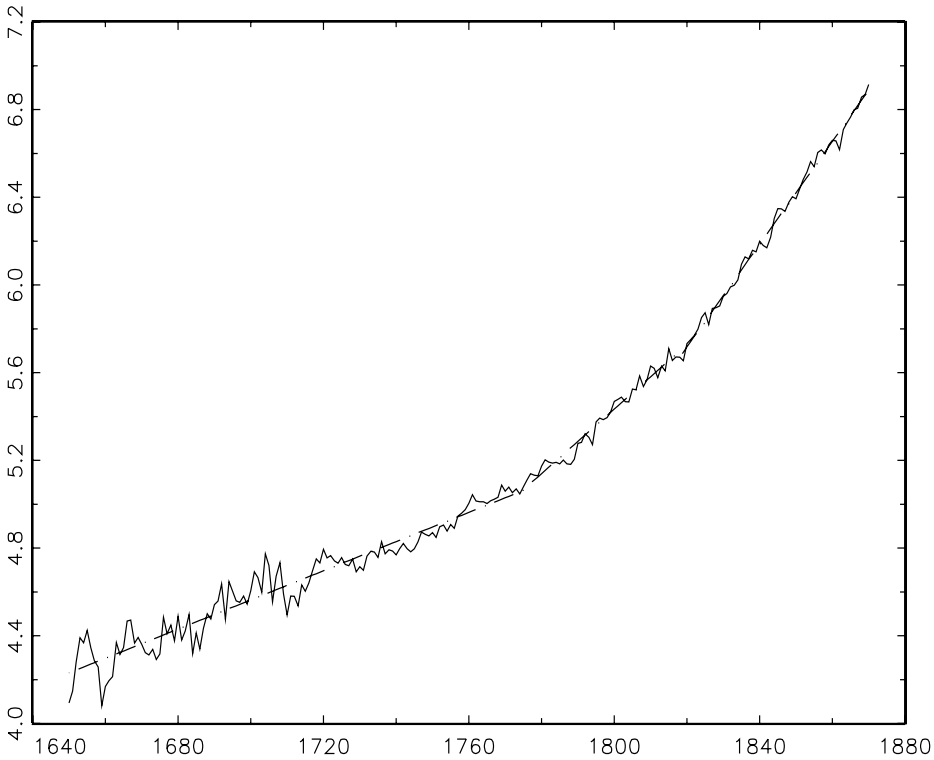

Figure 6. Logarithms of UK GDP and fitted broken trend, 1650-1870: — GDP, - - - fitted values

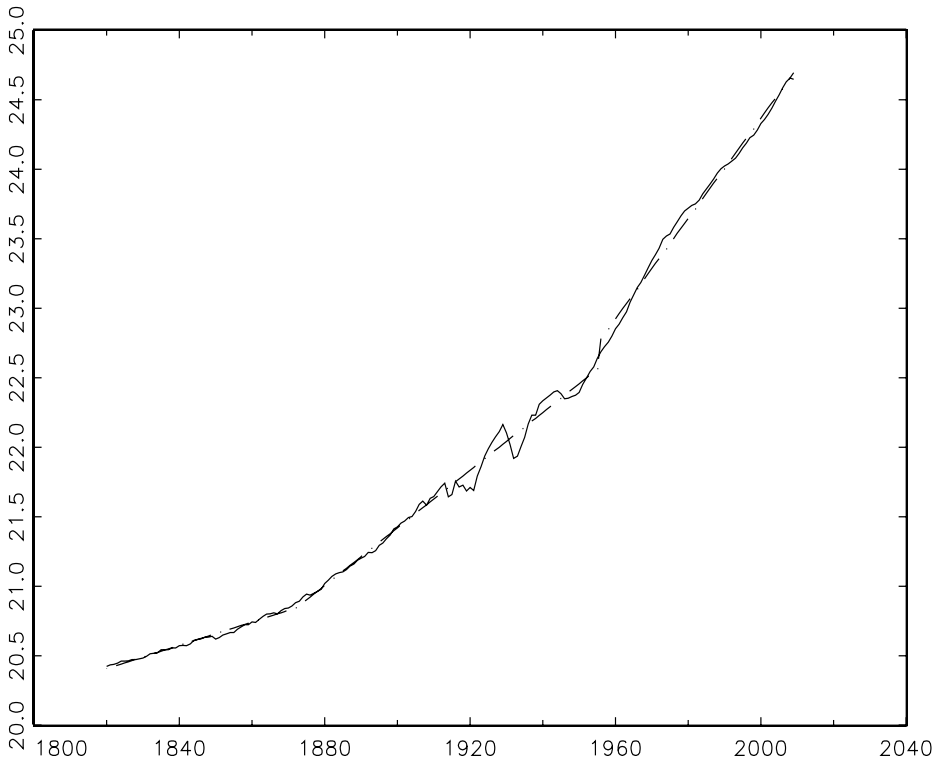

Figure 7. Logarithms of World GDP and fitted broken trend, 1820-2009: — GDP, - - - fitted values

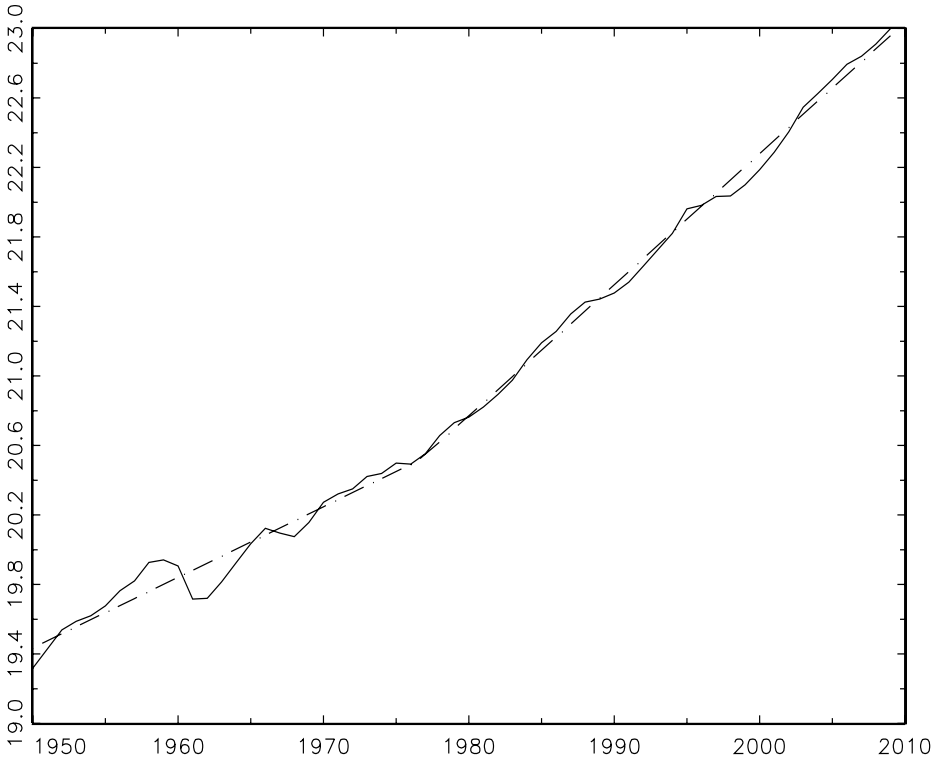

Figure 8. Logarithms of China GDP and fitted broken trend, 1950-2009: — GDP, - - - fitted values

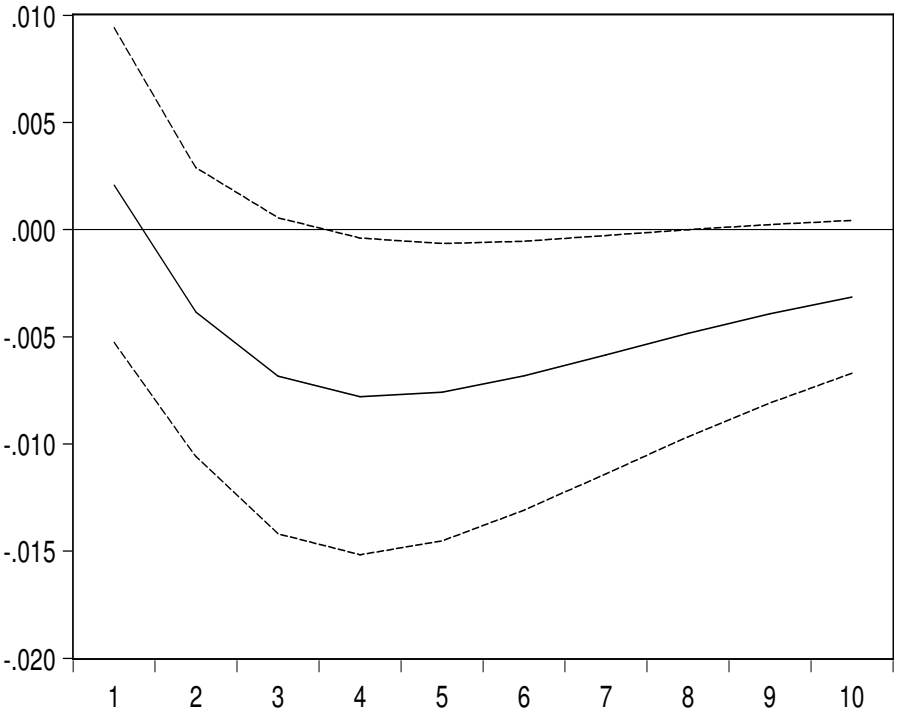

Figure 9. Response of USA GDP to Cholesky 1 s.d CCPI innovation

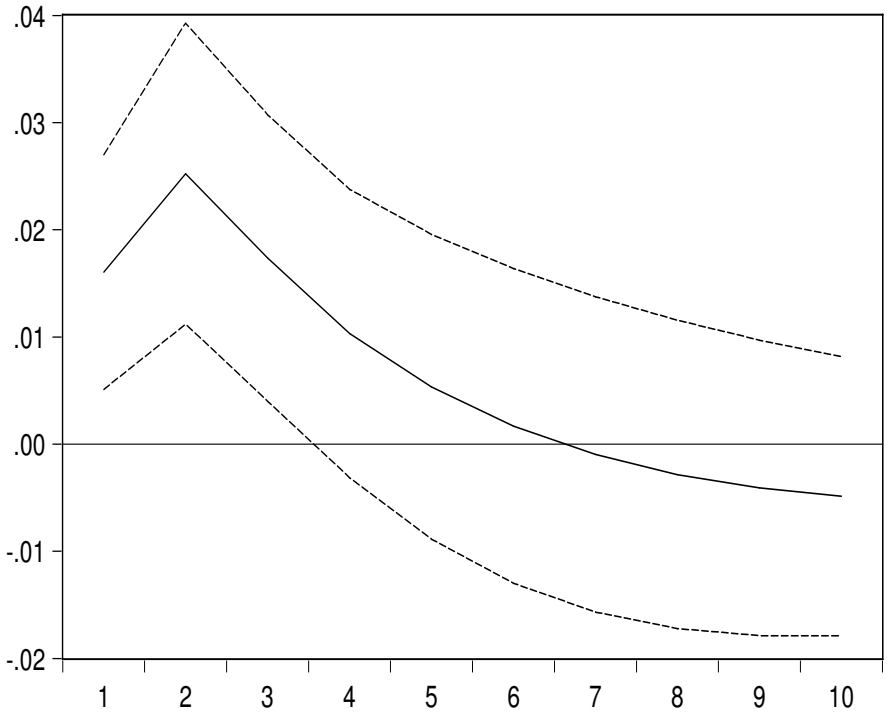

Figure 10. Response of Chile GDP to Cholesky 1 s.d Copper innovation

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

Panel A. 1650-2014					
	$t_\beta^{RQF}(MU)$	Growth Rate (%)	90% c.i.	95% c.i.	99% c.i.
CCPI	-17.45***	-0.88	$-0.96, -0.80$	$-0.98, -0.78$	$-1.01, -0.75$
CCPI′	-17.06***	-0.84	$-0.92, -0.76$	$-0.94, -0.74$	$-0.97, -0.71$
Panel B. 1900-2008					
	$t_\beta^{RQF}(MU)$	Growth Rate (%)	90% c.i.	95% c.i.	99% c.i.
CCPI	-0.25	-0.32	$-2.40, +1.77$	$-2.79, +2.16$	$-3.56, +2.93$
CCPI′	-0.37	-0.35	$-1.87, +1.18$	$-2.16, +1.47$	$-2.73, +2.03$
GYCPI	-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)
$F_T(1\,\|0)$	9.17***	1881	8.88***	1882
$F_T(2\,\|1)$	9.51***	1823, 1946	8.81***	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	$H_0 : \beta = 0$	-11.14***	-12.79***
1821-1872/3	$H_0 : \beta + \gamma_1 = 0$	-1.21	-2.02**
1873/4-1946	$H_0 : \beta + \gamma_1 + \gamma_2 = 0$	-5.17***	-5.40***
1947-2014	$H_0 : \beta + \gamma_1 + \gamma_2 + \gamma_3 = 0$	-2.31**	-3.30***

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

Table 4. Tests for a trend and estimated growth rates.

	$t_{\beta}^{RQF}(MU)$	Growth Rate (%)	90% c.i.	95% c.i.	99% c.i.
UK GDP (1650-1870)	4.65***	1.28	$0.83, 1.74$	$0.74, 1.82$	$0.57, 1.99$
World GDP (1820-2009)	5.44***	2.23	$1.56, 2.91$	$1.43, 3.04$	$1.18, 3.29$
USA GDP (1820-2009)	15.35***	3.45	$3.08, 3.82$	$3.01, 3.89$	$2.87, 4.03$
Chile GDP (1870-2009)	6.43***	3.22	$2.39, 4.04$	$2.24, 4.20$	$1.93, 4.50$
China GDP (1950-2009)	9.26***	6.24	$5.13, 7.35$	$4.92, 7.56$	$4.51, 7.96$
Interest rate (1703-2009)	-0.18	0.00	$-0.93, 0.75$	$-1.09, 0.91$	$-1.40, 1.22$

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

Table 5. Sequential tests for multiple breaks in level/trend.

	UK (1650-1870)	
	$F_T(l+1\,\|l)$	Estimated break date(s)
$F_T(1\,\|0)$	31.04***	1790
$F_T(2\,\|1)$	69.10***	1773, 1817
	World (1820-2009)	
	$F_T(l+1\,\|l)$	Estimated break date(s)
$F_T(1\,\|0)$	15.13***	1933
$F_T(2\,\|1)$	23.73***	1872, 1955
	USA (1820-2009)	
	$F_T(l+1\,\|l)$	Estimated break date(s)
$F_T(1\,\|0)$	11.53***	1913
$F_T(2\,\|1)$	8.45***	1930, 1945
	Chile (1870-2009)	
	$F_T(l+1\,\|l)$	Estimated break date(s)
$F_T(1\,\|0)$	3.70**	1930
	China (1950-2009)	
	$F_T(l+1\,\|l)$	Estimated break date(s)
$F_T(1\,\|0)$	12.07***	1976

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

Table 6. Unit root tests.

	ADF
CCPI (1650-2009)	−5.95***
CCPI′ (1650-2009)	−6.02***
UK GDP (1650-1870)	−7.75***
UK-World GDP (1650-2009)	−5.10**
World GDP (1820-2009)	−6.03***
USA GDP (1820-2009)	−4.39**
Chile GDP (1870-2009)	−4.13**
Interest rate (1703-2009)	−2.06

Note: *,** and *** denote rejection at the 10%, 5% and 1% significance levels respectively. The UK-World GDP series is an index of UK GDP until 1869 and then World GDP thereafter.

Table 7. VAR Granger causality tests.

Panel A. CCPI and UK-World GDP (1650-2009)

	p_t	y_t	r_t	All	Lag length
p_t	-	0.900	-	0.900	1
y_t	0.044	-	-	0.044	
r_t	-	-	-	-	

Panel B. CCPI, UK-World GDP, Interest Rates (1703-2009)

	p_t	y_t	r_t	All	Lag length
p_t	-	0.171	0.107	0.093	1
y_t	0.113	-	0.741	0.274	
r_t	0.349	0.373	-	0.386	

Panel C. CCPI and USA GDP (1820-2009)

	p_t	y_t	r_t	All	Lag length
p_t	-	0.683	-	0.683	1
y_t	0.027	-	-	0.027	
r_t	-	-	-	-	

Panel D. CCPI, USA GDP and Interest Rates (1820-2009)

	p_t	y_t	r_t	All	Lag length
p_t	-	0.900	0.064	0.170	1
y_t	0.045	-	0.152	0.028	
r_t	0.041	0.931	-	0.123	

Panel E. Copper and Chile GDP (1870-2009)

	p_t	y_t	r_t	All	Lag length
p_t	-	0.293	-	0.293	2
y_t	0.026	-	-	0.026	
r_t	-	-	-	-	

Panel E. Copper, Chile GDP and Interest Rates (1870-2009)

	p_t	y_t	r_t	All	Lag length
p_t	-	0.180	0.027	0.045	2
y_t	0.035	-	0.119	0.021	
r_t	0.015	0.005	-	0.001	

Note: Variables listed vertically are dependent, whilst those listed horizontally are potentially causal. Tabulated numbers are p-values.