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Super Cycles of Commodity Prices Since the Mid-Nineteenth Century

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Summary. — Decomposition of real commodity prices suggests four super cycles during 1865–2010 ranging between 30 and 40 years with amplitudes 20–40% higher or lower than the long-run trend. Non-oil price super-cycles follow world GDP, indicating they are essentially demand-determined; causality runs in the opposite direction for oil prices. The mean of each super-cycle of non-oil commodities is generally lower than for the previous cycle, supporting the Prebisch–Singer hypothesis. Tropical agriculture experienced the strongest and steepest long-term downward trend through the twentieth century, followed by non-tropical agriculture and metals, while real oil prices experienced a long-term upward trend, interrupted temporarily during the twentieth century.

Key words — super cycles, commodity prices, Prebisch–Singer hypothesis, band-pass filters

1. INTRODUCTION

The recent global economic crisis was preceded by a commodity price boom that was unprecedented in its magnitude and duration. The real prices of energy and metals more than doubled in five years from 2003 to 2008, while the real price of food commodities increased 75%. While in the former case prices reached one of the highest levels in history, in the case of agriculture it was a reversal of the strong downward trends experienced since the 1980s. In this sense, it can be said that there was a boom of mineral, not of agricultural prices. Similar to earlier commodity booms, the recent one came to end when the global economic growth slowed down, diminishing demand pressures on commodity prices. However, commodity prices started to recover surprisingly fast, in such a way that the world economy experienced again high commodity prices in 2010–12, which can be seen as a continuation of the 2004–mid 2008 boom. The remarkable strength and length of this upswing in commodity prices reflect the extraordinary resilience of growth performance of major developing country demanders of commodities, particularly China. [1]

The rapid pace of industrial development and urbanization in China, India, and other emerging economies has caught the attention of financial and metal industry analysts who argued that the world economy has been going through the early phases of a super-cycle expansion. This expansion is often defined as decades-long, above-trend movements in a wide range of commodity prices (Cuddington & Jerrett, 2008a, 2008b; Heap, 2005; Rogers, 2004). Super cycles differ from short-term fluctuations tied to microeconomic factors in two ways. First, they tend to span a much longer period of time with upswings of 10–35 years, generating 20–70 years complete cycles. Second, they are observed over a broad range of commodities, mostly inputs for industrial production and urban development of an emerging economy. For example, the rapid economic growth of the United States in the late nineteenth and early twentieth centuries gave rise to a super-cycle expansion in commodity prices. Another upswing took place during the post-war reconstruction in Europe, augmented by the economic emergence of Japan. According to Heap (2005), these two earlier super cycles in commodity prices were driven by the resurgence of demand for raw materials during the industrialization of a major economy or group of economies. Likewise, he attributes the current phase of super-cycle expansion to the rapid and sustained Chinese industrialization and urbanization. The demand-driven nature of these cycles also implies that the individual commodity prices tend to move together with strong positive correlation (Pindyck & Rotemberg, 1990).

The presence of super cycles in commodity prices matters for a number of decisions in production as well as in policy making. First, trends in commodity prices have been considered for a long time a central policy issue for commodity-dependent developing countries. Second, since the decision to increase capacity is directly related to expected future prices, and investment projects might take several years and even decades (when they involve the development of new regions) to complete in capital-intensive mining sectors, firms must pay special attention to such medium-term price trends as they make investment decisions. Third, financial investors used the recent surges in commodity prices as a way to hedge against potential risks in portfolio management. The new commodity indexes developed by financial corporations have not only become profitable investment vehicles, but also fueled demand in commodity markets.

Finally, the analysis of commodity prices in a super-cycle framework is an important innovation over the more traditional analysis of trends and structural breaks for at least two reasons. First, it allows us to analyze the gradual change in long-term trends instead of a priori assuming a constant deterministic or stochastic trend. Second, as we will show, analyzing the gradual evolution of long-term trends provides an alternative interpretation of the Prebisch–Singer hypothesis, as a sequential decline in mean prices through super-cycles, a pattern that characterized non-fuel commodities over the course of the twentieth century, as we will show.

The objectives of this paper is twofold: (1) to identify the duration and magnitude of succeeding super cycles in the real commodity prices based on the non-oil commodity price data set developed by Grilli and Yang (1988) and extended by Ocampo and Parra (2010), and the WTI crude oil price data

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used in the IMF's *World Economic Outlook 2011*; and (2) to provide insights for the recent commodity price cycle from a long-term perspective by analyzing the long-run relationship between commodity prices cycles and global output fluctuations. The next section begins with a review of the literature on medium-term cycles and their importance in theoretical and empirical analyses. The following section provides an empirical framework to identify and extract super cycles from the original price series. The empirical results from the commodity price decomposition establish the duration and amplitude of each cycle since the late nineteenth century for each non-oil and oil price index. The penultimate section uses a vector error correction model to explore the short-run and long-run relationships between commodity prices and global GDP from 1870 to 2008. The paper ends with a summary of conclusions and discusses some policy implications.

2. LITERATURE REVIEW ON LONG CYCLES

Three strands of the economic literature are relevant for the analysis of long cycles of real commodity prices: (1) the Schumpeterian analytical framework, (2) the Prebisch–Singer hypothesis, and (3) the recent literature on the macroeconomics of medium-term cycles based on new time-series econometric techniques used in this paper. This section provides a brief review of theoretical arguments proposed to explain the occurrence of overlapping long cycles in real commodity prices, derives some hypotheses to be tested in the empirical analysis, and provides the background for the choice of empirical methodology. [2]

(a) *Schumpeterian framework*

Early analytical frameworks to explain long cycles in commodity prices were developed by Nikolai Kondratiev and Joseph Schumpeter. [3] Focusing on series of commodity prices, industrial production, interest rates, and foreign trade from late eighteenth to early nineteenth centuries, Kondratiev documented the presence of long waves spanning 40–60 years. As an explanation, Kondratiev rejected any exogenous changes such as wars, revolutions, or gold production, arguing instead that endogenous factors such as technological changes inherent in capital accumulation are the major drivers of the long waves.

Influenced by this notion of endogenous technological change, Schumpeter emphasized the role of the entrepreneur in investing technological change that gave rise to the long cycles of growth and contraction. In *Business Cycles* (Schumpeter, 1939), Schumpeter identified overlapping cycles of various durations: long Kondratiev cycles lasting about 50 years, shorter Juglar cycles lasting about 9 years, and short Kitchen cycles lasting 3 years. His explanation for the Kondratiev cycles rests on his theory of creative destruction, in which changes in investment opportunities due to evolving technological innovations create economic growth in emerging sectors of production and decay in obsolete sectors of production. The transformation of the economy through these clusters of innovations in emerging sectors characterizes the prosperity phase, which is followed by the stagnation phase in which innovations are assimilated across the industries.

Commodity prices are directly related to these phases of prosperity and stagnation. In the prosperity phase, the initial competition for productive inputs (metals, minerals, agricultural goods) tends to increase their prices relative to manufactured goods. The gradual imitation of innovations and the resulting reduced opportunities for the entrepreneurs to obtain economic rents slows down the demand for commodities. The rising commodity prices observed in the prosperity phase is reversed as the economy enters the stagnation phase. It is important to note that Schumpeter rejected the idea that depressing prices caused declines in output, which was a thesis proposed during the debate on the Great Depression of 1873–1896 in Britain when some observers argued that the falling prices was due to a decrease in gold production, which resulted in a profit squeeze and discouraged investment. Schumpeter argued that this could give rise to smaller cycles, but that a prolonged decline in prices over fifty to seventy years' duration could not be explained solely by monetary factors. [4] Instead, he put forward the alternative hypothesis that it is the declining growth of industrial production and the underlying endogenous technological changes that pushed prices down. [5] In Section 5, we will consider whether changes in global output are a leading predictor of changes in global commodity prices.

Schumpeter identified three long cycles in the development of modern capitalism. First, the period 1786–1842 was the one in which the first industrial revolution took place in Britain. Second, the period 1842–1897 was characterized by the core industrial countries exploiting new opportunities in coal, iron, railways, steamships, textiles, and clothing, or shortly a period of "railroadization". A third cycle, starting in 1897, was associated with the next set of big opportunities involving steel, electricity, organic chemicals, the internal combustion engine, automobiles, or shortly a period of "electrification". Since Schumpeter was writing in 1938, he considered this cycle incomplete.

The tendency for technological innovations to cluster in this fashion, and as a result produce long-term price cycles carries its importance for analyzing the terms of trade movements between agriculture and industry. For example, W. Arthur Lewis observed that the Kondratiev price swing (declining prices from 1873 to 1895 followed by rising prices from 1895 to 1913) was accompanied by a change in the terms of trade between agriculture and industry: agricultural prices fell more up to 1895 and then rose relative to industrial prices, to 1913 (Lewis, 1978: 27). This corresponds to the first super cycle of real commodity prices as we will show in Section 4.

(b) *The Prebisch–Singer hypothesis*

Parallel to these extensions of Schumpeter's insights into terms of trade between primary and manufactured goods was the controversy surrounding the developing countries' terms of trade. Based on data for Britain's terms of trade since late nineteenth century, Singer (1950) and Prebisch (1950) showed that, given the then prevailing international division of labor, the improvement for Britain's terms of trade indicated a deterioration for the terms of trade for countries exporting primary commodities to Britain.

Their argument was composed of two complementary hypotheses (Ocampo, 1986; Ocampo & Parra, 2003). First, the low income-elasticity of demand for primary commodities tends either to depress the prices of primary goods relative to manufactures or to constrain the growth rate of developing countries *vis-à-vis* industrialized ones, with the low price-elasticity of demand for commodities amplifying the magnitude of this effect. Second, the asymmetries in the labor markets of advanced *versus* developing countries suggest that the technological progress in manufactures benefits producers in advanced countries in the form of higher income whereas the technological progress in primary goods benefits the consumers in advanced countries due to lower prices. Recent studies have found evidence of a secular, deteriorating trend for a significant portion of primary commodities (Harvey, Kellard, Madsen, & Wohar, 2010), and for several groups of developing countries that are exporters of non-oil commodities (Erten, 2011).

Singer (1998) extended the original Prebisch–Singer hypothesis with reference to Schumpeter's theory of creative destruction, and showed that the terms of trade between standardized products and innovative products has also a tendency to deteriorate. Even though developing countries could industrialize and produce mature manufactured products, the fact that these products are standardized implies that they do not create new economic rents. Instead, economic rents emerge for the fruits of innovation undertaken mostly in advanced countries, which means that they are captured by these countries' entrepreneurs. The implications of this revision of the Prebisch–Singer hypothesis are that low-technology manufactures produced by developing countries in their earlier stages of development could be subject to falling prices relative to higher technology manufactures produced by industrialized countries (see Sarkar & Singer, 1991), and that there is a need to coordinate the entry of developing country producers into standardized product markets in order to prevent the crowding-out effects in the presence of a fallacy of composition (see Sapsford & Singer, 1998).

(c) *The recent literature on medium-term cycles*

Until recently, mainstream economics was quite skeptical about the presence of long cycles. For example, when Paul Samuelson published a new edition of the text *Economics* in 1985, he left out his earlier reference to both short- and long-term cycles, and instead argued: "in their irregularities, business cycles more closely resemble the fluctuations of the weather," later also regarding long waves as "science fiction". Similarly, Gary S. Becker stated that "if long cycles of the Kondratieff or Kuznets type exist, we will need another 200 years of data to determine whether they do exist or are just a statistical figment of an overactive imagination" (Becker, 1988). In turn, Rosenberg and Frischtak (1983) criticized the neo-Schumpeterian analysis for misleadingly interpreting stochastic changes in production or output as long cycles, which could simply be random ups and downs in chosen economic variables.

Despite this skepticism, a growing number of recent studies began to examine long cycles under the name of "medium-term" cycles since the late 1990s. Blanchard (1997) wrote convincingly: "Macroeconomics is largely divided into two subfields. One focuses on the short run, on the study of business cycles. The other focuses on the long run, on growth and its determinants. The assumption implicit in this division is that the medium run is primarily a period of transition from business cycle fluctuations to growth. This simplification is clearly convenient, but it is misleading. Modern economies are characterized by medium-run evolutions that are quite distinct from either business cycle fluctuations or steady-state growth" (Blanchard, 1997: 1).

Several studies have focused on studying macroeconomic dynamics in the medium-run. These include Krugman (1998), Sargent (1999), Solow (2000), Comin and Gertler (2006), Braun, Toshihiro, and Nao (2008), and Boshoff (2010). The latter three employ band-pass filtering techniques that resemble the ones used in this paper to identify medium-term cycles of 40–50 years in various macroeconomic variables. Comin and Gertler (2006) point out that conventional business cycle filters tend to push medium-term cycles into the trend, preventing them to be used in the analysis of growth cycles experienced by many industrialized countries in the post-war period. Defining medium-term cycles as the sum of high-frequency (up to 8 years) and medium-frequency (8–50 years) variations in the data and extracting them through band-pass filters, they find that these cycles are not only more persistent than the shorter business cycles but also that they vary cyclically with indicators of technological change, R&D expenditures, and resource utilization (Comin & Gertler, 2006). The band-pass filters were applied to study medium-term cycles in real metal prices by Cuddington and Jerrett (2008a, 2008b), which we turn to discuss in the next section.

3. IDENTIFICATION OF SUPER CYCLES BY THE BAND-PASS FILTER

Recent statistical decomposition techniques focused on filtering methods are particularly useful in identifying super cycles. The band-pass (BP) filter approach allows the economic time series to be decomposed into cyclical components of a range of periodicities or frequencies. Christiano and Fitzgerald (2003) identify one of the advantages of the spectral analysis theory upon which the BP filter rests as the absence of any commitments to a particular statistical model of the data. Regardless of the underlying dynamics, the time series can be decomposed into different frequency components with the application of the ideal BP filter.

The BP filter yields a long-term trend that evolves gradually over time whereas the univariate models of stochastic or deterministic trends assume that the trends remain constant until a structural break occurs in the series. Filtering methods have been developed as part of the business cycle research in macroeconomics with the purpose of isolating particular frequencies in an economic series, such as the recessionary cycles in the GDP. Among these, the Hodrick–Prescott (HP) filter is the most commonly used, however, it has been noted that it is difficult to choose the appropriate smoothness parameter λ (Baxter & King, 1999). The BP filter designed by Baxter and King (1999) provides an alternative to the HP filter by extracting stochastic cyclical components with a specified range of periodicities from individual time series. There are two types of BP filters: symmetric and asymmetric. While the use of symmetric BP filters results in a loss of a number of observations at the beginning and the end of the data sample, the application of asymmetric ones developed by Christiano and Fitzgerald (2003) allows one to extract the filtered series over the entire data sample. The latter property of asymmetric Christiano and Fitzgerald (ACF) BP filters provides an advantage given that one of the purposes of this paper is to analyze the recent commodity boom captured by the observations at the end of the data set.

This paper follows the empirical methodology introduced in Cuddington and Jerrett (2008a, 2008b) in using the ACF BP filter to decompose the natural logarithms of real commodity price indices into three components: (1) the long-term trend (LP_T), (2) the super-cycle component (LP_SC), and the other shorter cycle component (LP_O):

$$LP_t \equiv LP\_T_t + LP\_SC_t + LP\_O_t. \quad (1)$$

The first point is to consider how long a super cycle lasts. Cuddington and Jerrett infer from Heap's (2005) discussion that super cycles have upswings of 10–35 years, yielding a complete cycle of roughly 20–70 years. Note that the Kondratieff price swings analyzed by Schumpeter and Lewis are within this range, consisting of about 50–55 years. If we keep the span of the cycle more flexible to include relatively shorter and longer cycles, the BP (20, 70) filter can be used to extract super cycles that have periodicities ranging from 20 to 70 years:

$$LP_S C \equiv LP_{BP}(20, 70). \tag{2}$$

The long-run trend is then defined as all cyclical components whose periodicities exceed 70 years:

$$LP\_T \equiv LP\_BP(70, \infty). \tag{3}$$

This assumption allows the long-term trend to change gradually over time. The remaining other short cycles can be filtered out as cycles with 2–20 years periodicities:

$$LP\_O \equiv LP\_BP(2, 20). \tag{4}$$

The total "non-trend" components are defined as the total deviation from the long-term trend, or equivalently, the summation of the super cycles with the other shorter cycles:

$$LP\_NT \equiv LP\_BP(2, 20) + LP\_BP(20, 70). \tag{5}$$

The cycle-trend decomposition in Eqn. (1) can thus be written as follows:

$$\begin{aligned} LP_t &\equiv LP\_T_t + LP\_SC_t + LP\_O_t, \\ LP_t &\equiv LP\_BP(70, \infty) + LP\_BP(20, 70) + LP\_BP(2, 20), \\ LP_t &\equiv LP\_T_t + LP\_NT_t. \end{aligned} \tag{6}$$

4. EMPIRICAL RESULTS FROM THE ACF BP FILTER DECOMPOSITION

The source of data on commodity price series used in this analysis is twofold. First, for the non-oil commodity prices, we use annual data composed of prices for 24 commodities up to 1961 and 32 since 1962, grouped into five indices: total, metals, total agriculture, tropical agriculture, and non-tropical (or temperate zone) agriculture. These time series spanning from 1865 to 2010 come from Ocampo and Parra (2010), who extended backward to 1865 and forward to 2009 the original price indices developed by Grilli and Yang (1988). Second, for oil prices, the analysis is based on spliced series of West Texas International (WTI) using data from the World Economic Outlook (WEO) and the Global Financial Data (GFD). Real price indices were computed on the basis of Lewis' series for world manufacturing prices for the earlier part of the sample and the Manufacturing Unit Value (MUV) index developed by the United Nations and updated by the World Bank for the later part (Ocampo & Parra, 2010). The use of international manufacturing trade price indices as deflators of commodity prices is clearly preferable to the alternative of consumer price from major countries (generally the UK or the US), as they both refer to international trade and thus exclude non-tradables, which may distort price trends. [6] Price series were updated up to 2010 for this paper. [7]

The ACF BP filter is applied to the natural logarithm of each real commodity price index to extract the long-term trend, non-trend, and super-cycle components. Figure 1 illustrates the decomposition of the real total non-oil commodity price series. In the top section, the figure displays the natural logarithm of the real total non-oil commodity price and the long-term trend superimposed on it. Thus, the slope of the line at any point yields the growth rate of the price series. Note that real commodity prices trended very slightly upward from 1865 to the mid 1910s, trended downward until late 1990s, and then trended upward through the end of the sample.

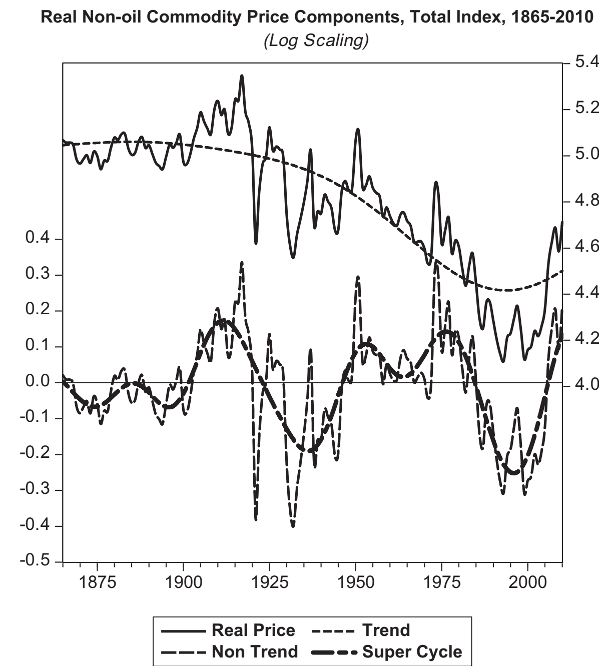

Figure 1. *This figure indicates the decomposition of the log of the real non-oil total commodity price index into its various components, as explained in the text, using the asymmetric Christiano and Fitzgerald (2003) band-pass filter.*

The non-trend component representing the difference between the actual series and the long-run trend is shown in the bottom portion of Figure 1. The left scaling in logarithms shows that a value of 0.40 indicates a 40% deviation from the long-term trend. Hence the cyclical fluctuations illustrated by the non-trend component are rather significant in size. These fluctuations contain shorter-term as well as the super cycles, which are not always symmetrical. The latter are estimated to be in the 30–40 years range (on the basis of a possible 20–70 years range). The super-cycle component is shown in the bottom section of Figure 1 and reveals three and a half long-term cycles in real commodity prices since the late nineteenth century. The first long cycle begins in late 1890s, peaks around World War I, and ends around 1930s, and shows strong upward and downward phases. The second takes off in 1930s, peaks during the post-war reconstruction of Europe, and fades away in mid 1960s. It shows a strong upward phase but a weak downward one. The early 1970s marks the beginning of third cycle, which peaks around early 1970s and turns downward during mid 1970s and ends in late 1990s. This cycle shows a weak upward phase and a strong downward one. The post-2000 episode is the beginning of the latest cycle, which has shown a strong upward phase which does not seem to have been exhausted so far.

The degree to which the total non-trend component deviates from the super-cycle component shows the significance of other shorter cycles induced by business cycle conditions and medium-term factors. These shorter fluctuations appear to be strikingly large, particularly in the interwar period of the twentieth century. This implies that periods of high volatility resulting from business cycles often accompany the long-term trend and super cycle in real commodity prices. The presence of shorter-term high volatility further brings large price risks for those involved in the investment decisions that may be long-term in nature.

The respective decompositions for the metals, total agriculture as well as tropical and non-tropical agriculture are shown in Figure 2. Note that there is significant variation in the long-term trends, with metal prices entering into a downward trend much earlier than total agricultural prices, and falling steadily until mid 1970s, and rising quite rapidly thereafter. Unlike metal prices, none of the agricultural price indices exhibit a strong long-term upward trend in recent decades. Although total agricultural prices follow a remarkably similar pattern to the total non-oil commodity price index, this averages considerable variation between tropical and non-tropical agricultural prices. After trending upward until mid 1890s, the tropical prices trend downward steadily and strongly over time. By contrast, non-tropical prices trend mildly downward from 1865 to 1890s, upward until mid 1920s, and then downward through the end of the sample, with a steady trend over the last few decades. Overall, tropical agriculture has experienced the longest and strongest long-term downward trend, followed by non-tropical agriculture and by metals (see Table 1). This implies that the excess supply of labor in tropical agriculture has exerted a downward pressure on prices for tropical products, as predicted by the second variant of the Prebisch–Singer hypothesis and by Lewis (1969). Labor market dynamics, therefore, are very important in determining price formation in commodity markets. Other production sectors in non-tropical agriculture or mining does not suffer as

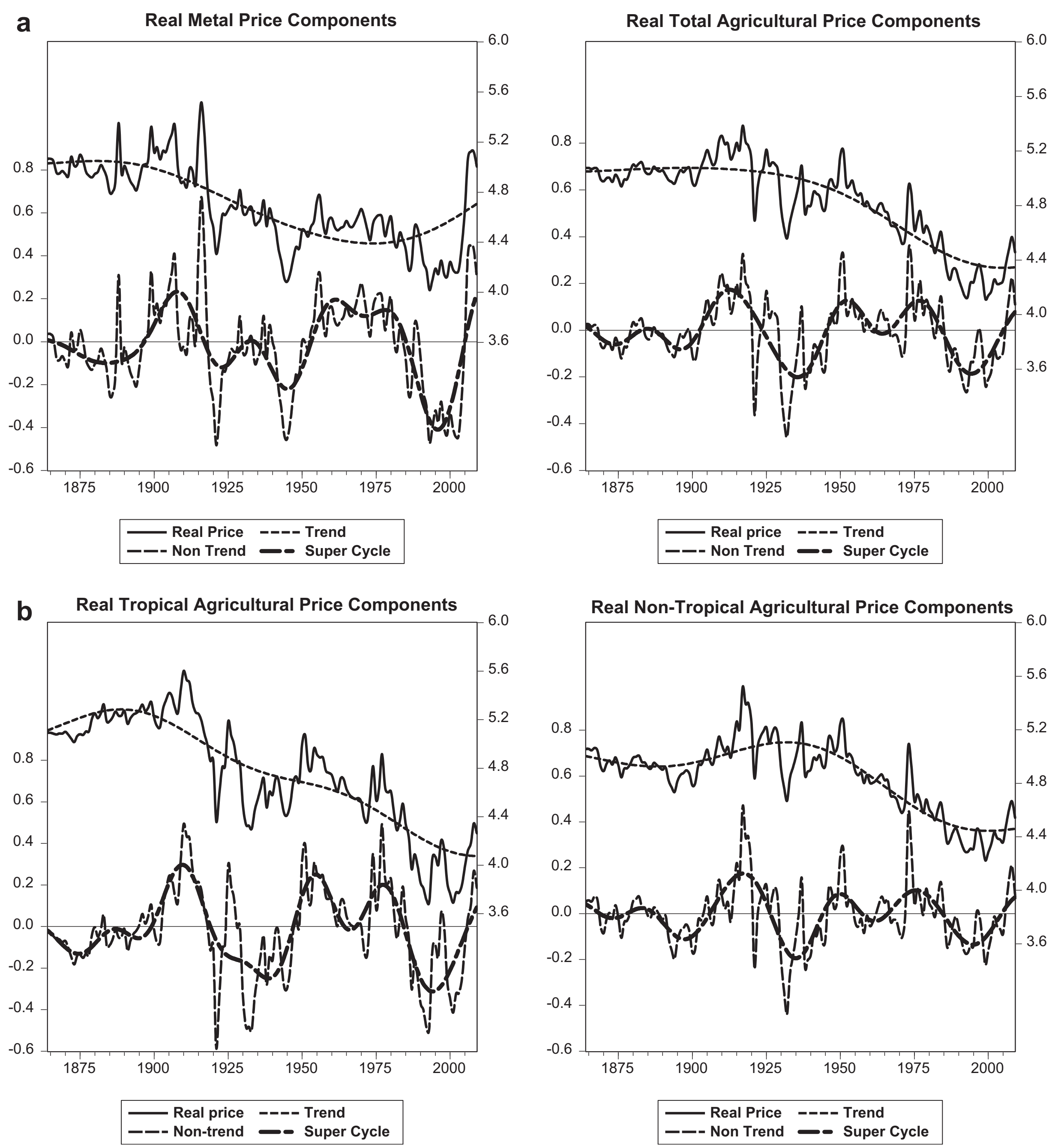

Figure 2. *Real price decompositions for: (a) metals and total agriculture, (b) tropical and non-tropical agriculture. This graph shows the decomposition of the natural logarithm of real prices series into a long-term trend, a super-cycle and short-term cycle components.*

Table 1. *Descriptive statistics of the long-term trends in real commodity prices*

	Upward trend	Downward trend	Upward trend
Non-oil commodity prices (total index)	1865–1885	1885–1994	1994–2010
Annual compound growth rate	0.1%	−0.6%	0.5%
Cumulative growth rate	1.4%	−47.2%	8.3%
Duration (years)	20	109	16
Metal prices	1865–1881	1881–1974	1974–2010
Annual compound growth rate	0.1%	−0.7%	1.0%
Cumulative growth rate	1.7%	−48.2%	43.8%
Duration (years)	16	93	36
Total agriculture prices	1865–1893	1893–1998	1998–2010
Annual compound growth rate	0.1%	−0.6%	0.4%
Cumulative growth rate	1.7%	−49.2%	4.5%
Duration (years)	28	105	12
Tropical agriculture prices	1865–1888	1888–2002	2002–10
Annual compound growth rate	0.7%	−1.0%	0.3%
Cumulative growth rate	16.3%	−67.2%	2.5%
Duration (years)	23	114	8
Non-tropical agriculture prices	1889–1932	1932–94	1994–2010
Annual compound growth rate	0.4%	−1.0%	0.4%
Cumulative growth rate	20.2%	−46.9%	6.9%
Duration (years)	43	62	16
Crude oil prices	1875–1925	1925–62	1962–2010
Annual compound growth rate	1.5%	−1.1%	2.8%
Cumulative growth rate	114.2%	−32.5%	280.0%
Duration (years)	50	37	48

This table displays the descriptive statistics of long-term trends identified in the ACF BP filter decomposition analysis.

much from unlimited supplies of labor that prevents wages from rising as the tropical agriculture does.

Comparing the super-cycle components of the metals with agricultural prices, it is clear that the metal price cycles vary considerably from all the rest. Their initial super cycle begins in 1890s, but continues only until 1921. In contrast, the contraction phase of the agricultural price cycle lasts one more decade, until 1932. Metal prices enter into an additional cycle from 1921 to 1945, which does not exist in the series of agricultural prices. The next two super cycles seem to be combined but, as already indicated, are asymmetrical. The post-Korean war downward phase is weak for agricultural indices compared to other downward phases, and almost imperceptible for metals. Finally, the extent of upswing in the final super cycle is very strong for metals.

Overall, whereas agricultural prices exhibit and indeed determine the super cycle of non-oil commodities, the periodization of the long cycles for the real metal prices can more correctly be stated, from trough to trough, as follows: 1885–1921, 1921–45, 1945–99, and 1999–ongoing (see Table 2). It is also interesting to note that tropical agricultural prices exhibit not only a stronger long-term downward trade, as already indicated, by also much more pronounced super cycles compared to non-tropical agriculture. The strength and length of the collapse of tropical prices from 1920s to 1940s is an additional distinguishing feature that is absent in other series.

The corresponding decomposition for real crude oil prices is shown in Figure 3. The time span covers from 1875 to 2010 due to data availability. Figure 3 illustrates that the oil prices trended upward until roughly 1920s, but then declined slightly until about 1960s before resuming its upward trend with a steeper slope. A strikingly rising long-run trend is a unique characteristic of real oil prices in comparison to all the other commodity price trends, which are predominantly downward, as we have seen.

Super cycles in oil prices shown in the lower part of Figure 3 are not as strongly marked in the earlier years as they are during the latter part of the sample, and their amplitude has increased in recent periods. The rise of electrification and the automobile industry since the late nineteenth century is reflected in a strong upward trend in real oil prices, which ended in the 1920s, rather than in a super cycle, which was rather moderate. The second super cycle in oil prices is a fairly small one from 1947 to 1973 that resembles the post-war super cycle in other commodities, but its expansion phase begins much later. This is followed by a very intense super cycle marked initially by the oil price shocks of the 1970s. The final super cycle is still going on being fueled by rising demand from newly emerging industrial centers and also by the increasing dominance of index traders in financialized commodity future markets (Pollin & Heintz, 2011).

These findings match well with the results of Cuddington and Zellou (2012), including strong evidence of super cycles in oil prices in the post-war period and its overlapping timing with metal price super cycles in the same period, reflecting the industrialization and urbanization processes of economic development in the United States, then Europe and finally Asian economies. [8]

Figure 4 shows the super cycles of non-oil and oil prices on the left hand side, and the super cycles of non-oil sub-indices on the right hand side. While the non-oil and oil super-cycle pair do not seem to exhibit co-movement until the mid-twentieth century, they do so after World War II and strongly so since the 1970s. As seen in Table 4 in the next section, the correlation between non-oil and oil super cycles is 0.42 for the entire sample, but it rises significantly to 0.69 for the period after 1950 and to 0.87 for the period after 1970. In other words, the co-movement of the non-oil and oil super cycles becomes stronger in the second part of the twentieth century as we approach the end points of the sample. The right-hand side of Figure 4 shows that the overlaps among the non-oil sub-indices are substantial. The high degree of correlation in the super-cycle components in the various commodity groups further suggests that the super cycles are largely demand driven (see Table 4 in the next section for correlation coefficient statistics).

Table 2. *Descriptive statistics of super-cycles in commodity prices (from trough to trough)*

	1894–1932	1932–71	1971–99	1999–ongoing
Total non-oil commodity prices				
Peak year	1917	1951	1973	2010
Percent rise in prices during upswing	50.2%	72.0%	38.9%	81.3%
Percent fall in prices during downswing	−54.6%	−43.3%	−52.5%	—
Length of the cycle (years)	38	39	28	—
Upswing	23	19	2	11
Downswing	15	20	26	—
Mean (of the full cycle)	157.3	119.4	86.2	82.2
Standard deviation	24.8	15.6	18.8	17.0
Coefficient of variation	15.8	13.1	21.8	20.8
Skewedness	−0.7	0.9	0.6	0.5
Kurtosis	3.6	4.0	2.6	1.6
	1885–1921	1921–45	1945–99	1999–ongoing
Metal prices				
Peak year	1916	1929	1956	2007
Percent rise in prices during upswing	105.7%	66.6%	98.0%	202.4%
Percent fall in prices during downswing	−70.2%	−51.9%	−47.4%	—
Length of the cycle (years)	36	24	54	—
Upswing	31	8	11	8
Downswing	5	16	43	—
Mean (of the full cycle)	151.6	95.7	85.2	109.3
Standard deviation	35.7	16.3	14.6	45.9
Coefficient of variation	23.5	17.1	17.2	43.7
Skewedness	0.5	−0.8	−0.3	0.4
Kurtosis	3.4	3.0	2.3	1.4
	1894–1932	1932–71	1971–99	1999–ongoing
Total agricultural prices				
Peak year	1917	1951	1973	2010
Percent rise in prices during upswing	52.8%	90.3%	52.0%	76.6%
Percent fall in prices during downswing	−56.2%	−49.6%	−56.0%	—
Length of the cycle (years)	38	39	28	—
Upswing	23	19	2	11
Downswing	15	20	26	—
Mean (of the full cycle)	163.2	127.0	87.5	74.3
Standard deviation	26.6	19.5	20.5	11.6
Coefficient of variation	16.3	15.3	23.5	15.7
Skewedness	−0.6	0.7	0.8	0.7
Kurtosis	3.5	3.8	3.1	2.2
	1891–1933	1933–72	1972–99	1999–ongoing
Tropical agricultural prices				
Peak year	1910	1951	1977	2010
Percent rise in prices during upswing	54.5%	116.6%	74.3%	85.4%
Percent fall in prices during downswing	−72.8%	−50.9%	−65.2%	—
Length of the cycle (years)	42	39	27	—
Upswing	19	18	5	11
Downswing	23	21	22	—
Mean (of the full cycle)	170.6	106.7	74.8	56.8
Standard deviation	49.8	19.6	25.4	12.8
Coefficient of variation	29.2	18.4	33.9	23.7
Skewedness	−0.4	0.7	0.6	0.6
Kurtosis	2.5	3.2	2.6	1.9
	1894–1932	1932–71	1971–99	1999–ongoing
Non-tropical agricultural prices				
Peak year	1917	1951	1973	2010
Percent rise in prices during upswing	119.8%	81.7%	66.1%	59.7%
Percent fall in prices during downswing	−57.4%	−49.5%	−58.0%	—
Length of the cycle (years)	38	39	28	—
Upswing	23	19	2	11
Downswing	15	20	26	—
Mean (of the full cycle)	156.8	138.0	93.8	86.5

(*continued on next page*)

Table 2. *(Continued)*

	1894–1932	1932–71	1971–99	1999–ongoing
Standard deviation	31.6	23.3	20.5	11.6
Coefficient of variation	20.2	16.9	21.8	13.8
Skewedness	0.8	0.6	1.5	0.5
Kurtosis	3.6	3.1	5.8	2.3
	1892–1947	1947–73	1973–98	1998–ongoing
Crude oil prices				
Peak year	1920	1958	1980	2008
Percent rise in prices during upswing	402.8%	27.4%	363.2%	466.5%
Percent fall in prices during downswing	−65.2%	−23.1%	−69.9%	—
Length of the cycle (years)	55	26	25	—
Upswing	28	11	7	10
Downswing	27	15	18	—
Mean (of the full cycle)	36.9	24.8	53.2	91.2
Standard deviation	3.9	0.7	8.5	16.4
Coefficient of variation	27.9	7.5	42.0	47.4
Skewedness	0.0	−0.3	0.8	0.3
Kurtosis	3.0	2.2	2.4	1.9

This table displays the descriptive statistics of four periods of super-cycles identified in the ACF BP filter decomposition analysis.

Table 2 reports the descriptive statistics of complete super cycles measured from trough to trough and extracted by the asymmetric Christiano–Fitzgerald BP filter. Each commodity group (i.e., total non-oil, metals, total agriculture, tropical, and non-tropical agriculture) exhibits four long cycles that tend to overlap as seen in Figure 4. An interesting finding shown in Table 2 is that mean real non-oil price of each super cycle is lower than that of the previous cycle, with the exception of metal prices during the ongoing one. Note, however, that the final super cycle is not over, which means that the contraction phase of the cycle that will follow might lower the cycle mean once it is completed. The evidence of declining mean over the super-cycle succession is present for all non-oil commodity groups. For example, for tropical agricultural commodities, the average prices has collapsed from 170.6 over 1894–1933 to 106.7 over 1933–72, and it continued to decline from 74.8 over 1972–99 to 53.9 over the ongoing super cycle.

To estimate the significance of the changes in the mean over long commodity cycles, Table 3 conducts a simple time-series econometrics exercise with intercept dummies for the beginning date of second, third, and fourth super cycles. The estimation results are consistent with our expectations. All coefficients of the intercept dummies are negative for three of the five non-oil commodity groups: total, total agriculture, and non-tropical agriculture. This finding implies that the mean of each super cycle in prices is significantly lower than the previous one, and supports the view that the real commodity prices exhibit a step-wise deterioration over the past century (Ocampo & Parra, 2010). In case of tropical agricultural prices, the coefficients for all dummies are negative, but significant only for the second and third breaks. Lastly, the metal price estimates indicate that the coefficients for 1921 and 1945 intercept dummies are both negative and significant, and the coefficient for 1999 dummy is positive but insignificant.

5. RELATIONSHIP BETWEEN COMMODITY PRICES AND GLOBAL OUTPUT: SHORT- AND LONG-TERM

(a) *Data and preliminary analysis*

Any attempt to explain the dynamics of super cycles in real commodity prices necessarily begins with an examination of the drivers of the price booms, which are often highly associated with the length and strength of the economic booms underlying them. Studying the macroeconomic contexts of the three major booms since the Second World War, Radetzki shows that demand shocks have generally been the trigger (Radetzki, 2006). For the most recent boom, between 2002 and 2007, global economic growth was the most prolonged and strongest since the mid 1970. This unprecedented global growth performance has been attributed as the single most important driver of commodity markets, being most pronounced for metals (Farooki, 2009).

The primary source of the global output series is Angus Maddison's data, covering 1820–2003, and the version updated until 2008 by the Groningen Growth and Development Centre's Total Economy Database. Real GDP is calculated based on the 1990 International Geary–Khamis dollars. [9] We use two series for world GDP. The first one is the annual GDP series for 16 "core" OECD countries (referred to below simply as OECD) from 1870 to 2008. This series includes the same list of countries used in Maddison (1989) and more recent papers such as Deaton and Laroque (2003). The second is the annual GDP series for the world reported by Maddison, which has complete data from 1950 to 2008, and point estimates for 1870, 1900, 1913, and 1940. To interpolate the missing data points, we used the first GDP series for 16 OECD countries, which account for about half of the world GDP estimated by Maddison. [10]

The left-hand side of Figure 5 displays the super-cycle components of global output and total non-oil commodity prices that are extracted by applying the asymmetric Christiano–Fitzgerald BP (20, 70) filter to the original series. The global output is represented by the OECD GDP and world GDP, which lie below the price index and tend to move together with slight diversions at the peaks and troughs of super cycles. The correlation between commodity prices and global output indicators is rather large as indicated by the Pearson correlation coefficient of 0.53 for OECD countries' GDP, and 0.58 for world GDP in Table 4. These figures rise up to 0.61% and 0.73% for the metal prices *vis-à-vis* OECD GDP, and the metal prices *vis-à-vis* world GDP, respectively. The right-hand side of Figure 5 shows the close co-movements in the super-cycle components of global output and real metal prices. The correlations for the world GDP series are much stronger than those

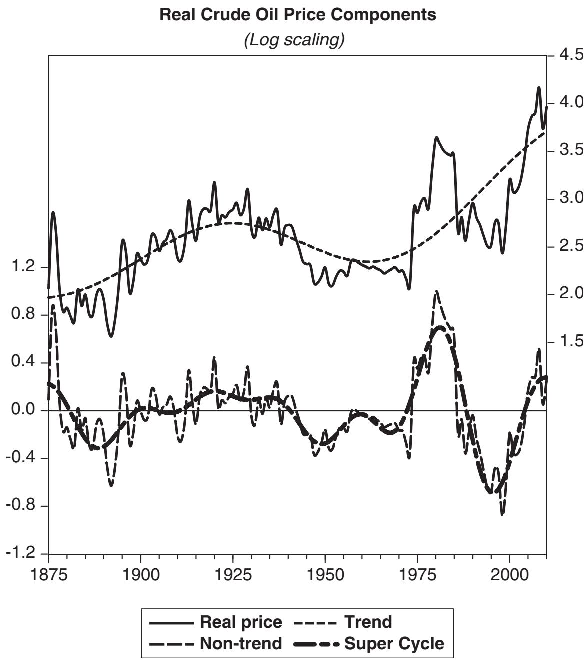

Figure 3. *This graph shows the decomposition of the natural logarithm of real prices of petroleum into long-term trend, a super-cycle, and a short-term cycle.*

for the OECD GDP index (as seen by the last two columns of Table 4). The greatest difference is for the petroleum correlations with output indices: 0.19 for OECD GDP with 5% significance and 0.46 for world GDP with 1% significance.

Concerning the possible lead–lag relationships among the super-cycle components of commodity prices and those between commodity prices and global output fluctuations, it is useful and interesting to examine the cross correlograms displayed in Figures 6 and 7. In general, the contemporaneous correlations are larger than the correlations at lags and leads. The high significance of cross correlations at lag zero indicates strong co-movement of the super cycles of the various commodity price indices. This pattern is evident not only for the total non-oil commodity price cross correlogram, but also for the other cross correlograms, which are fairly similar to this one and therefore omitted to save space.

The cross correlograms shown in Figure 7 differ significantly from the one in Figure 6 in terms of the lead–lag relationships that they imply. Figure 7 shows the cross correlogram of commodity prices and world GDP. The super-cycle components of price indices are more correlated with the lags of the world GDP super cycle, which suggests that the world GDP super cycle has led the super cycles in tropical and non-tropical agriculture by 6 years, and in oil prices by roughly twelve years, respectively. Hence, the lead–lag relationship runs from world GDP cycles to commodity price cycles, and not vice-versa. Same types of lead–lag relationships are observed for other sub-indices, which are left out to save space and avoid repetition.

(b) *Cointegration analysis*

In order to assess the significance of lead–lag relationships among commodity prices and world output fluctuations in the long-run, a more formal econometric analysis can be performed. To this end, this section provides a vector error correction model (VECM) to test the long-term and short-term causal relationships between commodity prices and world output cycles with annual data covering 1870–2008 in the world economy.

The basic premise is that commodity prices and world GDP have a long-term relationship over time because the robust growth episodes in the world economy are accompanied by a rapid pace of industrialization and urbanization, which in turn require an increasing supply of primary commodities as inputs of production. However, there is often a lag between the investment in further commodity production and the actual results, which leads to price hikes in periods of strong world economic growth. As growth slows down and investment generates with a lag an increase in commodity supplies, the pressure on commodity prices eases. This hypothesis im-

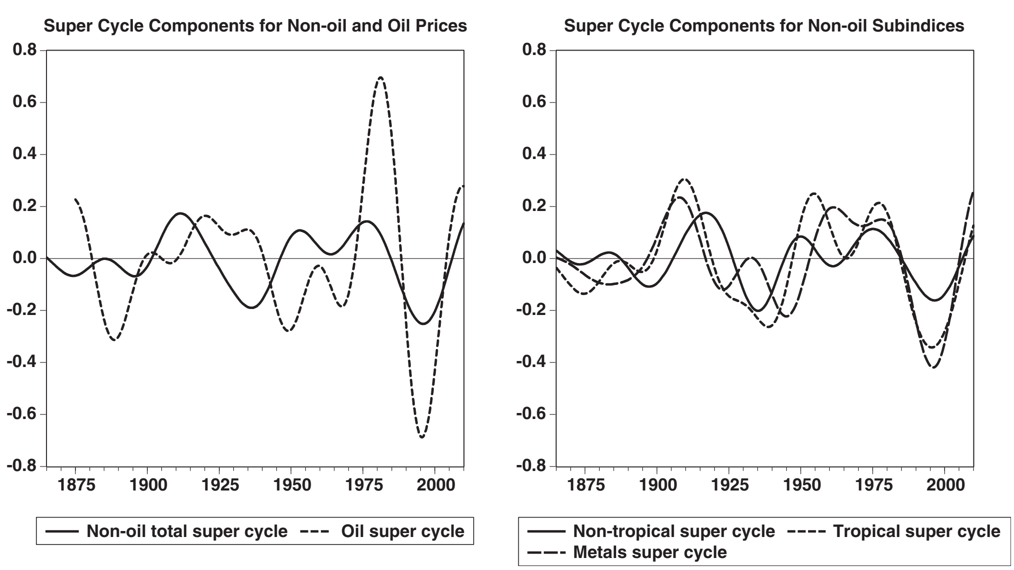

Figure 4. *This figure displays super-cycle components for non-oil and oil prices (the left panel), and for non-oil subindices including metals, tropical, and non-tropical agriculture (the right panel). Each component is extracted by applying the asymmetric Christiano–Fitzgerald BP (20, 70) filter to the original real price series. The log scaling in the left axis shows the percentage deviations from the long-term trend.*

Table 3. *Estimation with structural changes over super-cycles in commodity prices*

	Total	Metals	Total agriculture	Tropical agriculture	Non-tropical agriculture
C1	4.982***	4.957***	5.028***	4.865***	4.989***
C1921		−0.360***			
C1932	−0.205***		−0.215***		−0.140***
C1933				−0.114	
C1945		−0.109*			
C1971	−0.212**		−0.253**	−0.192***	−0.215*
C1999	−0.134**	0.070	−0.179***	−0.275***	−0.140***
AR(1)	0.778***	0.721***	0.749***	0.925***	0.763***
MA(1)	0.191**	0.240	0.196**	0.053	0.155*
Adj. R^2	0.91	0.85	0.91	0.93	0.86
AIC	−1.93	−1.28	−1.82	−1.27	−1.70

For each price index, the beginning date of second, third, and fourth super-cycle marks the initial date for which the intercept dummy takes the value one. For example, C1921 takes the value 1 for 1921 and thereafter, and zero otherwise. For tropical agriculture, the beginning of the third super-cycle is 1972, and initially the 1972 dummy was included in the regression. However, its coefficient was insignificant, and therefore, it was replaced by the 1971 dummy, which is significant at 1% level. This is the single exceptional case. All other estimations are based on the starting point of super-cycles given in Table 2.
* Significance at 1% levels.
** Significance at 5% levels.
*** Significance at 10% levels.

plies that the super cycles in world output fluctuations generate corresponding super cycles in real commodity prices.

The Engle and Granger (1987) cointegration technique is an appropriate method for analyzing the long-term relationships among variables that may individually exhibit stochastic processes. Engle and Granger have shown that if two or more time series are individually integrated but some linear combination possesses a lower order of integration, these series are cointegrated. Hence, if the individual series are first-order integrated [I(1), i.e., non-stationary], the existence of a cointegrating vector of coefficients implies a stationary linear combination of them, i.e., I(0). When two variables are cointegrated, Engle and Granger highlight that there will be a causal relationship at least in one direction, and the direction of causality can be identified through a vector error correction model. The error correction model framework allows us to distinguish between a long-term relationship among two variables—the way in which the variables drift upward or downward together—and the short-term dynamics—the deviations from the long-term trend.

In general form, VECM can be expressed as follows:

$$\Delta LP_t = \alpha_1 + \beta_1 ECT_{1t-1} + \sum_{i=1}^{2}(\delta_{1i}\Delta LP_{t-i}) + \sum_{i=1}^{2}(\theta_{1i}\Delta LY_{t-i}) + u_{1t},$$
$$\Delta LY_t = \alpha_2 + \beta_2 ECT_{2t-1} + \sum_{i=1}^{2}(\delta_{2i}\Delta LY_{t-i}) + \sum_{i=1}^{2}(\theta_{2i}\Delta LP_{t-i}) + u_{2t},$$
$$ECT_{1t-1} = LY_{t-1} - \gamma_1 LP_{t-1}, \quad ECT_{2t-1} = LP_{t-1} - \gamma_2 LY_{t-1}. \tag{7}$$

where LP is the logarithm of a real commodity price index and LY is the logarithm of a real world output indicator (i.e., world GDP). Δ indicates a difference operator, ECT is the error correction term resulting from cointegration that is normalized with respect to each variable, and u_{it} is a white-noise random error term. The coefficients δ and θ are short-run parameters showing the immediate effects of lagged endogenous variables on themselves and on each other, respectively. The coefficient of ECT, β_i, measures the speed of adjustment of the i-th endogenous variable toward the long-run equilibrium.

The coefficient β_i indicates whether the deviation from long-run equilibrium is corrected gradually through a set of partial short-run adjustments. Thus, it is crucial for understanding the nature of long-run equilibrium relationship between endogenous variables. If the estimated coefficient β is statistically significant with the correct negative sign, it indicates the presence of a long-run relationship—i.e., any deviation from the long-run equilibrium gets corrected with adjustments over time. For instance, if β_1 is significant but β_2 is insignificant, this implies that commodity prices react to disequilibrium errors while world output does not, which suggests a unidirectional causality running from world output to commodity prices. If, however, β_1 is insignificant and β_2 is significant, a unidirectional causality running from commodity prices to world output is implied. The condition of both β_1 and β_2 being statistically significant indicates a bi-directional causal relationship among the two variables over the long run.

Before estimating the VECM, it is important to check the order of integration for the variables used in estimation by using the unit root tests. Table 5 reports the results of Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. The results show that the null hypothesis of a unit root in all variables in level form cannot be rejected, while the null hypothesis of a unit root in the first differenced variables is rejected at 1% level of significance. Thus, all variables used in the study are integrated of order one, I(1).

The next step is to test for whether there is a long-run cointegrating relationship between commodity prices and world output indicators. Table 6 summarizes the results of the two test statistics suggested by the Johansen cointegration likelihood ratio procedure (Johansen, 1988; Johansen & Juselius, 1990): the trace test and the maximum eigenvalue test. The LR and information criteria tests suggest that the optimum lag lengths of all variables are one. The results for the variable pairs of total non-oil price index and OECD GDP, and the same price index and world GDP, are reported in the first two rows of Table 6. The null hypothesis of zero cointegrating vectors ($r = 0$) is rejected by the maximum eigenvalue test at 5% level for both variable pairs. However, the null hypothesis that there are at least zero cointegrating vectors ($r \leqslant 0$) cannot be rejected at 5% level by the trace statistic for the total non-oil price index and OECD output, whereas it can be rejected at 5% level for the total non-oil price index and world output. Thus, if a 5% level criterion is taken, the Johansen test yields inconclusive results for the first variable pair with the Lambda-trace (λ_{trace}) statistic failing to reject the null of no

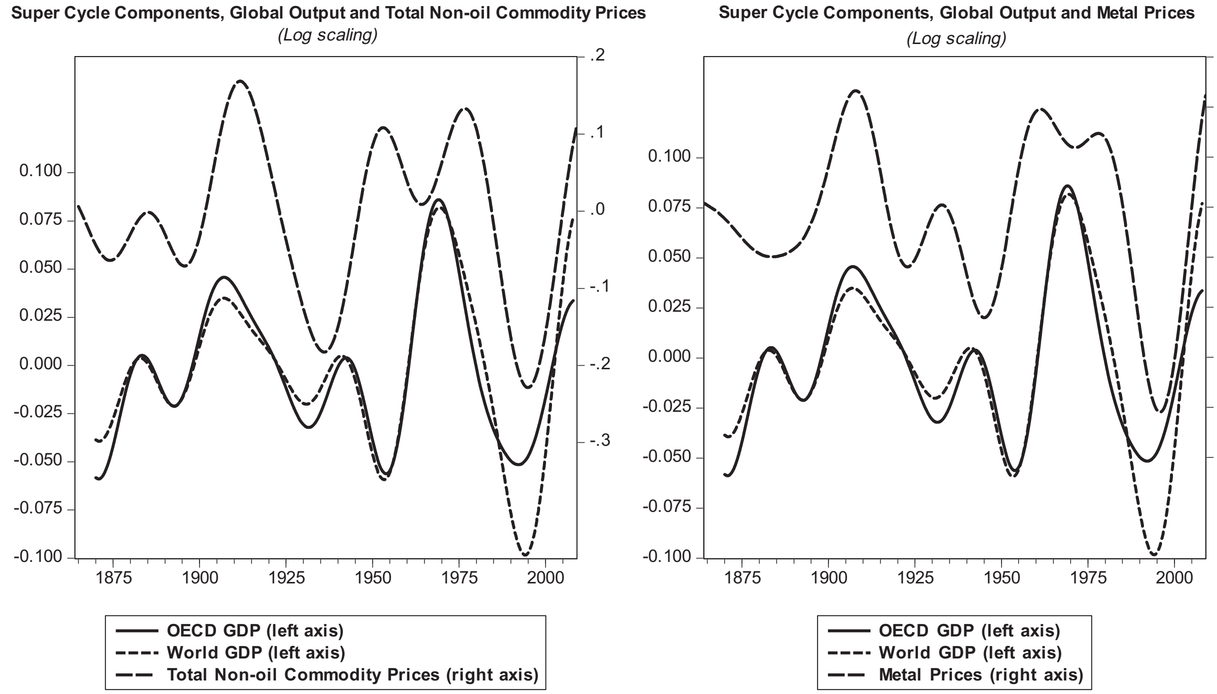

Figure 5. *This figure displays super-cycle components for global output and real metal price index. Each component is extracted by applying the asymmetric Christiano–Fitzgerald BP (20, 70) filter to the original series. The log scaling in both axes shows the percentage deviations from the long-term trend.*

Table 4. *Correlations: SC components of real prices and GDP*

	Total	Metals	Total agriculture	Tropical agriculture	Non-tropical agriculture	Petroleum	OECD GDP	World GDP
Total	1.00							
Metals	0.73**	1.00						
Total agriculture	0.99**	0.61**	1.00					
Tropical agriculture	0.94**	0.78**	0.92**	1.00				
Non-tropical agriculture	0.87**	0.37**	0.91**	0.68**	1.00			
Petroleum	0.42**	0.56**	0.34**	0.33**	0.34**	1.00		
OECD GDP	0.53**	0.61**	0.46**	0.43**	0.42**	0.19*	1.00	
World GDP	0.58**	0.73**	0.49**	0.47**	0.44**	0.46**	0.93**	1.00

The figures reported are the contemporaneous Pearson correlation coefficients for all the SC components for the balanced data 1875–2008.
* Significance at 5% levels.
** Significance at 1% levels.

cointegration and the Lambda-max ($\lambda_{\max}$) statistic rejecting the null of no cointegration.[11] However, the results of the Johansen test for the latter pair of interest conclude that the total non-oil commodity prices and world GDP have a long-run cointegrating relationship. The residual-based cointegration tests in a single equation setting reported in Appendix confirm this conclusion. Hence, overall the cointegration tests provide evidence that the non-fuel commodity prices are cointegrated with global output indices (both OECD and world GDP series) and their cointegrating relationship allows one variable to be used to predict the other.

The evidence for cointegration between the subindices of commodity prices and world GDP is mixed. For oil prices, the Johansen test results cannot reject the null of no cointegrating vectors. However, there is strong evidence of cointegration for the metals and total agricultural prices, and partial evidence for the tropical and non-tropical agricultural price indices from the trace tests. Recent studies based on small samples have used the evidence from trace test due to its robustness to nonnormality of errors compared to the maximum eigenvalue test (Phylaktis & Girardin, 2001).

The direction of long-term and short-term causalities (or predictabilities) for variable pairs can be illustrated by VECM if two variables are cointegrated. Table 7 shows that total non-oil commodity prices and OECD output have a long-run equilibrium relationship, but the coefficients of the error correction terms (ECT_{t-1}) imply unidirectional causality that runs from OECD output to commodity prices without any feedback effect in the long-run. Moreover, since the coefficients of $\Delta LP1_{t-1}$ and ΔLY_{t-1} are not statistically significant, this result implies that these two variables do not have a short-run causality relationship. The interaction of total non-oil commodity prices with the world output series is pretty similar in the long-run, but the higher coefficients of error correction term indicate faster adjustment to long-run equilibrium following any deviations in the short-run. This comes as no surprise since the long-run cointegrating relationship between world GDP and commodity prices is stronger than the one between OECD GDP and commodity prices. In all, there is clear evidence that the world GDP fluctuations are a useful predictor of non-oil commodity price cycles in the long-run (shown by the highly significant ECT_{t-1} term for ΔLP_t and insignificant ECT_{t-1}

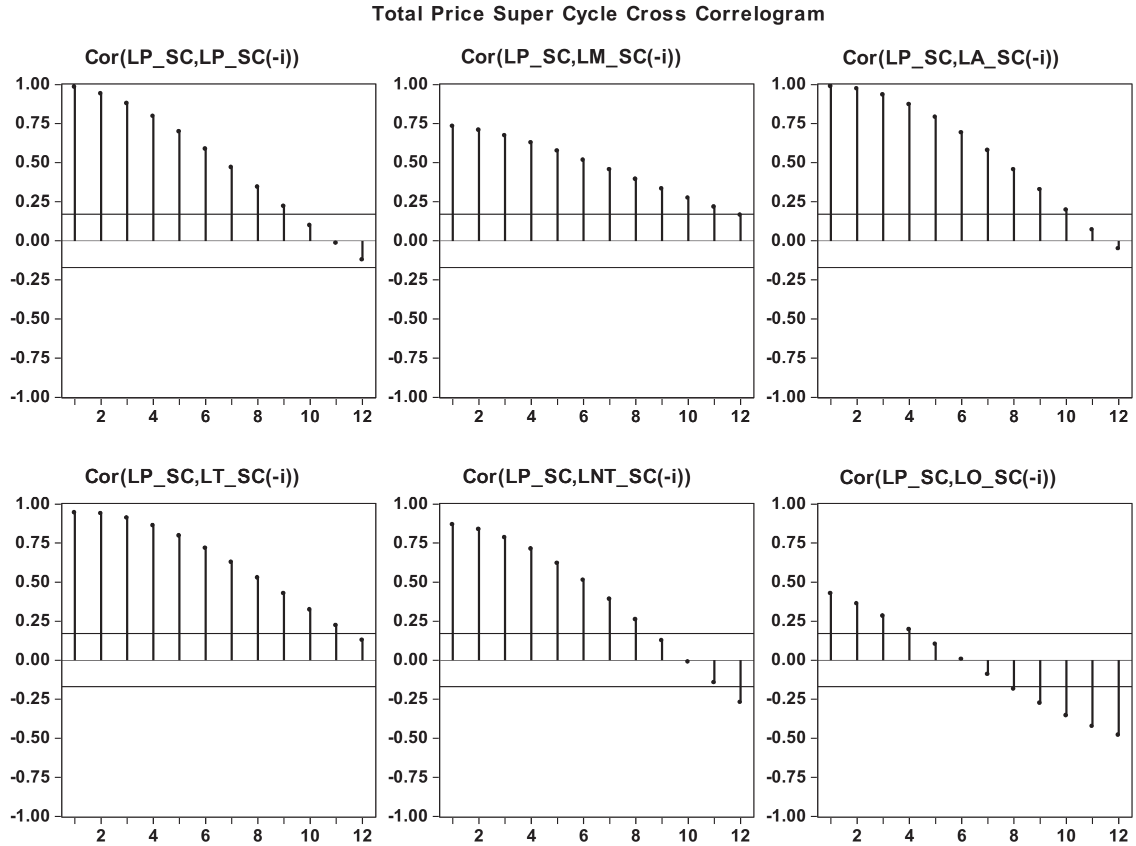

Figure 6. *Cross correlograms for the total price SC component with the other price indices' SC components. Most cross correlations at lag zero are highly significant, implying strong co-movement among SCs in commodity prices.*

term for $\Delta LY2_t$ in the sixth row of Table 7). This outcome also reflects that the world GDP level is weakly exogenous as one would have expected from a Schumpeterian perspective. [12]

The cointegrating relationship between metal prices and world GDP follows a similar pattern. The error correction term in the metal price equation shows that the real metal prices change by 26% in the first year following a deviation from long-run equilibrium. This speed of adjustment is the highest compared to other adjustment rates, showing that the metal prices are particularly sensitive to changes in economic activity in the long run. There are no statistically significant effects in the short run.

Similarly, the results of VECM involving the agricultural price indices and world GDP provide evidence for a long run relationship running from output to agricultural prices without any feedback effects. The speed of convergence to equilibrium is much higher for the total agricultural price index, followed by non-tropical and tropical price indices. As in the case of total non-oil and metal prices, the short-run effects are not statistically significant. The weak exogeneity of world GDP applies to the VECMs with metal and agricultural price indices as well.

This lead–lead relationship, i.e., the world GDP leading global non-oil commodity prices, is crucial to understand the nature of previous super cycles. In particular, the weakness of the downward phase experienced after the Korean war relative to those that started in the 1920s and 1980s is a reflection of the strong growth of the world economy in the 1950s and 1960s. In turn, the weakness of the upward phase experienced in the 1970s relative to all the others is a reflection of the fact that world economic growth slowed down significantly after the end of the "golden age" of industrial countries, which coincided with the first oil shock. This is also essential to understand the nature of the current upward phase. So, this analysis indicates that the commodity price boom could last as long as the growth boom lasts, which under current conditions will essentially be determined by the capacity of China and other major developing countries to delink from the period of slow economic growth that is expected in the industrial world. Thus, although previous super cycles would tend to expect an upward phase of perhaps 20 years (two thirds of which have gone by), it may be cut short by weak world economic growth—quite a likely scenario.

Table 8 displays the results from Granger causality test through VAR for the oil prices and world GDP pair that were not cointegrated. The results indicate that there is a short-run relationship running from crude oil prices to world output as seen from the highly significant coefficient of ΔLPO_{t-1} for $\Delta LY2_t$. This finding supports the widely observed hypothesis that oil price hikes constrain economic growth performance in the short run. Thus, oil prices constrain on the supply side the evolution of world GDP, in sharp contrast to non-oil prices, which follow world GDP and are thus essentially demand-determined.

6. CONCLUDING REMARKS

The decomposition of real commodity prices based on the BP filtering technique provides evidence of four past super

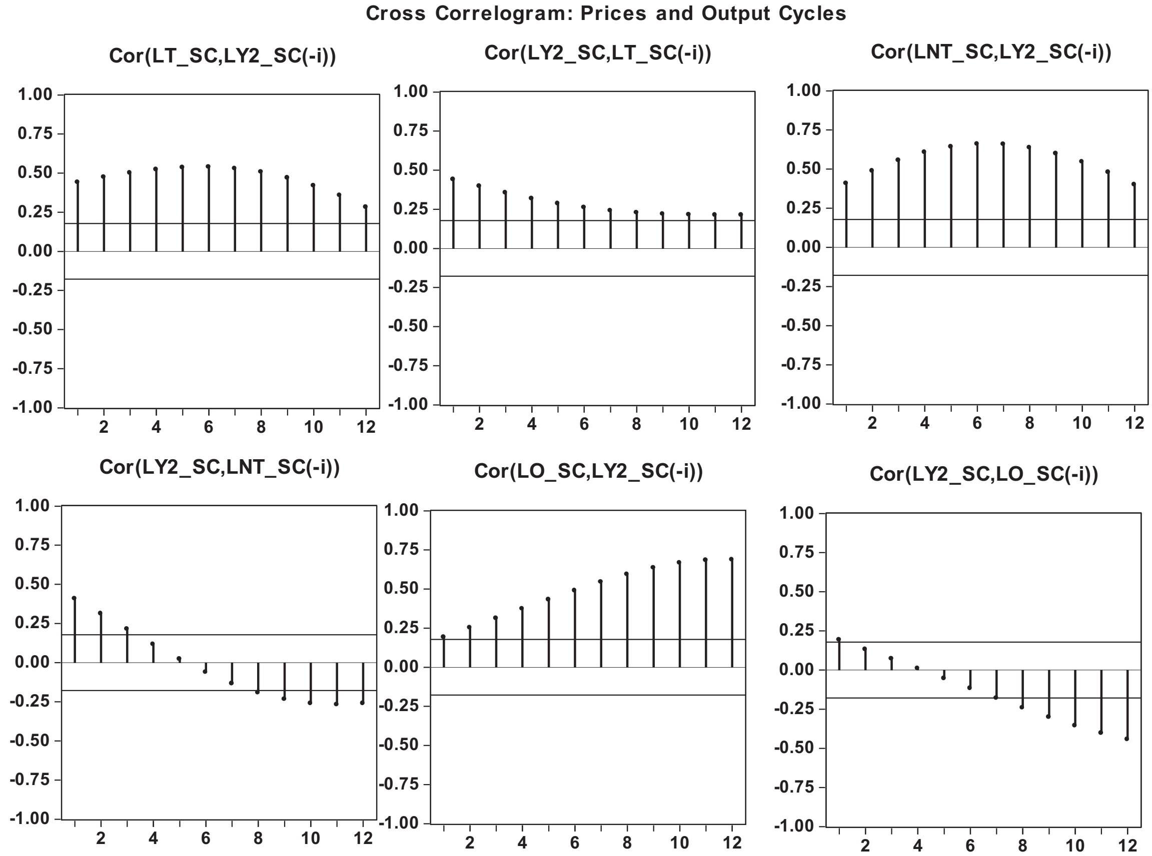

Figure 7. *Cross correlograms for the SC components of tropical, non-tropical agriculture, and oil price indices, and world output. This figure plots the bivariate cross correlograms between SC components of different price indices (tropical, non-tropical agriculture, and oil) and world GDP. Note that the SC components of all indices are more correlated with the lags of the world GDP super-cycle, indicating that the world GDP SC has led the SCs in tropical and non-tropical agriculture by 6 years, and in oil prices by roughly 12 years, respectively.*

Table 5. *ADF and PP tests for unit root*

Variable	ADF		PP	
	Level	First difference	Level	First difference
LP (log of prices)				
Total (*LP*)	−1.911	−10.072**	−1.643	−12.380**
Metals (*LPM*)	−2.499	−10.769**	−2.509	−10.976**
Total agriculture (*LPA*)	−1.795	−10.508**	−1.557	−14.589**
Tropical agriculture (*LPT*)	−1.553	−11.630**	−1.537	−11.649**
Non-tropical agriculture (*LPN*)	−2.314	−10.569**	−2.204	−22.031**
Oil (*LPO*)	−1.873	−10.456**	−1.594	−12.806**
LY (log of output)				
OECD output (*LY*1)	0.168	−7.685**	0.483	−7.033**
World output (*LY*2)	1.626	−7.184**	2.254	−6.833**

* Significance at 5%.
** Significance at 1%.

cycles ranging between 30 to 40 years. For the total real non-fuel commodities, these cycles, estimated from trough to trough, have occurred (1) from 1894 to 1932, peaking in 1917, (2) from 1932 to 1971, peaking in 1951, (3) from 1971 to 1999, peaking in 1973, and (4) the post-2000 episode that is still ongoing. These long cycles, which possess large amplitudes varying between 20% and 40% higher or lower than the long-run trend, are also a characteristic of sub-indices. Among the agricultural indices, the tropical agriculture exhibits super cycles with much larger amplitude relative to non-tropical agriculture. The amplitudes of super-cycle components of real metal and crude oil prices are comparable to those of agricultural products in earlier parts of the twentieth century, but they become much more pronounced and strong in the latter parts of the century. The presence of co-movement among non-fuel commodity indices is supported by the corre-

Table 6. *Results of Johansen cointegration likelihood ratio test*

Trace test				Maximum eigenvalue test			
Null hypothesis	Alternative	λ_{trace} stat.	Prob.**	Null hypothesis	Alternative	λ_{max} stat.	Prob.**
Total price and OECD GDP (LP and LY1)							
$r \leqslant 0$	$r = 1$	14.56	0.068	$r = 0$	$r = 1$	14.54*	0.045
$r \leqslant 1$	$r = 2$	0.03	0.871	$r = 1$	$r = 2$	0.03	0.871
Total price and World GDP (LP and LY2)							
$r \leqslant 0$	$r = 1$	18.23*	0.019	$r = 0$	$r = 1$	15.39*	0.033
$r \leqslant 1$	$r = 2$	2.84	0.092	$r = 1$	$r = 2$	2.84	0.092
Metals and World GDP (LPM and LY2)							
$r \leqslant 0$	$r = 1$	16.17*	0.040	$r = 0$	$r = 1$	16.08*	0.026
$r \leqslant 1$	$r = 2$	0.09	0.763	$r = 1$	$r = 2$	0.09	0.763
Total agriculture and World GDP (LPA and LY2)							
$r \leqslant 0$	$r = 1$	20.05**	0.010	$r = 0$	$r = 1$	16.94**	0.018
$r \leqslant 1$	$r = 2$	3.11	0.078	$r = 1$	$r = 2$	3.11	0.078
Tropical agriculture and World GDP (LPT and LY2)							
$r \leqslant 0$	$r = 1$	15.90*	0.043	$r = 0$	$r = 1$	12.97	0.079
$r \leqslant 1$	$r = 2$	2.94	0.087	$r = 1$	$r = 2$	2.94	0.087
Non-tropical agriculture and World GDP (LPN and LY2)							
$r \leqslant 0$	$r = 1$	16.23*	0.039	$r = 0$	$r = 1$	13.27	0.071
$r \leqslant 1$	$r = 2$	2.96	0.085	$r = 1$	$r = 2$	2.96	0.085
Oil and World GDP (LPO and LY2)							
$r \leqslant 0$	$r = 1$	10.42	0.250	$r = 0$	$r = 1$	9.50	0.247
$r \leqslant 1$	$r = 2$	0.92	0.338	$r = 1$	$r = 2$	0.92	0.338

The tests for metals and world GDP includes a deterministic dummy variable, D21, which takes the value 1 for years greater than and equal to 1921, and 0 otherwise. This variable captures the large structural break that took place in 1921.
*Significance at 5%.
**Significance at 1%.

Table 7. *Results of vector error correction model (VECM)*

	ΔLP_t	$\Delta LY1_t$
ECT_{t-1}	−0.201** (−3.85)	−0.013 (−0.73)
ΔLP_{t-1}	0.152 (1.75)	0.026 (0.88)
$\Delta LY1_{t-1}$	−0.093 (−0.38)	0.388** (4.66)
	ΔLP_t	$\Delta LY2_t$
ECT_{t-1}	−0.219** (−3.97)	−0.016 (−0.97)
ΔLP_{t-1}	0.155 (1.77)	0.027 (1.06)
$\Delta LY2_{t-1}$	0.047 (0.17)	0.448** (5.52)
	ΔLPM_t	$\Delta LY2_t$
ECT_{t-1}	−0.256** (−3.91)	−0.003 (−0.24)
ΔLPM_{t-1}	0.257** (2.78)	0.000 (−0.02)
$\Delta LY2_{t-1}$	−0.010 (−0.03)	0.418** (5.01)
	ΔLPA_t	$\Delta LY2_t$
ECT_{t-1}	−0.223** (−4.16)	−0.009 (−0.59)
ΔLPA_{t-1}	0.136 (1.58)	0.026 (1.08)
$\Delta LY2_{t-1}$	0.107 (0.37)	0.443** (5.49)
	ΔLPT_t	$\Delta LY2_t$
ECT_{t-1}	−0.157** (−3.41)	−0.001 (−0.12)
ΔLPT_{t-1}	0.092 (1.06)	0.011 (0.62)
$\Delta LY2_{t-1}$	0.180 (0.45)	0.431** (5.13)
	ΔLPN_t	$\Delta LY2_t$
ECT_{t-1}	−0.185** (−3.67)	−0.009 (−0.72)
ΔLPN_{t-1}	0.086 (0.99)	0.026 (1.18)
$\Delta LY2_{t-1}$	−0.001 (−0.01)	0.443** (5.67)

The VECM for the real metal prices and world GDP include D21 as a deterministic regressor, whose estimate is highly significant and negative.
**Significance at 5% level.

Table 8. *Results of VAR*

	ΔLPO_t	$\Delta LY2_t$
ΔLPO_{t-1}	−0.030 (−0.35)	-0.022^{**} (−2.05)
$\Delta LY2_{t-1}$	0.754 (1.26)	0.465^{**} (5.99)

** Significance at 5% level.

lation analysis across the entire sample, and a marked comovement between oil and non-oil indices is present for the second half of the twentieth century.

Another important finding of the paper is that, for non-oil commodities, the mean of each super cycle has a tendency to be lower than that of the previous cycle, suggesting a step-wise deterioration over the entire period in support of the Prebisch–Singer hypothesis. This finding applies especially to tropical and non-tropical agricultural prices, as well as metals in previous cycles. An exception to this rule is that of metals during the current super cycle, when the mean last cycle is higher than the preceding one; however, the contraction phase of this cycle has not even begun yet, which can lower the mean of the whole cycle in the upcoming years. Another way of capturing these trends is through long-term trends, with tropical agricultural prices experiencing a long severe long-term downward trend through most of the twentieth century, followed by non-tropical agriculture and metals. The duration of the long-term downward trends across all non-fuel commodity groups is on average 100 years. The magnitude of cumulative decline during the downward trend is 47% for the non-fuel commodity prices, with recent increases of around 8% far from compensating for this long-term cumulative deterioration. In contrast to these trends in non-oil commodity prices, real oil prices have experienced a long-term upward trend, which was only interrupted temporarily during some four decades of the twentieth century.

The recent commodity price hike of the early twenty-first century has commonly been attributed to the strong global growth performance by the BRICS economies, and particularly China, which is particularly metal- and energy-intensive. Based on the VECM results, it is found that super cycles in the world output level are a good predictor of the super cycles in real non-fuel commodity prices, both for the total index and sub-indices. This finding confirms that the global output accelerations play a major role in driving the commodity price hikes over the medium run. Therefore, the ongoing commodity price boom could last only if China and other major developing countries are capable of delinking from the long period of slow growth expected in the developed countries.

Given the current interest in analyzing commodity price fluctuations in the form of medium-term cycles, future research efforts highlighting the dynamics of long cycles and their demand and supply-side determinants would be highly valuable. This paper has emphasized the demand-side drivers of real non-oil commodity price cycles, in particular global demand expansion for raw materials and other industrial inputs during the rapid industrialization and urbanization of different economies (industrialized countries first, now emerging market economies). Supply side factors, such as increasing costs due to resource depletion or lack of investment in capacity enhancement, are additional drivers of price hikes that certainly play a crucial role in tandem with demand-side factors. A policy implication that follows from this analysis is that the mineral-abundant countries should be aware of the medium-term cycles in commodity prices, and develop policies to take advantage of the expansionary phases and take precautionary action against the contraction phases. The deviations of world GDP growth from the long-run trend are likely to give rise to the deviations from the long-run price trend that can be rather large in amplitude. Forecasting such deviations can be used as an important guide for determining longer term investments in various types of commodity production.

Another implication of the analysis presented in this paper is that the stepwise deterioration in real non-oil commodity prices with each super-cycle mean being lower than the previous one underlines the importance of diversifying toward the production of manufactured goods and services. Although not all manufactured goods (and probably not all services) are immune to deteriorating trends (especially low-technology ones), the high price elasticity associated with manufactures and services more than compensates for any such declining trend.

NOTES

1. See Kaplinsky (2006) for an analysis of the effect of the entry of China into the global market in increasing the demand for many "hard commodities" and reversing the declining trend in relative commodity prices.

2. For a more detailed version of the literature, see the working paper version of this paper.

3. The recognition of the presence of long-term cycles in commodity prices goes back to nineteenth century, most notably to the works of Clarke, Jevons, Tugan-Baranovski, and Wicksell. These studies, however, did not provide an explicit theory to explain the underlying dynamics of these long-term swings in commodity prices.

4. See Lewis (1978: 25–26) for a description of this debate.

5. Schumpeter referred to aggregate level of prices in general, and the extension of his analysis to the terms of trade between primary commodities and manufactures was done by Lewis and others as explained below.

6. For example, using the US CPI as deflator indicates that oil prices are below their real level after the second oil shock of the 1970s, but using the MUV indicates that current levels are higher.

7. Pfaffenzeller, Newbold, and Rayner (2007) extended the Grilli–Yang dataset providing detailed information on the construction of commodity price indices. The comparison of our data with Pfaffenzeller *et al.* (2007) indicates that the two set of series are very highly correlated. Over the overlapping period of 1900–2003, the correlation coefficients for total commodity price index is 1.00; that for the metal price index is 0.99; and that for the manufacturing unit value (MUV) index is 1.00. The food and non-food price indices of Pfaffenzeller *et al.* (2007) are not comparable to the tropical and non-tropical agriculture price indices that we used in this paper. The slight differences for the total commodity price indices, metal price indices and the MUV indices are due to the fact that our data covers a broader range of commodities as it is composed of prices for 24 commodities up to 1961 and 32 since 1962, whereas the data of Pfaffenzeller *et al.* is based on 24 commodities that were originally used by Grilli and Yang (1988).

8. Cuddington and Zellou (2012) compare the super cycles in crude oil prices to coal prices, and find that these overlap also in the post-war period. However, the long-term trends vary significantly: crude-oil prices trending upward while coal prices trending downward. Cuddington and Zellou argue that this difference is due to the relative supply scarcity for crude oil and the absence of such scarcity for coal.

9. This is a PPP-based measure that provides transitivity and other desirable properties, and it was invented by Roy Geary (1896–1983) and Salem Khamis (1919–2005) (see Background Note on "Historical Statistics" in www.ggdc.net/Maddison for more information).

10. For 1870, 1900, 1913, and 1940, OECD GDP accounts for 43%, 52%, 54%, and 55% of world GDP, respectively.

11. This result might be due to the lack of power of Johansen test in small samples and in series with structural breaks as reported by several studies (Cheung & Lai, 1993; Mallory & Lence, 2010; Nazlioglu, 2011; Toda, 1995).

12. Following Johansen (1992), we define weak exogeneity as follows: the *i*-th endogenous variable is said to be weakly exogenous with respect to the beta parameters (i.e., cointegrating vector parameters) if the *i*-th row of the alpha matrix (adjustment coefficients matrix) is all zero. This can be formally tested by imposing a restriction on the adjustment coefficient matrix such that the *i*-th row is all zero. Our test results indicated that we failed to reject the hypothesis that world GDP is weakly exogenous to the cointegrating equations of VECMs with all price indices except crude oil prices at 5% level of significance.

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APPENDIX

The Engle–Granger and Phillips–Ouliaris tests are applied to see whether the residuals obtained from the cointegrating equation is stationary with the only difference being that the former employs a parametric augmented Dickey–Fuller (ADF) method, while the latter applies the nonparametric Phillips–Perron (PP) approach. Results of both tests show that the null of no cointegration for both variable pairs is rejected at 5% level. The next test, Hansen parameter instability, involves a test of the null hypothesis of cointegration against the alternative of no cointegration. In the case of the alternative hypothesis of no cointegration, parameter instability is expected to be present. The results of the Hansen parameter instability test suggest that one fails to reject the null of cointegration at 5% level of significance for both variable pairs. Finally, Park's added variables test, which is computed by testing for the significance of time trends in a cointegrating equation, is used to test the significance of a linear time trend in the cointegrating equation and it fails to reject the null of cointegration that includes a linear time trend.

τ-Statistic				z-Statistic			
Null hypothesis	Alternative	τ-Stat.	Prob.**	Null hypothesis	Alternative	z-Stat.	Prob.**
1. Engle–Granger test							
Total price and OECD GDP (LP and $LY1$)							
No cointegration	Cointegration	-3.54^{**}	0.034	No cointegration	Cointegration	-24.14^{**}	0.018
Total price and World GDP (LP and $LY2$)							
No cointegration	Cointegration	-3.52^{**}	0.036	No cointegration	Cointegration	-25.14^{**}	0.015
2. Phillips–Ouliaris test							
Total price and OECD GDP (LP and $LY1$)							
No cointegration	Cointegration	-3.58^{**}	0.030	No cointegration	Cointegration	-24.72^{**}	0.016
Total price and World GDP (LP and $LY2$)							
No cointegration	Cointegration	-3.60^{**}	0.028	No cointegration	Cointegration	-26.37^{**}	0.011
Null hypothesis	Alternative	L_c-stat.	Prob.**				
3. Hansen parameter instability test							
Total price and OECD GDP (LP and $LY1$)							
Cointegration	No cointegration	0.599^{*}	0.056				
Total price and World GDP (LP and $LY2$)							
Cointegration	No cointegration	0.399	0.173				
Null hypothesis	Alternative	Chi-square	Prob.**				
4. Park's added variables test							
Total price and OECD GDP (LP and $LY1$)							
Cointegration	No cointegration	1.611	0.204				
Total price and World GDP (LP and $LY2$)							
Cointegration	No cointegration	1.726	0.189				

* Significance at 10%.
** Significance at 5%.