# SUPER-CYCLES OF COMMODITY PRICES SINCE THE MID-NINETEENTH CENTURY

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**Abstract**

*The decomposition of real commodity prices using the BP filtering technique provides evidence of four super-cycles over 1865 to 2009 ranging between 30 to 40 years and with amplitudes of 20 to 40 percent higher or lower than the long-run trend. Non-oil price super-cycles follow those of world GDP, indicating that they are essentially demand-determined. In contrast, causality runs in the opposite direction for oil prices. In turn, the mean of each super-cycle of non-oil commodities is generally lower than that of the previous cycle suggesting a step-wise deterioration in support of 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. Again, in contrast to these trends, real oil prices have experienced a long-tern upward trend, which was only interrupted temporarily during some four decades of the twentieth century.*

**JEL Classification:** C22, E3, Q02

**Keywords:** Super-cycles, commodity prices, band-pass filters, Prebisch-Singer hypothesis

## I. 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 percent. 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 (and, in the case of tropical agriculture, an incomplete one). In this sense, it can be said that there was a boom of mineral, not of agricultural prices. Similar to earlier periods of high prices, 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 is experiencing again high commodity prices, which in a sense can be seen as part of the 2004-08 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.

The rapid pace of industrial development and urbanization in China, India, and other emerging economies have caught the attention of financial and metal industry

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analysts who have 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 base material prices (Rogers 2004; Heap 2005). Super-cycles differ from short-term fluctuations restricted 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 year 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 economic growth in the United States from late nineteenth through the early twentieth century led to a super-cycle expansion in commodity prices that was rather well-sustained and prolonged. Another upswing has taken place during the post-war reconstruction in Europe and further enhanced by Japanese post-war economic emergence. 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 a 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 and Rotemberg, 1990; Cuddington and Jerrett, 2008).

Why should one focus on studying super-cycles in commodity prices? The presence of super-cycles in commodity prices matters for a number of decisions in production as well as in governance. First, trends in commodity prices have been considered for a long time a central policy issue for commodity-dependent developing countries. Second, the decision to increase capacity through new capital investments is directly related to the current price levels in comparison to the expected future trends. In mining sectors, it takes up to twenty years from the initial capital investment until the project is completed and new revenues are realized (Davis and Samis, 2006). Thus, private as well as state-owned firms must factor such trends into their investment decisions. Third, financial investors have found 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 in the Wall Street have not only become profitable investment vehicles, but also fueled the demand for speculation in commodity prices, both metal and agricultural. Fourth, approaching the analysis of commodity prices from the super-cycle framework is in itself an important innovation over the more traditional analysis of trends and structural breaks for at least two reasons. It allows us to analyze the gradual change in long-term trends instead of a priori assuming a constant deterministic or stochastic trend. Thus, the gradual evolution of long-term trends provides an alternative interpretation of the Prebisch-Singer hypothesis, as the tendency for the primary commodity prices to deteriorate relative to manufactured goods is not an inevitable persistent effect, but rather an evolving dynamics dependent on global demand trends and the effects of technological innovations. Yet, as we will see, the examination of these long cycles still shows that the mean of each price cycle has significantly declined over the course of the twentieth century, lending support to the original Prebisch-Singer hypothesis.

The objectives of this paper is twofold: (1) to identify and distinguish between the successive 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 oil price data used in the IMF's *World Economic Outlook*; 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. Section II begins with a review of the literature on long cycles and their importance in theoretical and empirical analyses. Section III provides an empirical framework to identify and extract super-cycles from the original price series. Section IV presents the empirical results from the commodity price decomposition and establishes the duration and amplitude of each cycle since late nineteenth century for each non-oil and oil price index. Section V adopts a vector error correction model to explore the short-run and long-run relationships between commodity prices and global GDP from 1870 to 2008. Section VI provides a summary of conclusions and discusses some policy implications.

## II. Literature Review on Long Cycles

The recognition of the presence of long-term economic fluctuations 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 or model to explain the underlying dynamics of these long-term swings in commodity prices.

The credit for developing major analytical frameworks goes to Nikolai Kondratiev and Joseph Schumpeter. Kondratiev was initially interested in documenting the existence of long swings spanning forty to sixty years using series of commodity prices, industrial production, interest rates, and foreign trade. Later on, his interest shifted to provide an explanation for the presence of these long waves. In his analysis of the long waves since late eighteenth century, Kondratiev discarded any exogenous changes such as wars, revolutions, or gold production in favor of endogenous factors such as technological changes inherent in capital accumulation as the major drivers of the long waves.

Schumpeter was influenced by Kondratiev's ideas a great deal, especially in the endogeneity of driving factors, but as an economist of the Austrian tradition, he located entrepreneurial innovations at the center of these long cycles of growth and contraction. In his *Business Cycles* (1939), Schumpeter identified overlapping cycles of various durations: long Kondratieff cycles lasting about 50 years, shorter Juglar cycles lasting about 9 years, and rather short Kitchen cycles of around 3 years of length. His explanation for the Kondratieff cycles rested 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 older, obsolete sectors/methods of production. The transformation of the economy through these clusters of innovations in emerging sectors forms the prosperity phase, which is later accompanied by the stagnation phase in which innovations are assimilated across the industries and technologies are more standardized.

Commodity prices are directly related to these phases of prosperity and stagnation that form the long cycles. In the prosperity phase, the initial competition for productive inputs (metals, minerals, agricultural goods) tends to increase their prices relative to products that are directly influenced by innovation. Hence, the relative price of commodities rises during the prosperity phase of the cycle. The gradual imitation of innovations by other producers and the resulting reduced opportunities to obtain economic rents slows down the demand for commodities, making them relatively cheaper again. It is important to note that Schumpeter rejected the idea that depressing prices caused declines in output, and put forward the alternative that it is the declining output growth that pushed prices down.

Schumpeter expected the prices in each cycle to lie below the corresponding point of the previous cycle due to the productivity improvements resulting from innovation. In particular, he identified three long cycles in the development of modern capitalism. First, the period 1786 to 1842 was the one in which the first industrial revolution took place in Britain. Second, the period 1842 to 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". The upswing in prices occurred in the initial phase of prosperity until 1873, after which the prices began to fall. Third, an incomplete cycle from 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". These innovations generated another upswing of prices. 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 cycles carries its importance to analyzing the terms of trade movements between agriculture and industry. Writing forty years after Schumpeter, Lewis observed that the Kondratieff 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 (1978: 27). Rostow (1979) observed 50-year long waves in commodity prices with upswings from 1790-1815, 1848-1873, and 1896-1920, and downswings from 1815-1848, 1873-1896, and 1920-1936. "The lags involved in responding to a relative rise in food or raw material prices, and the fact that the response often required the development of whole new regions, led to an overshooting of world requirements and a period of relative surplus. A relative fall in the prices of food and raw materials then followed … until expanding world requirements caught up with the excess capacity" (Rostow, 1979: 22).

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. Singer (1950) and Prebisch (1950), based on data for Britain's terms of trade since late nineteenth century, showed that, given the then prevailing international division of labor, the improvement for Britain's terms of trade could be understood as a deterioration for the terms of trade for countries exporting primary commodities. Their argument was composed of two complementary hypotheses (Ocampo, 1986; Ocampo and 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 meant 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.

What is perhaps more important to emphasize for the purposes of this paper is that 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 a tendency to deteriorate. This meant that even though developing countries could industrialize and produce mature manufactured products, the fact that these products are standardized meant that they did not create new economic rents. Instead, the rents emerged for the fruits of innovation undertaken mostly in advanced countries, which means that the economic rents were captured by these countries' innovating entrepreneurs. If the Prebisch-Singer hypothesis is reconsidered from this perspective, it is clear that the long cycles following innovations in output growth generate cyclical fluctuations of similar durations for relative prices of primary commodities. In expansionary periods with growing investment and innovation in the real sector, the prices of primary commodities and intermediate manufactured goods that are inputs in production tend to rise faster than final manufactured goods, leading to rising terms of trade for many developing countries. In periods of global slowdown or recession and declining rates of investment and innovation, the demand pressures ease down and the previous rising supply creates excess supply for many primary commodities and intermediate goods, pushing their prices down relative to final manufactured goods.

Kuznets (1940) criticized Schumpeter for not being able to explain why innovations happened in clusters over time. Since this recurring "bunching" of innovations is left unexplained, Kuznets argued that the periodic occurrence of long cycles is also left unexplained. Putting forward Kuznets cycle of about 25 years as an alternative, he argued that long-term trends in production and prices reflect the life-cycles of innovations in principal sectors of the economy.

On the neo-Schumpeterian side, Mensch (1979) argued that clusters of innovations emerge during depressions since under depressed economic conditions firms are desperate enough to revive profitability by investments in risky innovative technologies. Clarke, Freeman and Soete (1981) disputed this depression trigger hypothesis by arguing that innovations are subject to a delay during depressions, and a number of crucial innovations begin to emerge in the recovery phase of the long cycle.

Following Kuznets's approach, Rosenberg and Frishtak (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. This view prevailed in mainstream economics especially after 1985, when Samuelson's new edition of the text *Economics* left out his earlier reference to cycles of different periodicities (both short- and long-term) and instead argued: ''in their irregularities, business cycles more closely resemble the fluctuations of the weather,'' later also regarding long waves as "science fiction". Gary S. Becker, in his presidential address to the American Economic Association, 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).

Despite this skepticism about long cycles, a number of recent studies have examined them under the rubric of "medium-term" cycles. These include Solow (2000), Blanchard (1997), Krugman (1998), Sargent (1999), Boshof (2010), Comin and Gertler (2006), and Braun et al (2008). The latter three of them employ band-pass filtering techniques that resemble the ones used in this paper to identify medium-term cycles of about 40-50 years from various macroeconomic series. Braun et al (2008), for example, filter Japanese data to extract medium-term cycles with duration of 40 years or less, and then develop a growth cycle model to account for the sources of variation in total factor productivity for Japan. Other studies using these filtering techniques has increased greatly in number in the recent years, and some have been undertaken in the study of commodity prices as discussed in the next section.

## III. 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 $\lambda$ (Baxter and 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 (2008) 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, 2007) discussion that super-cycles have upswings of 10 to 35 years, yielding a complete cycle of roughly 20 to 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 twenty to seventy years:

$$LP\_SC \equiv LP\_BP\ (20, 70) \quad (2)$$

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

$$LP\_T \equiv LP\_BP\ (70, \infty) \quad (3)$$

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 to 20 year periodicities:

$$LP\_O \equiv LP\_BP\ (2, 20) \quad (4)$$

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:

$$LP\_NT \equiv LP\_BP\ (2, 20) + LP\_BP\ (20, 70) \quad (5)$$

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

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

## IV. 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 updated 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).[1]

[1] The authors would like to thank Joong Shik Kang from the IMF for providing the spliced oil price series.

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 and 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.[2] Price series were updated up to 2010 for this paper.

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. Fig. 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 upwards from 1865 to the mid 1910s, trended downward until late 1990s, and then trended upward through the end of the sample.

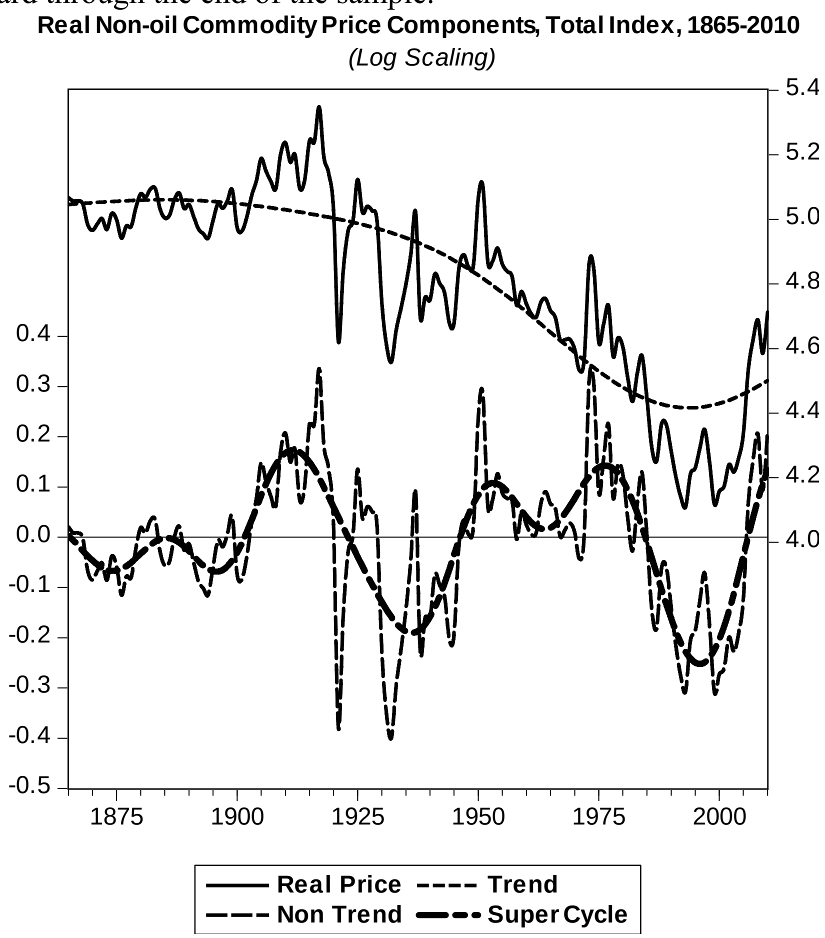


**Fig. 1.** This figure indicates the decomposition of the log of the real non-oil total commodity price index into its various components, as explained in the text, using the asymmetric Christiano and Fitzgerald (2003) band-pass filter.

[2] 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.

The non-trend component representing the difference between the actual series and the long-run trend is shown in the bottom portion of Fig. 1. The left scaling in logarithms shows that a value of 0.40 indicates a 40 percent 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 year range. The super-cycle component is shown in the bottom section of Fig. 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 Fig. 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 commodity price index, this averages considerable variation between tropical and non-tropical agricultural prices. After trending upward until mid 1890s, the tropical prices trend downwards steadily and strongly over time. By contrast, non-tropical prices trend mildly downwards 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). The excess supply of labor in tropical agriculture exerts a downward pressure on prices for tropical products, as predicted by the second variant of the Prebisch-Singer hypothesis. 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 much from unlimited supplies of labor that prevents wages from rising as the tropical agriculture does.

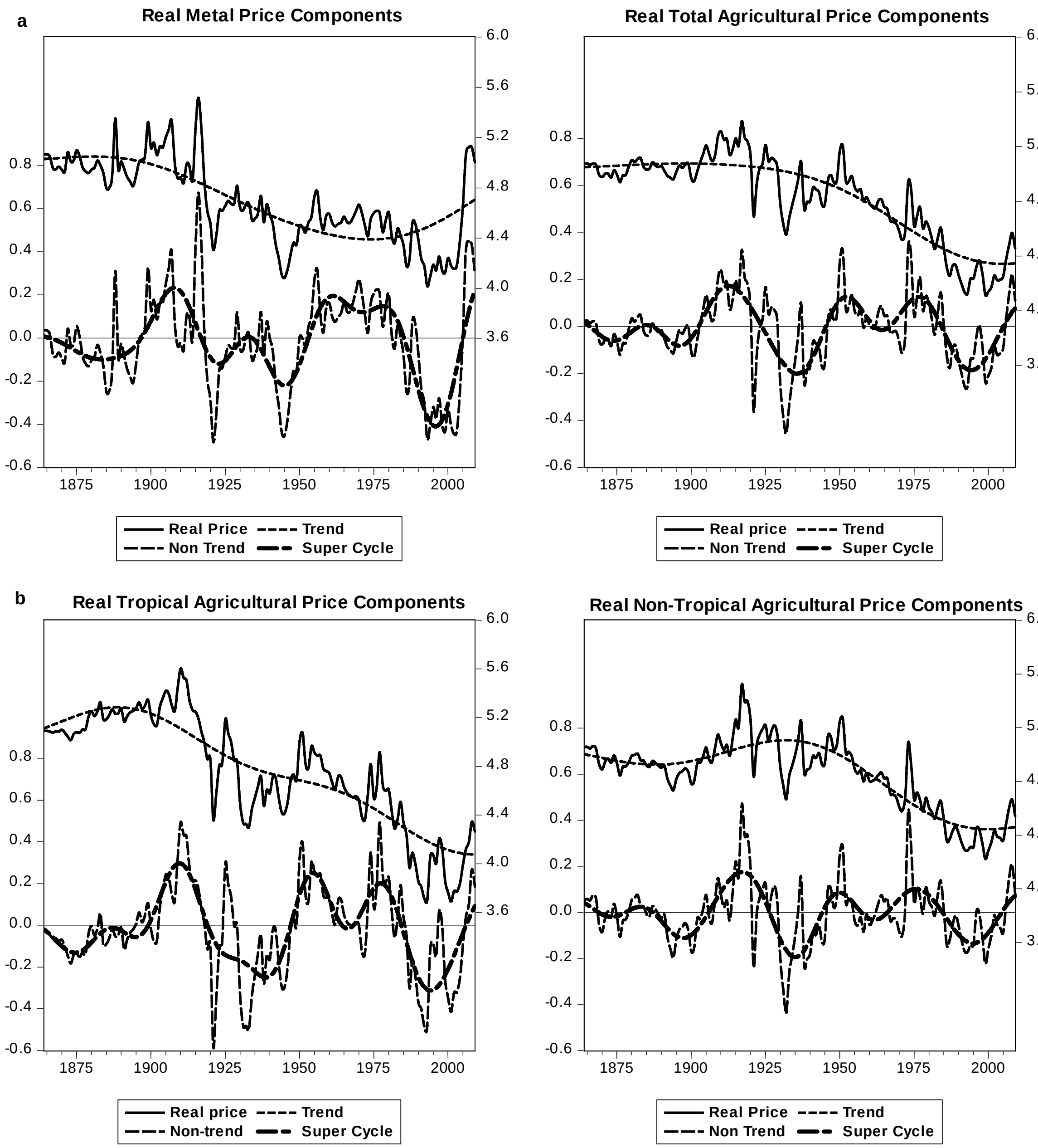


**Fig. 2.** Real price decompositions for **(a)** metals and total agriculture, **(b)** tropical and non-tropical agriculture. This graph shows the decomposition of the natural logarithm of real prices series into a long-term trend, a super-cycle and short-term cycle components.

**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 – 2010** |
| 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 – 1994** | **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 – 1962** | **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 |
| *Notes:* This table displays the descriptive statistics of long-term trends identified in the ACF BP filter decomposition analysis. | | | |

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 as follows: 1885-1921, 1921-1945, 1945-1999, 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 Fig. 3. The time span covers from 1875 to 2010 due to data availability. Fig. 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.

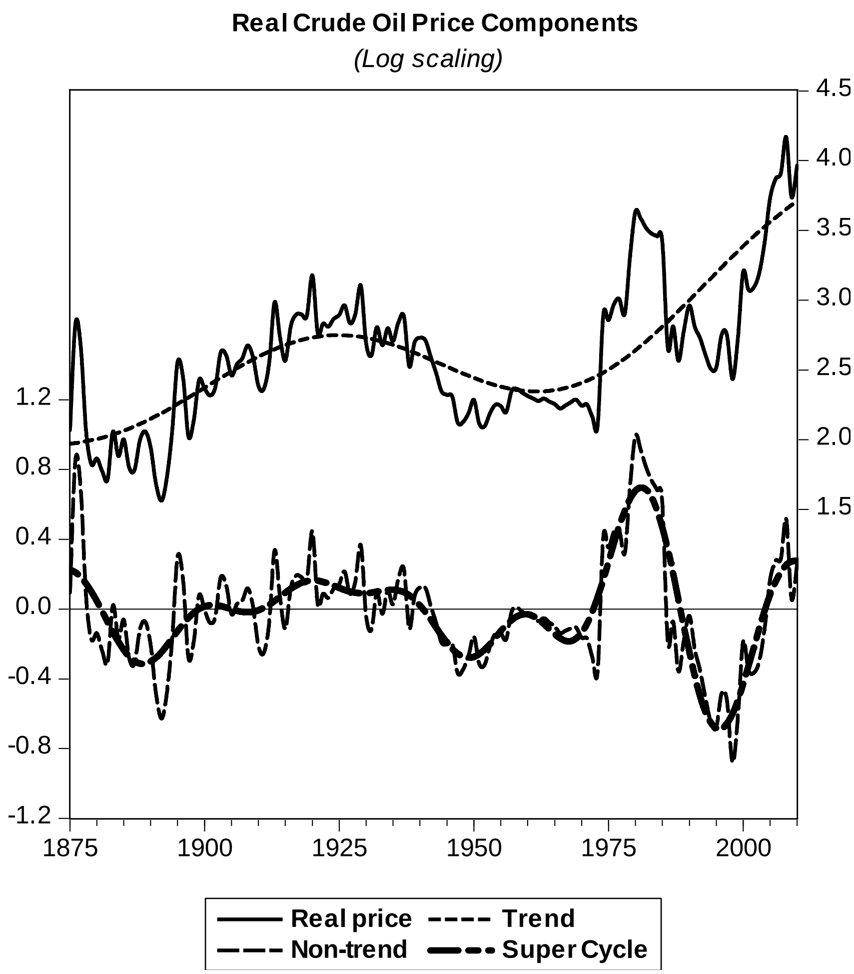


**Fig. 3.** This graph shows the decomposition of the natural logarithm of real prices of petroleum into long-term trend, a super-cycle and a short-term cycle.

Super-cycles in oil prices shown in the lower part of Fig. 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 real 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 futures markets (Pollin and Heintz, 2011).

Fig. 4 shows the super-cycles of non-oil and oil prices on the left hand side, and the super-cycles of non-oil subindices 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 Fig.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).

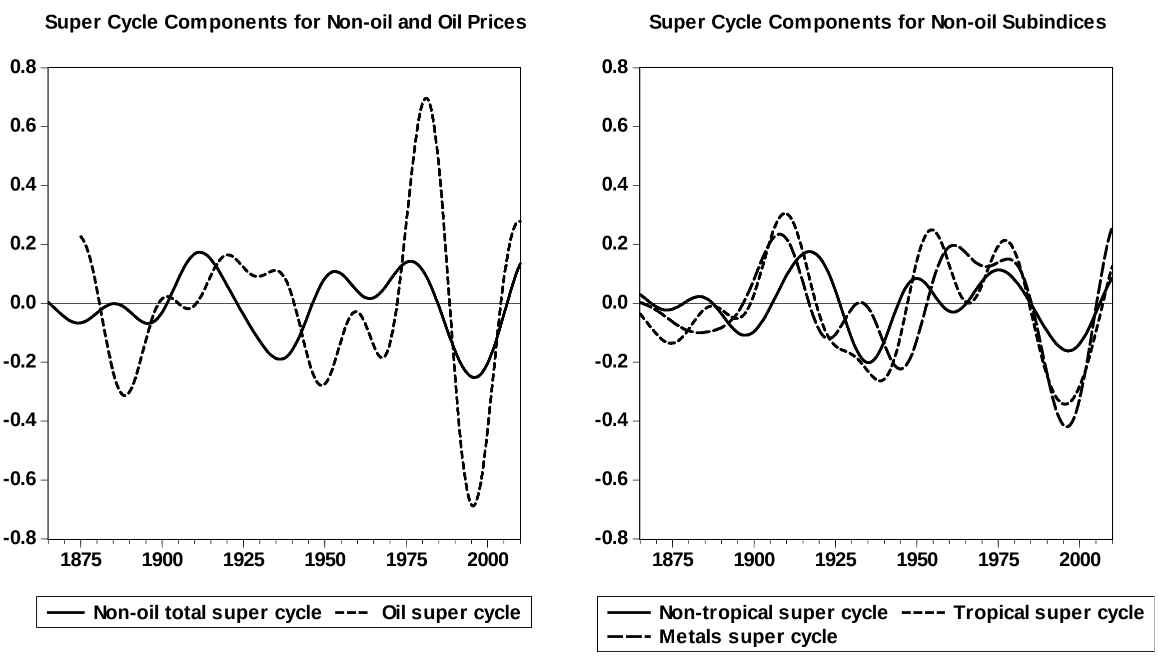


**Fig. 4.** This figure displays super-cycle components for non-oil and oil prices (the left panel), and for non-oil subindices including metals, tropical, and non-tropical agriculture (the right panel). Each component is extracted by applying the asymmetric Christiano-Fitzgerald BP (20, 70) filter

to the original real price series. The log scaling in the left axis shows the percentage deviations from the long-term trend.

Table 2 reports the descriptive statistics of super-cycles 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 Fig. 4. An interesting finding shown in Table 2 is that mean real non-oil prices 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 1933-1972, and it continued to decline from 74.8 over 1972-1999 to 53.9 over the ongoing super-cycle.

**Table 2.** Descriptive Statistics of Super-cycles in Commodity Prices

| **Total non-oil commodity prices** | | | | |
|---|---|---|---|---|
| | **1894-1932** | **1932-1971** | **1971-1999** | **1999-?** |
| 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 |
| Skewness | -0.7 | 0.9 | 0.6 | 0.5 |
| Kurtosis | 3.6 | 4.0 | 2.6 | 1.6 |
| **Metal prices** | | | | |
| | **1885-1921** | **1921-1945** | **1945-1999** | **1999-?** |
| 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 |
| Skewness | 0.5 | -0.8 | -0.3 | 0.4 |
| Kurtosis | 3.4 | 3.0 | 2.3 | 1.4 |

**Total agricultural prices**

| | 1894-1932 | 1932-1971 | 1971-1999 | 1999-? |
|---|---|---|---|---|
| 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 |
| Skewness | -0.6 | 0.7 | 0.8 | 0.7 |
| Kurtosis | 3.5 | 3.8 | 3.1 | 2.2 |

**Tropical agricultural prices**

| | 1891-1933 | 1933-1972 | 1972-1999 | 1999-? |
|---|---|---|---|---|
| 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 |
| Skewness | -0.4 | 0.7 | 0.6 | 0.6 |
| Kurtosis | 2.5 | 3.2 | 2.6 | 1.9 |

**Non-tropical agricultural prices**

| | 1894-1932 | 1932-1971 | 1971-1999 | 1999-? |
|---|---|---|---|---|
| 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 |
| Standard deviation | 31.6 | 23.3 | 20.5 | 11.6 |
| Coefficient of variation | 20.2 | 16.9 | 21.8 | 13.8 |
| Skewness | 0.8 | 0.6 | 1.5 | 0.5 |
| Kurtosis | 3.6 | 3.1 | 5.8 | 2.3 |
| **Crude oil prices** | | | | |
| | **1892-1947** | **1947-1973** | **1973-1998** | **1998-?** |
| 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 |
| Skewness | 0.0 | -0.3 | 0.8 | 0.3 |
| Kurtosis | 3.0 | 2.2 | 2.4 | 1.9 |

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

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 and 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.

**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 |

*Notes:* ***, **, * indicate significance at 10%, 5%, and 1% levels respectively. 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.

## V. Relationship between Commodity Prices and Global Output: Short-term and Long-term

*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[3]. 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

[3] 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).

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[4].

The left-hand side of Fig. 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 Fig. 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 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.

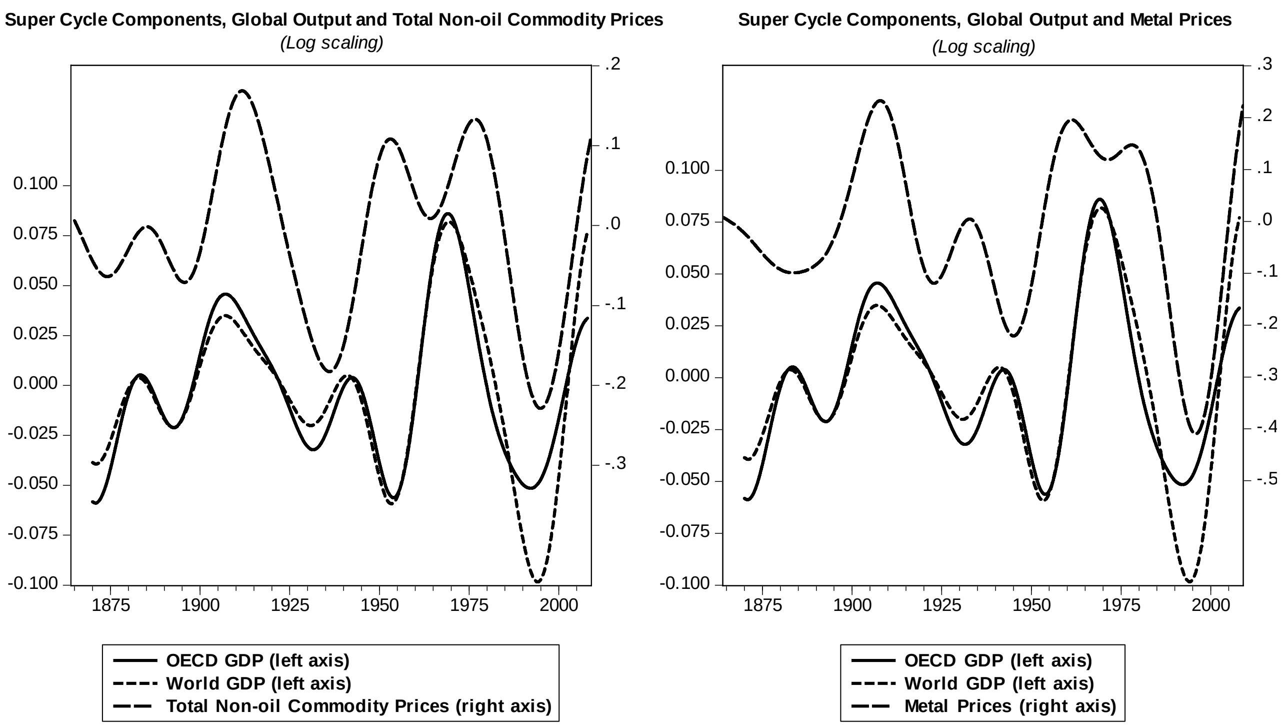


**Fig. 5.** This figure displays super-cycle components for global output and real metal price index. Each component is extracted by applying the asymmetric Christiano-Fitzgerald BP (20, 70) filter to the original series. The log scaling in both axes shows the percentage deviations from the long-term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

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

**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 |

*Notes:* The figures reported are the contemporaneous Pearson correlation coefficients for all the SC components for the balanced data 1875-2008. ** and * denote significance at 1% and 5 % levels, respectively.

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 Fig. 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 among the super-cycles in 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.

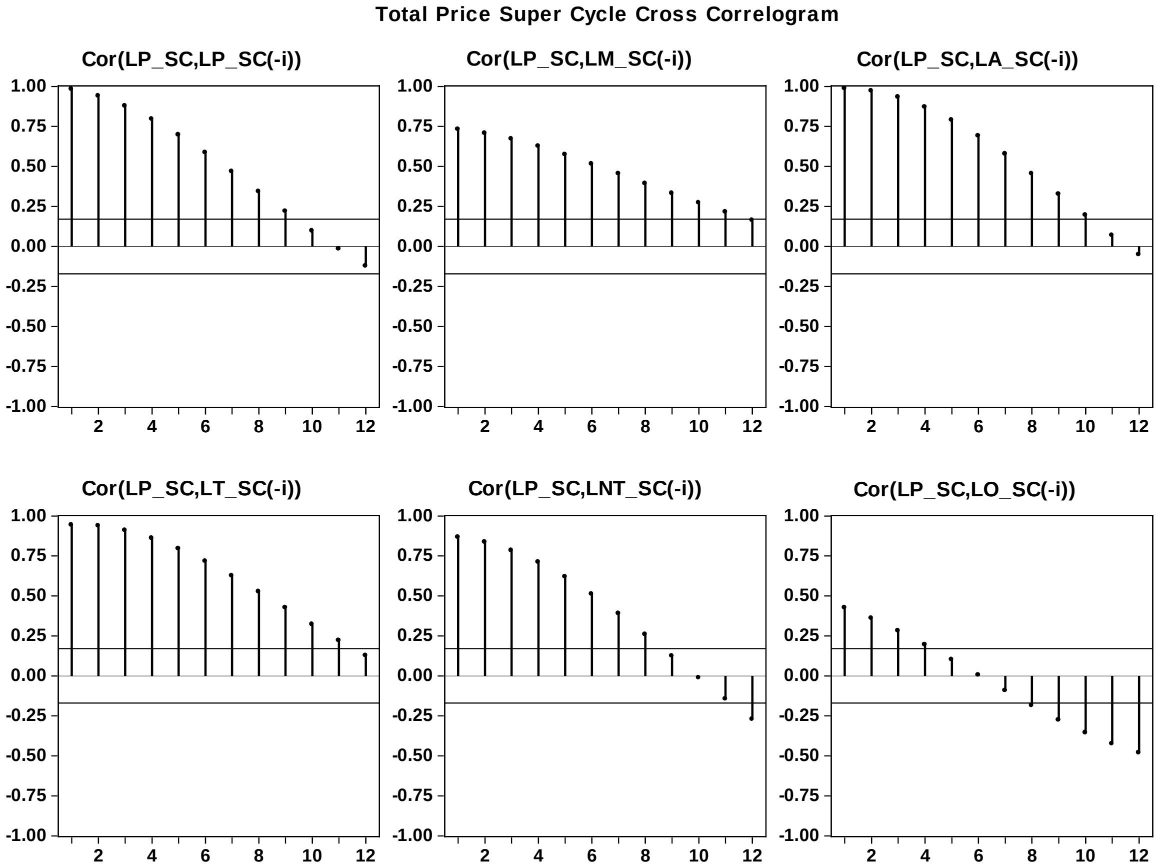


**Fig. 6.** Cross correlograms for the total price SC component with the other price indices' SC components. Most cross correlations at lag zero are highly significant, implying strong co-movement among SCs in commodity prices.

The cross correlograms shown in Fig. 7 differ significantly from the one in Fig. 6 in terms of the lead-lag relationships that they imply. Fig. 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 six 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.

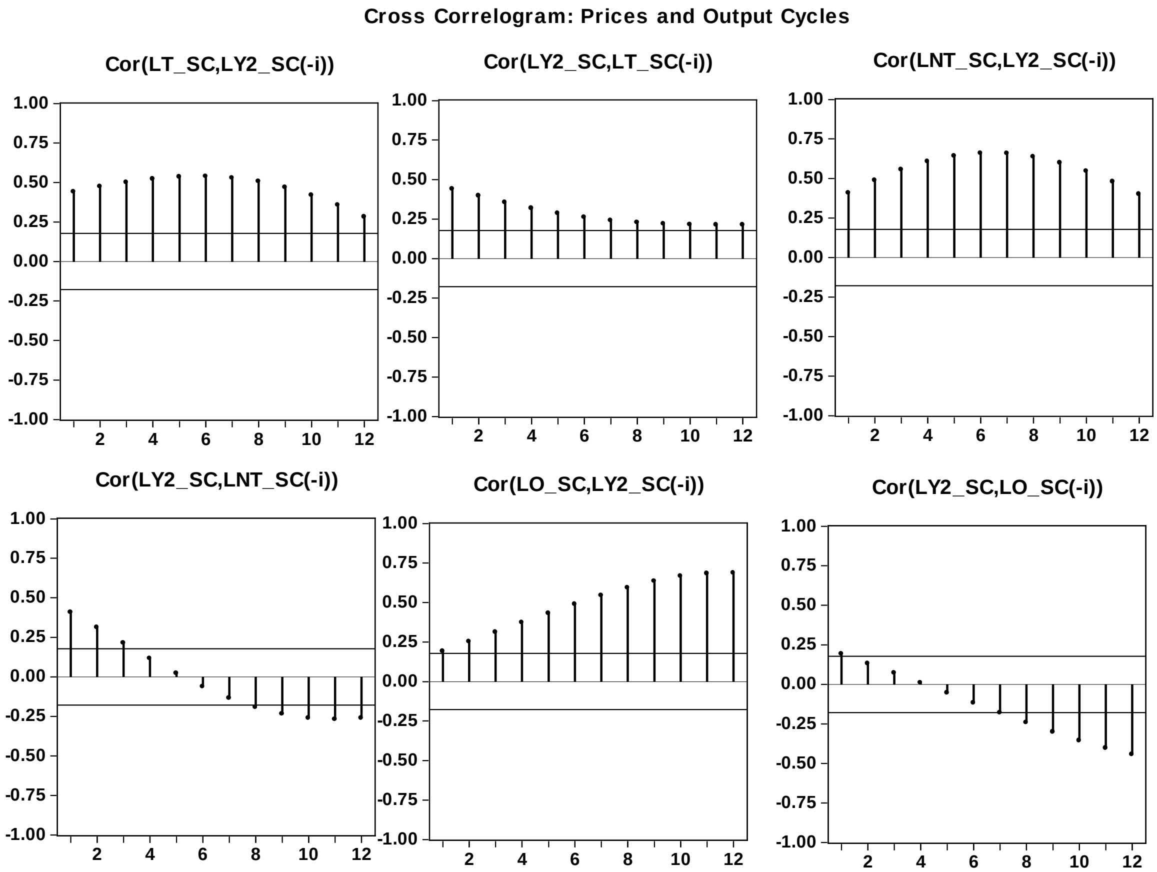


**Fig. 7.** Cross correlograms for the SC components of tropical, non-tropical agriculture, and oil price indices, and world output. This figure plots the bivariate cross correlograms between SC components of different price indices (tropical, non-tropical agriculture, and oil) and world GDP. Note that 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 six years, and in oil prices by roughly twelve years, respectively.

*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 implies 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:

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

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). $\Delta$ 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 coefficient of $ECT$ is crucial for understanding the nature of long-run dynamics by providing information regarding the long-run equilibrium relationships between the two variables. If the estimated coefficient $\beta$ is statistically significant, it indicates that the two variables have a long-term causal relationship. For instance, if $\beta_1$ is significant but $\beta_2$ is insignificant, the situation indicates a unidirectional causality running from world output to commodity prices. If, however, $\beta_1$ is insignificant and $\beta_2$ is significant, a unidirectional causality running from commodity prices to world output is implied. The condition of both $\beta_1$ and $\beta_2$ being statistically significant indicates a bi-directional causal relationship among the two variables over the long run.

The coefficients $\delta$ and $\theta$ illustrate the speed of adjustment back to a long-run equilibrium. Thus, their significance implies the presence of Granger causality for the short-term dynamic process among the two variables. For instance, if the null hypothesis ($\theta_2 = 0$) is rejected, it means that the prices of a set of commodities exert a short-run impact on the world growth performance.

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 percent level of significance. Thus, all variables used in the study are integrated of order one, I(1).

**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 (LY1) | 0.168 | -7.685** | 0.483 | -7.033** |
| World output (LY2) | 1.626 | -7.184** | 2.254 | -6.833** |
| *Notes:* * denotes significance at 5%, and ** denotes significance at 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 and 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 ($r \leq 0$) 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 ($\lambda_{trace}$) statistic failing to reject the null of no cointegration and the Lambda-max ($\lambda_{max}$) statistic rejecting the null of no cointegration[5]. However, the results of the Johansen test for the latter pair of interest conclude that the total commodity prices and world GDP have a long-run cointegrating relationship. The residual-based cointegration tests in a single equation setting reported in Appendix A 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.

[5] 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 and Lai, 1993; Toda, 1995; Mallory and Lence, 2010; Nazlioglu, 2011).

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

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

*Notes:* ** and * denote significance at 1% and 5% respectively. 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.

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 and 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 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 $\Delta LY_{t-1}$ are not statistically significant, this result implies that these two variables do not have a Granger causality relationship in the short-run. The interaction of total 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 at 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 $\Delta LP_t$ and insignificant $ECT_{t-1}$ 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.

**Table 7.** Results of Vector Error Correction Model (VECM)

| | $\Delta LP_t$ | $\Delta LY1_t$ |
|---|---|---|
| $ECT_{t-1}$ | -0.201** (-3.85) | -0.013 (-0.73) |
| $\Delta LP_{t-1}$ | 0.152 (1.75) | 0.026 (0.88) |
| $\Delta LY1_{t-1}$ | -0.093 (-0.38) | 0.388** (4.66) |
| | $\Delta LP_t$ | $\Delta LY2_t$ |
| $ECT_{t-1}$ | -0.219** (-3.97) | -0.016 (-0.97) |
| $\Delta LP_{t-1}$ | 0.155 (1.77) | 0.027 (1.06) |
| $\Delta LY2_{t-1}$ | 0.047 (0.17) | 0.448** (5.52) |
| | $\Delta LPM_t$ | $\Delta LY2_t$ |
| $ECT_{t-1}$ | -0.256** (-3.91) | -0.003 (-0.24) |
| $\Delta LPM_{t-1}$ | 0.257** (2.78) | 0.000 (-0.02) |
| $\Delta LY2_{t-1}$ | -0.010 (-0.03) | 0.418** (5.01) |
| | $\Delta LPA_t$ | $\Delta LY2_t$ |
| $ECT_{t-1}$ | -0.223** (-4.16) | -0.009 (-0.59) |
| $\Delta LPA_{t-1}$ | 0.136 (1.58) | 0.026 (1.08) |
| $\Delta LY2_{t-1}$ | 0.107 (0.37) | 0.443** (5.49) |
| | $\Delta LPT_t$ | $\Delta LY2_t$ |
| $ECT_{t-1}$ | -0.157** (-3.41) | -0.001 (-0.12) |
| $\Delta LPT_{t-1}$ | 0.092 (1.06) | 0.011 (0.62) |
| $\Delta LY2_{t-1}$ | 0.180 (0.45) | 0.431** (5.13) |
| | $\Delta LPN_t$ | $\Delta LY2_t$ |
| $ECT_{t-1}$ | -0.185** (-3.67) | -0.009 (-0.72) |
| $\Delta LPN_{t-1}$ | 0.086 (0.99) | 0.026 (1.18) |
| $\Delta LY2_{t-1}$ | -0.001 (-0.01) | 0.443** (5.67) |

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

The cointegrating relationship between metal prices and world GDP follow 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 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 third of which have gone by), it may be cut short by weak world economic growth, quite a likely scenario.

**Table 8.** Results of VAR

| | $\Delta LPO_t$ | $\Delta LY2_t$ |
|---|---|---|
| $\Delta LPO_{t-1}$ | -0.030 (-0.35) | -0.022 $^{**}$ (-2.05) |
| $\Delta LY2_{t-1}$ | 0.754 (1.26) | 0.465$^{**}$ (5.99) |
| Note: $^{**}$ indicate significance at 5% level. | | |

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 $\Delta LPO_{t-1}$ 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.

## VI. Concluding Remarks

The decomposition of real commodity prices based on the BP filtering technique provides evidence of four past super-cycles ranging between 30 to 40 years. For the total real non-fuel commodities, these cycles 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 to 40 percent 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 correlation analysis across the entire sample, and a marked co-movement 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 began 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 percent for the non-fuel commodity prices, with recent increases of around 8 percent 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 BRIC 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 towards 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.

## Appendix A

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **1. Engle-Granger Test** | | | | | | | |
| tau-statistic | | | | z-statistic | | | |
| Null hypothesis | Alternative | τ-stat. | Prob.** | Null hypothesis | Alternative | z-stat. | Prob. ** |
| 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** | | | | | | | |
| tau-statistic | | | | z-statistic | | | |
| Null hypothesis | Alternative | τ-stat. | Prob.** | Null hypothesis | Alternative | z-stat. | Prob. ** |
| 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 |

| 3. Hansen Parameter Instability Test | | | | |
|---|---|---|---|---|
| Null hypothesis | Alternative | $L_c$-stat. | Prob.** | |
| 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 | |
| | | | | |
| **4. Park's Added Variables Test** | | | | |
| Null hypothesis | Alternative | Chi-square | Prob.** | |
| 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 | |
| *Notes:* ** and * denote significance at 5% and 10% respectively. | | | | |

The Engle-Granger and Phillips-Quliaris 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.

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