Super Cycles in Metals Prices?

by

John Cuddington and Daniel Jerrett\(^1\)

October 24, 2007

Abstract

“The study of super cycles necessarily begins with the measurement of super cycles.”\(^2\)

Are metal prices currently in the early phase of a ‘super cycle’? Many market observers believe the answer is ‘yes.’ Academics, on the other hand, are generally skeptical about the presence of long cycles. This paper searches for evidence of super cycles in metal prices by using band-pass filters to extract particular cyclical components from time series data. The evidence is consistent with the hypothesis that there have been three super cycles in the past 150 years or so, and that we are currently in the early phase of a new super cycle – presumably driven by Chinese urbanization and industrialization.

\(^1\) Coulter Professor of Mineral Economics and Ph.D. candidate, respectively, at the Colorado School of Mines. Helpful discussions with John Tilton are gratefully acknowledged.

\(^2\) This is an adaptation of a comment that Baxter and King (1999) made about business (rather than super) cycles.
Introduction

Economists and financial analysts have a long standing interest in studying trends and cycles in various macroeconomic and financial variables. Both very short cycles and very long cycles have been considered, as has every length of cycle in between: seasonal fluctuations, business cycles (6-32 quarters), lesser known Kitchin inventory cycles of 3-5 years and Juglar fixed-investment cycles of 7-11 years, Kuznets cycles of 15-25 years, Bronson asset allocation cycles of roughly 30 years, and Kondratieff waves or cycles of length 45-60 years.

Academic economists have generally expressed skepticism about the existence of long cycles. Many have argued that “it amounts to seeing patterns in a mass of statistics that aren’t really there.” Kuznets cycles, for example, have been critiqued by Adelman (1965), Howrey (1968) and, more recently, Cogley and Nason (1995). Nelson and Kang (1981) highlight the “spurious periodicity” that can be introduced by inappropriate detrending techniques. That is, long cycles may be a statistical artifact.

Like macroeconomists, natural resource economists also have a keen interest in trends and cycles. Regarding long-term trends, Harold Hoteling (1931) argued that the real price of nonrenewable resources should rise at a rate equal to the real interest rate (under rather severe assumptions of zero marginal costs of extraction costs, a fixed resource endowment, and no technological change). Prebisch (1950) and Singer (1950), in contrast, hypothesized that there would be a secular decline in the relative price of primary commodities (both nonrenewable resources and agricultural products) in terms of

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manufacturing goods due to various supply and demand factors. See Cuddington et al (2007) for a detailed discussion. Turning to cyclical behavior, business cycle analysts identify metals prices as being highly cyclical and some believe that metals prices are leading indicators of general economic activity. In resource exporting countries, there is widespread concern that commodity booms and busts can cause “Dutch Disease” as the real currency appreciation caused by export booms renders non-traditional exports uncompetitive in world markets. Moreover, the temporary surge in government revenues during booms often leads to spending sprees that continue long after the booms have subsided. A recent study by Marian Radetzki (2006) identifies three commodity booms in metals, energy, and agricultural goods in the postwar period: 1950-1951, 1973-1974, and 2004-present. Radetzki concludes that each of the three booms primarily caused by surges in commodity demands rather than supply-side shocks.

Super Cycles

Recently, the financial press and financial industry researchers have been highlighting the possibility that metals are currently in the early phase of a super-cycle expansion. Jim Rogers (2004), who cofounded the Quantum Fund with George Soros, was among the first to highlight commodities as a long-term investment opportunity in the new millennium. Others in the investment industry followed. Alan Heap (2005) of Citigroup argued in March 2005 that “a super cycle is underway, driven by material intensive economic growth in China.” Morgan Stanley (2006) suggests the current upswings in metals prices will continue due to considerable supply-side production shortfalls, as well as capacity and input supply constraints that will continue for a number
of years. Armstrong, Chaundry, & Streifel (2006) suggest the current increase in metals prices is in line with past cycles, but the increase has been stronger and may be more prolonged than recent cycles. They point to China and, to a much lesser extent, Brazil, India, and Russia, as the major demand side drivers of the current cycle.

What are ‘super cycles’? Alan Heap (2005, pp. 1-2) defines a super cycle as a “prolonged (decades) long-trend rise in real commodity prices, driven by urbanization and industrialization of a major economy.” That is, they are demand driven. Heap believes there have been two earlier super cycles in the past 150 years. The first super-cycle he identifies ran from the late 1800s through the early 1900s driven by economic growth in the USA. The second was from roughly 1945 through 1975, initiated by post-war reconstruction in Europe and fueled by Japanese post-war economic expansion.

Although discussions of the super cycle have not explicitly identified this point, super cycles should be characterized by a sustained surge in metals prices generally, not just one or two metals. If there are significant low frequency fluctuations in many metal prices, but these cycles are not highly correlated with each other (due to large variations in their timing), it would be difficult to argue that the price surges are, in fact, caused by a sustained demand driven expansion. Thus, in identifying a super cycle, we should find ‘co-movement’ in the long cycles across metals and perhaps other commodities as well. Earlier authors have examined co-movement at the business cycle frequency, but not lower frequency cycles. See Pindyck and Rotemberg (1990) and Cashin and McDermott (2002).

It is conventional wisdom in the metals industry that short-run price elasticities of both demand and supply are low, the latter due to short-run capacity constraints in the
mining and processing (smelting, refining and treatment) sectors. The long-run price elasticity of supply, however, is thought to be much higher. For example, John Tilton and Gustavo Lagos (2007) argue: “the long-run supply curve for most metals rises at first (reflecting the dwindling number of exceptional deposits with unusually low costs), but then levels off and becomes relatively flat… if the relatively flat portion of the supply curve covers the relevant range of future global demand, which seems likely, whether it is nearly or completely horizontal matters little. In either case, demand has little influence of long-run prices.”

In order for prolonged demand expansion to have a super-cycle effect on prices -- where they are above their long-run trend for a decade or more -- one must argue that capacity constraints and/or the sharp run up in mining input costs (super truck tires, energy inputs, mining engineer services, permitting costs, etc) remain in place for more than a year or two. Bulk shipping and port facilities have also been stretched to the limit in recent years. Thus, sharp rises in transportation costs may also put sustained upper pressure on metals prices. In order for these supply constraints and surging input costs to give rise to a super cycle in metals prices, they must be alleviated only gradually over a decade or more.

World Bank and Wall Street analysts both agree that supply responses in the current super cycle will be much different than in prior cycles. Underinvestment in the mining sector over the past decade due to sustained low metals prices, implies that there are very few large capacity-enhancing projects in the pipeline. The result will be longer periods to bring new capacity online. Environmental permitting and sustainability issues are adding to this lag time. In addition, declining ore grade is necessitating a return to
deep underground mining, with the concomitant loss of scale economies from open-pit mines. The lack of skilled labor is an acute problem for the mining sector. Contract negotiations have also led to strikes in various countries, as mine workers have fought for their ‘fair share’ of the windfall profits resulting from surging metals prices.

Speculation on the strength of the demand expansion in current super cycle and the projected severity of supply-side constraints has led Citigroup and Morgan Stanley analysts to increase the price forecast for copper over the next five to ten years nearly 20% which reflects optimism in the continuation of the super cycle.

Methods of Studying Trends and Cycles

There have been numerous studies of trends and cycles ranging from informal graphical inspection of the data, combined with a good knowledge of economic history and the peculiarities of the metals markets being studied, to rigorous statistical decomposition techniques. Good examples of the former approach include Heap (2005), (2007), Radetzki (2006), and Tilton (2006).

Times series econometrics approaches have also been used to study cycles and trends in times series data. See Cuddington et al (2007), Cashin and McDermott (2002), Pindyck and Rotemberg (1990), among many others. The present paper applies recent statistical decomposition or filtering methods to the problem of identifying super cycles. Using these approaches, economic time series can be represented as a combination of cyclical components of various periodicities or frequencies. As Christiano and Fitzgerald (1999, p. 1) explain, “The theory of the spectral analysis of time series provides a rigorous foundation for the notion that there are different frequency components of the
data. An advantage of this theory, relative to other perspectives on decomposing time series, is that it does not require a commitment to any particular statistical model of the data. Instead it relies on the Spectral Representation Theorem, according to which any time series within a broad class can be decomposed into different frequency components. The theory also supplies a tool for extracting those components. That tool is the ideal band pass filter.”

Unlike univariate models that assume deterministic or stochastic trends that are constant over time, with the possible exception of detected break points, the trend-cycle decomposition or filtering methods used in this paper allow for gradual change in long-term trends, as well as cycles of different frequencies or periodicities. Filtering techniques to isolate particular frequencies in an economic time series have been primarily developed in the context of business cycle research in macroeconomics. The Hodrick-Prescott Filter (HP) is the most popular, but more flexible alternatives are now available. Hodrick and Prescott’s (1997) objective is to decompose a series $y_t$ into growth (or trend) and cyclical components:

$$y_t = g_t + c_t$$

The HP filter defines the growth component $g_t$ to be the solution to the following optimization algorithm:

$$\min \left\{ \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T} \left[ (g_t - g_{t-1}) - (g_{t-1} - g_{t-2}) \right]^2 \right\}$$

4 The periodicity and frequency a cycle are inversely related. The period of the cycle is its duration from one trough, through the expansion and contraction phase, to the beginning of the next trough. The frequency is the number of cycles per unit of time measured in days, month, years, etc, depending on the frequency with which the data are reported.
The ‘smoothness’ parameter $\lambda$ is the penalty applied to changes in the trend component. Hodrick and Prescott recommended setting $\lambda = 100 \ (1600)$ when attempting to extract business-cycle frequency fluctuations using annual (quarterly) data. The larger the chosen value of $\lambda$, the smoother is the trend line. Increasing $\lambda$ towards infinity, the trend component becomes a linear trend in the limit.

It is well-known that the de-trending method has a profound influence of the definition of cycles, i.e. the deviations from trend. To illustrate how the choice of $\lambda$ affects the decomposition of an economic time series, consider applying the HP filter to the natural logarithm of the real price of the copper using a range of lambda values 1, 10, 100, … to 10,000,000. The resulting decompositions are shown in Fig.1. As expected, the trend line becomes smoother as $\lambda$ rises. Note that the amplitude and period of cyclical component rise as the trend becomes smoother. For metals prices, the cycles are huge in amplitude: the scaling on the left side of each graph indicates a 50% deviation from the trend. Clearly, the de-trending method has important consequences for the characterization of cycles.

Baxter and King (1999) (BK) argued that it is difficult to know how to choose $\lambda$ in the HP filter in order to study cycles of different periodicities. As an alternative, they develop and recommend the use of so-called band-pass (BP) filters, which are designed to extract cyclical components with a specified range of periodicities from individual time series. Baxter and King show that if a BP(6,32) filter is applied to a series $Y$ of quarterly data, the result is a stationary series with cyclical components with periods (i.e.
Fig 1: Real Copper Prices (in logs):
The Effects of Changing the Smoothness Parameter ($\lambda$) in the HP Filter
the complete cycle) between 6 and 32 quarters. This would imply upward expansion phases of one half these amounts -- 3 and 16 quarters – if upswings and downturns were of equal duration. BK argue convincingly that when applied to quarterly data, the BP(6,32) filter yields a filtered series with business-cycle frequency fluctuations. Both
lower frequency cycles (and ‘trends’) and higher frequency components (e.g. seasonality and noise) are filtered out.

Christiano and Fitzgerald (1999) (CF) extend the BK analysis of band pass filters in a number of ways. The “ideal” band-pass filter is of infinite order in terms of the leads and lags of the series that are included, so some type of approximation is needed. Using a longer time span of data allows for more precise results. The Christiano-Fitzgerald asymmetric filters, unlike the symmetric CF filter and the BK filter, have the advantage that they allow us to compute cyclical components at the beginning and end of the data span. The cost, as they show, is very minor phase shifting, introduced when filters are not symmetric in the number of leads and lags used.

Although Christiano and Fitzgerald (like Baxter-King and Hodrick-Prescott) are interested in business-cycle analysis, they also provide a couple of interesting applications of their symmetric and asymmetric filters for extracting lower frequency components. The first involves an analysis of the Phillips curve relationship between unemployment and inflation in the long-run (i.e. the low frequency components) vs. the short run (i.e. the high frequency components). The second application examines the correlations between the low frequency components of monetary growth and inflation.

In sum, the band pass filters are well-suited to this study of metal price super-cycles. One can define the range of cyclical periodicities that are ‘super cycles,’ then use the band pass filter to extract those cyclical components. Given the interest in whether a
new super cycle is emerging in the final years of our data sample, the asymmetric band-pass filter of Christiano-Fitzgerald (ACF) is especially useful.5

Applying the Christiano-Fitzgerald Asymmetric Band Pass Filter to Metal Prices

Given our interest in detecting possible super cycles in long-span metal price series, asymmetric CF band pass filters will be used to decompose the natural logarithms of (real or nominal) prices into three components: the long-term trend (LP_T), the super cycle component (LP_SC) and other shorter cyclical components (LP_O). By construction, there three components sum to the price series itself:

\[ LP_t \equiv LP_{-T} + LP_{-SC} + LP_{-O}, \quad (1.1) \]

One must first decide what cycle periods encompass super cycles. Alan Heap (2005, 2007) argues that super cycles have upswings that last from 10 to 35 years. This would imply complete cycles ranging from 20 to 70 years. Thus, we apply the BP(20,70) filter to each price series to extract its super-cycle component:

\[ LP_{-SC} \equiv LP_{-BP(20,70)} \quad (1.2) \]

With this definition of the super cycle, it is natural to define the long-run trend as all cyclical components with periods in excess of 70 years:

\[ LP_{-T} \equiv LP_{-BP(70,\infty)} \quad (1.3) \]

5 We are in the process of carrying out a sensitivity analysis comparing the decompositions resulting from the asymmetric and symmetric variants of the CF filter to determine how this affects the dating of super cycles, due to the phase shifting caused by the use of the asymmetric CF filter.
Note that this approach does not assume the trend is constant over the entire 150 years span of our dataset, as trend stationary and difference stationary models do. Rather the trend can evolve only very slowly over time.

Having identified the long-term trend and the super cycle, what remains are the shorter cyclical components, which therefore include cycles with periods from 2 (the minimum measurable period) through 20 years:

\[ LP_{O} \equiv LP_{BP}(2,20) \quad (1.4) \]

It will be convenient, in the graphical analysis below to examine the ‘non-trend’ component of prices \( LP_{BP}(2,70) \), which is the total deviation from the long-term trend.\(^6\) That is, it is the sum of the super cycle and other shorter cycles:\(^7\)

\[ LP_{NT} \equiv LP_{SC} + LP_{O} \quad (1.5) \]

Equivalently, in BP filter notation:

\[ LP_{BP}(2,70) \equiv LP_{BP}(2,20) + LP_{BP}(20,70) \quad (1.6) \]

**Empirical Results**

Our long-span annual dataset is from Alan Heap (2005). Among other series, it includes the six LME-traded nonferrous metals: aluminum, copper, lead, nickel, tin, and zinc, in some cases going back to 1850, and real prices are computed using the U.S. CPI

\(^6\) Note that the BP(2,70 and BP(70,∞) are complements, i.e. their sum equals the actual price series.
\(^7\) The total non-trend component \( P_{NT} \) can be thought of as including the following components: business cycles (BC), ranging from 2 to 8 years, intermediate cycles (IC) of 8-20 years, and super cycles (SC) of 20-70 years. In this presentation, the focus will be on super cycles, relative to the long-run trend. For a detailed analysis of the shorter cycles, see Cuddington and Jerrett (2007, in progress).
\(^8\) Interestingly, the first version of our paper considered the five LME base metals (excluding tin). The later inclusion of tin in the super cycle dating analysis at the end of the paper had remarkably little effect on our conclusions. Thus, our results are robust in that sense, at least.
(base year 2006) as the deflator. For the natural log of each real price series, the ACF filter is applied to extract the long-term trend, non-trend and super-cycle components, as defined above. The resulting decompositions are shown graphically below. The following questions are addressed:

- Do the metals prices exhibit any long-term upward or downward trends, or are they more or less flat, as Tilton and others have hypothesized is typical?
- Is there evidence of a strong super-cycle component for each series, and does its timing more or less match the super-cycle periods identified by Heap: (1) the late 1800s through the early 1900s, (2) the post world War II period through the early 1970s, and (3) the post 2000 episode, which is still ongoing?
- Are the super-cycle components in the various metals highly correlated, as would be expected if the super cycle is demand driven? That is, is there strong co-movement?
- After accounting for the long-term trends and super cycles, how pronounced are the shorter cycles? Do they indicate considerable price risk at the business and intermediate cycle frequencies that would be relevant for firms undertaking capital investment decisions?

As an illustration, consider the application of the CFA band-pass filter to the real copper price series (LRP_CU, where R indicates ‘real’). The top portion of Fig.2 shows

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9 Although the producer price series from industry sources span many decades, LME trading began at different times for the various metals: copper and tin (1877), lead (1903), zinc (1915), aluminum (1978), nickel (1979).

10 Note that a strong positive correlation in the SC component of various metals could be explained by technology shocks, if these shocks were predominantly general technology improvements (such as improved blasting or hauling techniques) that can be applied to all metals. To the extent that technological improvements are metal specific (the SX-EW process for copper), however, one would not expect to see high correlation in SC components.
the log of the real copper price series, with the long term trend superimposed. Note that real copper prices trended downward from 1850 through to the mid 1920s, but remained relatively flat thereafter. This finding is consistent with the Tilton hypothesis that a flat long-run marginal cost schedule being the primary determinant of real copper prices in the long run – at least for the post 1920s period.

The non-trend component LRP_CU_NT, which is the difference between the actual series LRP_CU and the long-run trend LRP_CU_T, is shown in the lower panel of Fig.2. The scaling on the left is in logarithms, so a value of 0.50 is a 50 percent deviation from the long-term trend. Thus, the cyclical fluctuations from the long-term trend are huge. Recall that a portion of these fluctuations is the super cycle; the super-cycle component LRP_CU_SC is superimposed on the lower panel. The timing of the super-cycle expansions for copper matches up remarkably well with the dating highlighted in Heap’s analysis, although the band pass filter analysis dates the beginning of the second super cycle earlier (i.e. the mid 1930s rather than post WWII).

The extent to which the super-cycle component differs from the total non-trend component in the lower panel reflects the importance other shorter cycles (such as business and intermediate term cycles). As the lower panel shows, these shorter cycles are substantial. Even if one has confidence about the long-term trend and the super cycle in copper prices, the shorter cycles imply huge price risks for those in the industry making long-run investment decisions.
The decompositions for real prices of aluminum, lead, nickel, tin and zinc are shown in Fig.3. Note that the time span covered by the four series differs. There is considerable variation in the long-term trends, with aluminum falling steadily over time while nickel falls sharply through the mid-1920s before easing upward thereafter. Like copper, the long-run trend for zinc was relatively flat for most of the post-1920 period, although it seems to have drifted higher in the last 10-15 years of our data sample. Comparing the non-trend component in the lower panels to the superimposed super cycle, it is clear that all price series reflect large cyclical fluctuations above and beyond what is captured by the super cycle.
Fig 3: Real Price Decomposition for LME Metals

Real Aluminum Prices (in logs)

Real Nickel Prices (in logs)

Real Lead Prices (in logs)

Real Zinc Prices (in logs)
As the date scaling differs for the various metal price series shown in Fig.3, it is useful to collect all of the super cycles, as is done in Fig.4. There appears to be a general tendency for the super cycle components to be in a trough in the late 1800s and to rise through the mid-1920s. During the post-WWII period up to about 1975, many but not all of the metal prices are in a strong super-cycle phase. Finally, all of the metals seem to be moving out of a super-cycle trough in the 1990s into a super-cycle expansion, albeit with differences in timing across the metals.
There is often a considerable, but variable, lag between movements in nominal metal prices and movements in the U.S. consumer price index. Therefore, it is worthwhile to repeat the above analysis using (the natural logs of) nominal metal prices. This is done for each of the six metals in Fig.5. The CPI is added to the nominal graphs in order to illustrate the dynamic interactions between general inflation and nominal metal price movements.
Fig. 5: Nominal Price Decomposition for LME Metals
Co-Movement in Metals Prices

Fig. 4 suggested that there has been considerable co-movement in the super-cycle components of the six real metals prices. Figure 5 highlights a rather complicated dynamic interaction between nominal metals prices and the CPI, with the former typically leading the latter. Therefore, it is informative to reconsider the timing of super cycles using nominal metal prices series. These are shown in Fig.6.
Fig. 6 shows that the correlation between the nominal super cycles in the six LME metals is strikingly high. Also there is some tendency for the super-cycle component of the CPI to lag those of the various metals. One can summarize the graphical impression that the super cycles of the six metals are highly correlated more formally by examining their correlation matrix and by carrying out principal component analysis.

When calculating the correlation matrix among the super-cycle components of the six metal prices, there are a couple of options. One might consider the balanced sample
where one include only the years where all six of the series are available (1909-2006).

Alternatively, one could calculate each cell in the correlation matrix using the maximum
data span for each pair-wise calculation. The results are very similar, so just the
balanced sample results (1909-2006) are reported in Table 1. P-values are shown under
the correlations, so that the reader can assess the statistical significance of each
correlation coefficient. Except for the correlation between lead and aluminum,
correlations among the metals are all significant and positive at the 1% level.

Principal component analysis allows one to assess the importance of unobservable
‘common factors’ affecting the super-cycle components of the six metals prices by
decomposing their variance-covariance matrix. If you include all six metals, the principal
components can only be calculated over the balanced sample from 1909 through 2006.
The principal component analysis is summarized in Table 2.
Table 1: Ordinary Correlation Analysis

Correlation Analysis: Ordinary
Date: 10/10/07   Time: 09:40
Sample (adjusted): 1909 2006
Included observations: 98 after adjustments
Balanced sample (listwise missing value deletion)

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<th>LP_CU_SC</th>
<th>LP_NI_SC</th>
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**Table 2: Principal Component Analysis of Six LME Metals**

Sample (adjusted): 1909 2006  
Included observations: 98 after adjustments  
Balanced sample (listwise missing value deletion)  
Computed using: Ordinary covariances  
Extracting 6 of 6 possible components  

Eigenvalues: (Sum = 0.3028041, Average = 0.05046736)

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Eigenvectors (loadings):  

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It is striking that the first principal component (PC1) explains 73 percent of the joint co-
variation in the individual metal super-cycle components. All six metals have a strong 
positive factor loading on the PC1. It seems natural to interpret the first principal 
component obtained from the covariance decomposition of the six metals’ super cycles as 
a summary measure of the super cycle in metals prices. PC1 is shown along with the 
individual metal super-cycle components in Fig. 7. Clearly, the principal component 
analysis substantiates the claim that there is a strong positive correlation in the timing of 
the super cycles across the six metals. This is consistent with the hypothesis that the 
super cycles are demand driven, but, of course, need not ruled out supply-side 
explanations as long as they are broad based across many or all metals.
In an effort to define the super cycle further back in the data sample, the above analysis was re-done using only the three metals whose prices are available from 1875: copper, nickel and zinc. As Table 3 shows, the first principal component here explains 83 percent of the joint variation in these prices.
Table 3: Principal Component Analysis for Copper, Nickel, and Zinc

Principal Components Analysis

Sample (adjusted): 1875 2006
Included observations: 132 after adjustments
Balanced sample
Computed using: Ordinary covariances
Extracting 3 of 3 possible components

<table>
<thead>
<tr>
<th>Number</th>
<th>Value</th>
<th>Difference</th>
<th>Proportion</th>
<th>Cumulative Value</th>
<th>Cumulative Proportion</th>
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<tbody>
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<td>0.12</td>
<td>0.10</td>
<td>0.83</td>
<td>0.12</td>
<td>0.83</td>
</tr>
<tr>
<td>2</td>
<td>0.02</td>
<td>0.01</td>
<td>0.11</td>
<td>0.14</td>
<td>0.94</td>
</tr>
<tr>
<td>3</td>
<td>0.01</td>
<td>---</td>
<td>0.06</td>
<td>0.14</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Eigenvectors (loadings):

<table>
<thead>
<tr>
<th>Variable</th>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>LP_CU_SC</td>
<td>0.66</td>
<td>-0.08</td>
<td>-0.75</td>
</tr>
<tr>
<td>LP_NI_SC</td>
<td>0.44</td>
<td>0.85</td>
<td>0.30</td>
</tr>
<tr>
<td>LP_ZN_SC</td>
<td>0.61</td>
<td>-0.52</td>
<td>0.59</td>
</tr>
</tbody>
</table>

PC1_3 can now be calculated all the way back to 1875. As Fig. 8 shows, the timing of the super cycle based on the PC1_3 matches well (over their common sample) that obtained from the six metal analyses.
Fig 8: Comparing Principal Components from 3 and 6 Groups

- LP_CU_SC
- LP_NI_SC
- LP_ZN_SC
- Principal Component from SC3 Group
- Principal Component from SC6 Group
Using the lower panel of Fig.8, one can date the super cycles (using SC_6 when both CS_3 and SC_6 are both available). The analysis suggests that the first super-cycle expansion lasted roughly 28 years from 1891 through 1919. The second super-cycle expansion lasted 15 years, from 1937 to 1952, then after a 15-year pause gave rise to a third super cycle from 1965 through 1981 (15 years). Heap’s discussion, in contrast, characterizes the post-WWII period through the early 1970s as a single, very long super cycle. The final super cycle began in 1999 and as of 2006 was not yet at the mid-point in the expansion phase of the super cycle. Thus, if we are indeed in a super cycle and the duration of past super cycles are any guide, the current cycle may still have some time to run.

Conclusions

The band-pass filtering technique used in this paper has identified considerable evidence of super cycles in metal prices, defined here as cyclical components with expansion phases from 10 to 35 years. The amplitude of the super cycles is large with variations of 20-40 percent above and below the trend. Both simple correlations and principal component analysis confirm that the super-cycle components for six LME metals are highly correlated. The dynamic interaction between nominal metal prices and the CPI is important. The super cycle is more clearly defined when one looks at nominal rather than real prices.

The statistical evidence from the band pass filter analysis is consistent with the claim by industry experts that metal prices are in the early phase of a super cycle. The main driver of the current metals demand surge is presumably China and to a lesser
extent India and other developing countries, but the analysis in this paper does not attempt to identify the sources of the super cycle.

Even if one is convinced that a super-cycle expansion is in process, the ultimate success of capital investment and acquisitions in the metals industry will depend as much on business-cycle fluctuations as it will on correctly assessing long-term trends and riding super cycles. Trends and super cycles can be obscured for rather long periods of time by business cycles and intermediate cycle effects. As usual, in the highly volatile mining and minerals business, timing is everything!11

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11 The Appendix shows graphs of deviations of metals prices from their trend cum super cycle lines for the interested reader.
APPENDIX

The deviations of metals prices from their trend sum super-cycle lines are huge, which should be a major concern for those contemplating long-term investments in the metals industry. These decompositions are shown here.
References


