150 Years of Boom and Bust - What Drives Mineral Commodity Prices?

Martin Stürmer*

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Abstract

This paper examines the dynamic effects of demand and supply shocks on mineral commodity prices. It provides empirical insights by using annual market data on copper, lead, oil, tin and zinc from 1840 to 2009. Long-term price fluctuations are driven mainly by persistent aggregate and market-specific demand shocks rather than supply shocks. A notable exception is formed by fluctuations in the price of oil, which are driven by supply instead of aggregate demand shocks. At the same time, aggregate demand shocks have persistent and strong positive effects on mineral production. This suggests that rapid industrialisation in China and other emerging economies may cause prices to return to their declining or stable trends in the long run.

JEL classification: E32, F14, Q31, Q33

Keywords: Mineral Commodity Markets, Prices, Oil, World Trade, Industrialization, Structural VAR

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*Institute for International Economic Policy (IIW), University of Bonn, Lennéstraße 37, 53113 Bonn, Germany. Email: martin.stuermer@uni-bonn.de.
1 Introduction

The prices of mineral commodities, including fuels and metals, have repeatedly undergone periods of boom or bust over the last 150 years. These long-term fluctuations are a major source of inflation and affect the macroeconomic conditions of developing and industrialized countries alike. Moreover, strong booms have raised the issue of “security of supply” to the top of governments’ agendas again and again.

However, the literature is far from conclusive on the driving forces of these long-term fluctuations. Extensions of the Hotelling (1931) model explain price fluctuations by referring to the irregular exploration for deposits and so focus on the supply side (Arrow and Chang, 1982; Fourgeaud et al., 1982; Cairns and Lasserre, 1986). Storage models consider supply shocks, but ultimately leave the sources of shocks open, (Wright and Williams, 1982; Deaton and Laroque, 1992, 1996; Cafiero et al., 2009). Frankel and Hardouvelis (1985) and other authors point to monetary policy as a major driving force. Finally, Dvir and Rogoff (2009) and other authors argue that price booms are due to persistent aggregate demand shocks combined with supply constraints.

What empirical work there is tends to focus on the oil market. According to Kilian (2009), fluctuations of the price of oil are driven mainly by aggregate and oil-specific demand shocks. Thomas et al. (2010) find that a combination of supply and demand shocks determines the price of oil, whereas Peersman and Stevens (2010) point to supply shocks as an explanation for oil price fluctuations. Pindyck and Rotemberg (1990) claim that such macroeconomic variables as inflation and money supply go some way to explaining the concurrent movement of various commodity prices. Frankel and Rose (2010) find that, while global output and inflation have positive effects on the prices of 11 agricultural and mineral commodities, they are outstripped by such microeconomic variables as volatility and inventories.

This paper attempts to identify demand and supply shocks in mineral commodity markets from 1840 to 2009. To this end, I have used a new set of annual data, which includes prices and world production of copper, lead, oil, tin, and zinc, as well as world GDP.

I choose copper, lead, oil, tin and zinc, because they exhibit a substantial track record in industrial use and were traded in an integrated world market in the period considered. The
five mineral commodities studied are still among the top ten in world production by quantity and value.

Covering a far longer time period than previous work allows me to capture more than only a few periods of boom and bust. Commodities have always shown greater price volatility than manufactures (Jacks et al., 2011) and booms and busts are not a new phenomenon (Cuddington and Jerrett, 2008, see e.g.).

For ease of comparison, my approach is similar to that of Kilian (2009). I also use a structural vector autoregressive (VAR) model to decompose demand and supply shocks to fluctuations in the real price of the commodity concerned. Like Kilian, I capture three different shocks: supply shocks, shocks to the global demand for all commodities, known as "aggregate demand shocks", and demand shocks that are specific to a given mineral commodity market, known as "market-specific demand shocks". Compared to Kilian, I use annual data over a far longer time horizon, his data being monthly oil prices from 1973 to 2007.

The main conclusion drawn in this paper is that price fluctuations were basically driven by aggregate and market-specific demand shocks rather than by supply shocks from 1840 to 2009.

The exception is fluctuations in the real price of oil, which are driven mainly by supply shocks and oil-specific demand shocks, not by aggregate demand shocks. Hence, I find evidence, that viewed over a longer period supply shocks have an impact on the price of oil, which contradicts the results by Kilian (2009) for the period 1974-2007. Overall, the role of supply shocks appears to increase with the importance of oligopolies and price controls in the various markets.

Impulse response functions show that supply shocks have a significant impact only on the prices of tin and oil, both being markets long characterized by oligopolies and price controls. Aggregate demand shocks have had a large and statistically significant effect on the prices of all the commodities considered, reaching their peak after one or two years, the exception being oil, where the effect is insignificant. They persist for five to ten years. Market-specific demand shocks have a direct and significant effect on all commodities. At about 15 years, their persistence is greatest in the case of tin and oil.

I detect different responses of minerals production to aggregate and market-specific demand shocks. Whereas aggregate demand shocks have a strong, significant, persistent and
positive effect on the production of copper, lead and tin, they have only a positive, but in-
significant effect on oil and zinc production. Market-specific demand shocks generally have
no significant effect, except in the case of copper.

My study indicates the need for further research. As “market-specific demand shocks”
capture all shocks that are orthogonal to supply and aggregate demand shocks, it would
be important to disentangle these in greater detail. Natural candidates are non-linearities
in the specific use of each mineral commodity per unit of GDP, monetary variables and
stocks. Non-linearities in supply also need further investigation. Furthermore, Dvir and
Rogoff (2009) outline the role of structural changes in the oil market. In contrast to the other
mineral commodities, my findings on oil are not robust for different sub-periods of the sample,
and this requires further investigation. Finally, my work indicates the need to incorporate
endogenously determined mineral commodity prices so that their impact may be investigated
in macroeconomic models.

I have organized the remainder of this paper as follows. In section 2, I introduce some
basic ideas behind modeling mineral commodity markets. In section 3, I describe the data
set. Section 4 focuses on the econometric model and the identification scheme to separate the
different structural shocks. In section 5, I present the empirical results. Section 7 concludes.

2 Interpretation of Shocks to Mineral Commodity Prices

I use a similar approach as Kilian (2009) to classify the key determinants of mineral com-
modity prices. I distinguish three demand and supply shocks, notably “aggregate demand
shocks”, “supply shocks” and “commodity specific demand shocks”.

I define “aggregate demand shocks” as to capture shocks to the global demand for all
goods and services due to unexpectedly strong economic expansions or contractions of the
world economy. Hence, it also includes unexpectedly strong periods of industrialization such
as those of Great Britain, Germany and the USA in the 19th century, Japan in the 20th
century and China and other emerging economies at the beginning of the 21st century. They
also encompass the effects of innovations on interest rates in stimulating economic growth.

“Supply shocks” are shocks to the current physical availability of mineral commodities
due to unexpected action by cartels or export inhibiting trade policies. They also include
positive shocks due to e.g. innovations in mining technologies which expand production.

I do not directly model “commodity specific demand shocks” due to missing data on the world use and stocks of mineral commodities in the 19th century. Instead, controlling for aggregate demand shocks and supply shocks, I pin down the “commodity market specific” component of demand as the residual of a structural dynamic simultaneous-equation model. Hence, commodity specific demand shocks capture all omitted factors, which are orthogonal to supply and aggregate demand shocks.

Kilian (2009) interprets these commodity specific demand shocks as “precautionary demand shocks” arising “...from the uncertainty about shortfalls of expected supply relative to expected demand...” and reflecting the convenience yield from inventory holdings in the case of an interruption due to unexpectedly high demand or unexpectedly low supply.

As I use annual data and focus on a far longer time period, I add the interpretation that these shocks capture the non-linear relationship between the use of specific minerals and GDP. Positive shocks may thus arise from technological innovations like the spread of electricity, the telegraph or other technologies that unexpectedly raise the demand for the specific commodity. They may also arise from phases of economic development exhibiting high intensity of use of the respective mineral commodity due to e.g. the build up of specific infrastructure. Negative shocks are for example, the substitution of the commodity with other newly available commodities gained through new technologies (e.g. aluminum).

3 Data Description and Preliminary Data Analysis

I have compiled annual data on the real prices and the world production of copper, lead, tin and zinc as well as world GDP from 1840 to 2009. For oil, data is only available from 1861 onwards. I have chosen these mineral commodities as they have substantial track records in industrial and have been traded in integrated world markets since the 1840s.

A common definition for the existence of a world market is that prices for a homogeneous good strongly comove across different areas of the world. This implies that price movements are in accordance with the law of one price, even though the level of prices might differ due to transportation costs or trade barriers. Klovland (2005) shows that British and German
markets for copper, lead, tin and zinc were integrated from 1850 until World War I, whereas price gaps for pig iron and coal remain quite significant. O’Rourke and Williamson (1994) find a strong convergence of US and British copper and tin prices between 1870 and 1913.\footnote{Results are available from the author upon request.}

During World War I and II markets disintegrated according to Findlay and O’Rourke (2007). Unfortunately, to my knowledge there is no systemic study of price convergence for the above metals in the interwar period. However, data on German, British and US prices of the four commodities suggest that there has been at least some comovement across these prices from the start of the 1920s to the break-out of World War II.\footnote{Results are available from the author upon request.} Labys (2008) finds evidence for strong market integration after World War II.

Unfortunately, there is to my knowledge, no empirical evidence on the historical integration of the oil market. However, narrative evidence from Yergin (2009) suggests that rapidly after the first discovery of oil in Titusville in 1859, American kerosene became an internationally traded good. In the 1870s and 1880s it even was the 4th largest U.S. export in value. By the 1880s competition was already strong from Russian oil. Hence, I assume in the following sections that world oil markets have been as integrated over time as the non-ferrous metal ones described above and leave it to future research to find statistical evidence for this assumption.

I make use of price data for copper, lead, tin and zinc from the London Metal Exchange (LME) and its predecessors. I prefer LME-prices over US-American prices, as the LME was the principal price setter in the non-ferrous metals markets during the study period. Data sources are Schmitz (1979), the German Federal Institute for Geosciences and Natural Resources and national statistical yearbooks. The longest available price data for the oil market are US-prices from British-Petroleum (2010) reaching back to 1861.

Following Krautkraemer (1998) and Svedberg and Tilton (2006), I deflate all nominal prices by consumer price indices. In contrast to producer price indices (PPI), which would be the first choice for deflating the data, CPIs are readily available over the long period from Officer (2011a) and UK Office of Statistics (2011). To obtain the US-PPI, I have spliced together the wholesale price index for all commodities by Hanes (1998) and the producer price index for all commodities from U.S. Bureau of Labor Statistics (2011). Unfortunately, such an endeavor has proven difficult for the UK and will be accomplished at a later stage.
I have assembled data on the world production of the chosen mineral commodities from Schmitz (1979), Metallgesellschaft (1904), Metallgesellschaft (1913), the German Federal Institute for Geosciences and Natural Resources, Mitchell (2007) as well as from national statistical yearbooks.

I use world GDP data as a proxy for “aggregate demand”. In contrast to Kilian (2009) I do not create a freight rate index to measure global economic activity but use the more convenient, widely used and comparable measure of GDP from Maddison (2010). I use annual GDP data instead of the freight rate in Kilian’s regressions and find that it generates relatively similar results over the period from 1973 to 2007 as figures 6 to 8 illustrate.

Unfortunately, Maddison’s dataset only provides annual world GDP data from 1950 onwards. Therefore, I sum up country based annual data. For those years where country based annual data is missing, I generally interpolate the data with linear trends. For European countries and Western offshoots, I compute their respective shares of output related to neighboring countries, where data is available. I then interpolate these shares and multiply them with the data from those countries, where annual data is available. This process assumes that these countries follow a similar business cycle as their neighboring countries.

I account for the disintegration of world markets during the two World War periods by using yearly dummies for the war period and the three consecutive years.

I find evidence for unit root behavior in the production and GDP data by using the Augmented Dickey Fuller (ADF) test and the KPSS-test.\(^3\) For the metal price data, the ADF test clearly rejects the unit root hypothesis. For the oil price, the test does not reject the unit root. However, the ADF test is likely to fail to reject the unit root, if the time series is only slowly mean reverting and the sample size is not large (Pindyck, 1999). In our case, the sample size is 148. Pindyck shows that a sample size of 159 years of data would be necessary to reject the unit root at the 5 percent level. Considering variance ratio tests and the fact that a single discrete shift in the trend line can bias unit root tests, he concludes that unit root tests are unlikely to provide the information about the stochastic processes underlying long-run price evolution. Studying oil prices from 1870 to 1996, he finds that a

\(^3\)Results for all of the following tests are available from the author upon request.
model of reversion to a stochastically fluctuating trend performs better than a simple model with a fixed linear trend. However, he comes to this conclusion under the assumption that the oil price does not rise substantially during the first decade of the 21st century, which it actually did.

KPSS tests provide mixed evidence on unit roots for the price data depending on the lag length and the mineral commodity. All in all, I will assume in the following sections that prices are mean reverting.

Bi- and multivariate cointegration tests between world GDP, world production of the respective commodity and the real commodity price reveal contradicting evidence with respect to the co-integration rank depending on shift terms and lags included. Results are available from the author upon request.

4 Identification

Like Kilian (2009) I use a structural VAR model to decompose unpredictable changes in the real mineral commodity prices into mutually orthogonal components.4

The vector of endogenous variables is \( z_t = (\Delta Q_t, \Delta Y_t, P_t)' \), where \( \Delta Q_t \) denotes the change in world production of the respective mineral commodity, \( \Delta Y_t \) refers to the change in world GDP, and \( P_t \) is the respective real commodity price. All variables are expressed in logs. The sample period for the annual data is from 1840 to 2009 (except for oil where it is 1861-2009) with yearly dummies during the World War I and II periods and the three years immediately after. \( D_t \) denotes the deterministic terms, notably a constant, a linear trend, and the dummies. The structural VAR representation is

\[
A z_t = \Gamma_1 z_{t-1} + \ldots + \Gamma_p z_{t-p} + \Pi D_t + \epsilon_t.
\]

(1)

\( \epsilon_t \) is a vector of serially and mutually uncorrelated structural innovations. Assuming that \( A^{-1} \) has a recursive structure, I can decompose the reduced-form structural errors \( \epsilon_t \) according to

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4I do not account for cointegration between variables in the following. Using a VAR and not a vector error correction model (VECM), I ignore a rank restriction, which lowers the efficiency of the estimation. I have applied a VECM to the copper data and basically found the similar results as for the VAR.
\[ e_t = A^{-1} \epsilon_t: \]

\[
\begin{bmatrix}
\epsilon_t^Q \\
\epsilon_t^Y \\
\epsilon_t^P
\end{bmatrix} = 
\begin{bmatrix}
a_{11} & 0 & 0 \\
a_{21} & a_{22} & 0 \\
a_{31} & a_{32} & a_{33}
\end{bmatrix}
\begin{bmatrix}
\epsilon_t^Q \\
\epsilon_t^Y \\
\epsilon_t^P
\end{bmatrix}
\]

I use the same restrictions on the short term relations as Kilian (2009) to just identify the model. However, as he uses monthly and I annual data, I explain my restrictions in the following:

I define supply shocks as unpredictable innovations to the global production of the respective commodity. The underlying assumption is a vertical short-run supply curve of the respective mineral commodity. Shocks to demand or supply instantaneously change the price, as they shift the demand curve or the vertical supply curve. Hence, I assume that innovations due to neither aggregate demand nor market specific demand affect supply within the same year. This assumption is plausible as firms are rather slow in responding to demand shocks. Expanding extraction and first stage processing capacities is highly capital intensive and it take five or more years before new capacities become operational (Radetzki, 2008; Wellmer, 1992, see).

However, one could argue that firms might instantaneously respond to demand shocks by increasing capacity utilization. Kilian (2008) argues in the opposite direction and provides evidence that capacity utilization rates in world crude oil production were around 90 percent from 1974 to 2004. He states that firms run their oil production facility only at 90 percent of nominal capacity - and not at full nominal capacity - as there is uncertainty about the threshold of sustainable production. Exceeding it might permanently damage an oil field. I find similar high utilization rates in US-data for the oil extraction, mining and primary metal industry from 1967 to 2011 (U.S. Federal Reserve, 2011). In the case of the mining and primary metal industry, maintenance and repairs make a capacity utilization rate higher than 90 percent also unlikely. To sum up, this data provides evidence for our assumption that firms cannot react to instantaneous innovations to demand by increasing their utilization rate within a year.

I define aggregate demand shocks as innovations to global GDP that cannot be explained by supply shocks. Hence, I impose the exclusion restriction that changes in the price driven
by innovations to the market specific demand do not affect global GDP within a year. Kilian (2009) shows that price increases due to oil market specific demand shocks result in a gradual decline in the level of US-GDP, which is only statistically significant after three years. Furthermore, on a global scale a price increase is only a redistribution of income from importing to exporting countries such that global output should not be affected in the short run.

I employ ordinary least squares to consistently estimate the reduced-form VAR model. Based on these estimates, I obtain the estimated coefficients of the A-matrix by maximum likelihood using a scoring algorithm following Lütkepohl (2005). I obtain standard errors from bootstraps with 2000 replications. See tables 1 to 10 in the appendix for the estimated coefficients.

5 Empirical Results

In the following, I present the insights from the historical evolution of shocks, the impulse response functions and the cumulative effects of shocks on the respective mineral commodity prices. I attempt to present only the major results and refrain from presenting in detail the evolution of each market.

Historical evolution of the demand and supply shocks. Figures 9 to 13 present the evolution of the structural shocks. They show that all examined mineral commodities are affected simultaneously by a multitude of shocks.

Insert figures 9 to 13 about here.

Supply shocks evolve quite differently across the mineral commodity markets. However, in general they are most pronounced during the interwar period and the Great Depression. Visible inspection also reveals that the variance of supply shocks has decreased over the observed period with the notable exception of zinc. Surprisingly, it seems that the reduction in the variance of supply shocks is most pronounced in the oil market in the period from immediately after World War II until today with the exception of the two oil price shocks in 1974 and 1981. Looking at the history of these markets, most supply shocks can be traced back to the temporary successes and failures of firms to form cartels, as well as, the
unexpected finding of new resources, especially during the 18th century, and the invention of new mining methods. For lead, I find relatively few strong supply shocks, reflecting the wide dispersion of lead resources over the world.

The aggregate demand shocks are relatively similar for the examined mineral commodities. They capture the world business cycle and are strongly influenced by periods of fast industrialization in major economies. In the 1840s, the industrialization in the UK and elsewhere can be observed in the aggregate demand shocks. The long depression starting in 1873 is clearly observable in the shocks. They then follow the business cycle of the three major economies at that time: the US, UK and Germany. The macroeconomic shocks of the great depression are easily observable. There are other shocks in the build up to World War II and then in the 1950s with post war recreation and especially in the 1960s with the economic rise of Japan. The recessions in 1974 and 1981 are clearly visible. The negative aggregate demand shocks in the 1990s might be explained by the break up of the USSR and later on by the Asian crisis. The new century starts with the burst of the dotcom bubble, then the positive shock due to the unexpected rise of China and the negative shocks due to the recent crisis.

Commodity specific demand shocks evolve very differently across commodity markets. They are harder to interpret as they encompass all shocks orthogonal to aggregate demand and supply shocks. This includes demand due to precautionary demand, demand shocks due to the spread of technological innovation and non-linearities in the intensity of use. For the example of copper, the spikes in the 19th century might be due to technological innovations such as the telegraph or electricity, which had copper specific demand. There are also strong market specific demand shocks in the run ups to each of the two World-wars, the Vietnam war, the Gulf war and during China’s recent rise. The two oil crisis are clearly visible.

*Responses of GDP, mineral commodity production and real prices to demand and supply shocks.* Figures 14 to 18 plot the respective responses of world GDP, world commodity production and the real commodity prices to a one-standard deviation of the three examined structural shocks. I use accumulated impulse response functions for the shocks on world mineral commodity production and world GDP to trace out the effect on the level of these variables.
A positive unexpected shock to supply significantly decreases only the real price of oil. I find a similar but insignificant effect regarding the real price of tin. For the three other mineral commodities, such a shock triggers an insignificant but positive effect.

An unexpected positive rise in aggregate demand triggers a large increase in all examined real prices within a maximum of about one year after the shock. The shock continues to be significant over a time period of 5 to 10 years for copper, lead, tin and zinc. For oil, the effect is also positive but not significant.

I find that positive commodity specific demand shocks exhibit immediate, large, highly significant and persistent positive effects on real prices. In the case of copper, lead and zinc it lasts significantly for about five years. In the case of the prices of oil and tin it is up to 15 years.

Supply shocks exhibit strong, persistent and significant effects on supply. Aggregate demand shocks cause large positive and significant increases in the production of copper, tin and lead. The effect is not significant in the cases of oil and zinc. These shocks are relatively persistent, hinting at the long lead times of opening new mines.

Commodity specific demand shocks have only small and insignificant effects on production. An exception is copper, where it exhibits a significant and decreasing effect on the copper production.

*Cumulative effects of shocks on the real price of copper.* The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the respective real commodity prices from the base projection. As the vertical scales across the three sub-panels are identical, they show not only the positive and negative effects, but also the relative importance of a given shock.

The cumulative effects of supply shocks are only pronounced for the price of oil and to lesser extent for the price of tin. There is almost no effect on the prices of copper, lead and zinc. This is surprising given the long record of mine nationalization, export restrictions
by the International Council of Copper Exporting Countries for example, as well as other oligopolistic behaviour. It might be explained by the fact that most producer action to restrict supplies had only very short term effects due to the opening of new mines and additional oil production elsewhere. In contrast to the copper, lead and zinc market, the tin and oil market have experienced long periods of cartels, government price controls and international price stabilization.

The cumulative effects of aggregate demand shocks on the real commodity prices exhibit large fluctuations. They are strongly pronounced in the cases of copper, lead, zinc and to lesser extent for tin. The first large upswing is consistent with our knowledge about phases of rapid industrialization in the 1850s and 1860s. Then the long depression starting in 1973 exhibited negative aggregate demand shocks. After gradual recovery, positive aggregate demand shocks reach a high at the start of the 20th century. There are positive aggregate demand shocks in the 1920s, which are followed by the abrupt negative shock due to the Great Depression and again a hike in the run-up to World War II and post war reconstruction. The next trough lasting until around 1960 was followed by South-Korea and Japan’s strong industrial expansion, which caused further increases in the cumulative effects of positive aggregate demand shocks. The recessions in 1974 and 1981 are quite pronounced. The same is the case for the collapse of the USSR, the Asian crisis and the burst of the dotcom bubble. The most recent expansion sets in after 2000 due to the economic expansion of China and other emerging economies. In contrast, the cumulative effects of aggregate demand shocks have very modest to nearly no effect on the real prices of oil.

Finally, the cumulative effects of commodity specific demand shocks cause medium term price swings for all examined mineral commodities. They exhibit the strongest cumulative effects on the real prices of oil and tin. These two mineral commodities are basically driven by these shocks due to the oligopolistic nature of their respective markets. The large rise up of cumulative effects on zinc prices in the first half of the 20th century is due to the importance of zinc in the war industry. The strong rise in cumulative effects on tin prices might be explained by sustained purchases of tin by the international buffer stock until its collapse in 1985.

The cumulative effects of commodity specific demand shocks are of medium importance in the cases of copper, lead and zinc. In the case of copper, the negative demand shocks up until
the 1860s might be caused by the invention of the Bessemer process in 1855, which decreased prices for steel products significantly in the following years such that steel substituted for many copper appliances. However, from the 1870 to the 1890s the spread of inventions such as the telegraph, telephone (1875) or the electric bulb (1879) induced strong positive demand shocks as copper was essential for producing telecommunication and power cables. At the end of the 19th century, innovations pushed the price of aluminum down such that it substituted for some copper appliances and had a negative effect on copper specific demand. In 1950 the stock piling program by the US government seems to have had a strong effect on the lead, tin and zinc market.

Based on these results, the sharp spike of mineral commodity prices from 2003 to 2009 is basically explained by the cumulative effects of large commodity specific demand shocks and to a lesser extent by aggregate demand shocks.

6 Robustness checks

I have conducted several robustness checks. All results are quite robust to different choices of lag lengths. I also find similar results for copper, lead, tin and zinc when changing the observed time period to 1820 to 2009, 1850 to 2009, 1900 to 2009 and 1974 to 2009. The findings for oil are not robust to such changes, possibly reflecting the role of structural changes in the market structure (Dvir and Rogoff, 2009, see also). A detailed analysis is still work in progress.

Employing log world production and GDP in levels instead of percentage changes generates the same general results of the strong dominance of demand over supply shocks persists for copper, lead, and zinc. In this case, only market-specific demand shocks drive fluctuations in the oil and tin market.

In a former version, I also used a vector error correction model for the copper market, which also provided evidence for strong demand shocks and nearly no effect of supply shocks.

5Results are available from the author upon request.
7 Conclusion

This paper has examined the dynamic effects of demand and supply shocks on the real prices of copper, lead, oil, tin and zinc from 1840 to 2009. Using a historical decomposition, I have found that these prices are driven mainly by persistent aggregate and commodity-specific demand shocks. The exception is the real price of oil, which is - contrary to the finding by Kilian (2009) over the period 1973 to 2007 - driven mainly by supply shocks and oil-specific demand shocks, not by aggregate demand shocks.

Several limitations to our analysis possibly account for this finding and may guide further research. First, our model does not include asymmetric responses of prices to positive or negative shocks. This may be particularly important for the effect of positive and negative supply shocks on prices and vice versa. For example, (Radetzki, 2008, p. 61-3) describes the common experience in the extractive sector that firms keep their utilization rates high even after negative price and demand shocks hit the market.

Second, Dvir and Rogoff (2009) outline the role of structural change in the oil market. In contrast to the other mineral commodities, my findings on oil are not robust for different sub-periods of the sample, and this required further investigation.

Third, a major limitation of my approach is that “market-specific demand shocks” capture all shocks that are orthogonal to supply and aggregate demand shocks. Disentangling these shocks by checking for other, possibly important variables, such as monetary variables and stocks, and for the strong non-linearities in the ratio of commodity use and GDP (intensity of use) would enable further light to be shed on “market-specific demand shocks”.

It is to be hoped that additional work will advance our understanding of the determinants of boom and bust in mineral commodity markets.
References


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Appendix

![Graphs showing the historical evolution of World GDP, World Copper Production, and the Real Price of Copper.](image)

Figure 1: Historical Evolution of World GDP (percentage change), World Copper Production (percentage change) and the Real Price of Copper (logs), 1840-2009.

Notes: I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions. I have assembled the data from the following sources: World GDP: Maddison (2010); World Copper Production: Schmitz (1979), Metallgesellschaft (1904), Metallgesellschaft (1913), German Federal Institute on Geosciences and Natural Resources (direct correspondence with the author), and International Copper Study Group (2010). Real Price of Copper: Schmitz (1979) and German Federal Institute on Geosciences and Natural Resources. The price data relates to copper traded at the London Metal Exchange and its predecessors. Earlier price data in British Pounds has been converted to US-Dollar by using historical dollar-pound exchange rates from Officer (2011b). I disinflate the data with a standard historical consumer price index from the NBER and the US Bureau of Labor Statistics (2010) as no historical world CPI index is available over this time span.
Figure 2: Historical Evolution of World GDP (percentage change), World Lead Production (percentage change) and the Real Price of Lead (logs), 1840-2009.

Notes: I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions. I have assembled the data from the following sources: World GDP: Maddison (2010); World Lead Production: Schmitz (1979), Metallgesellschaft (1904), Metallgesellschaft (1913), German Federal Institute on Geosciences and Natural Resources (direct correspondence with the author), and International Copper Study Group (2010). Real Price of Lead: Schmitz (1979) and German Federal Institute on Geosciences and Natural Resources. The price data relates to lead traded at the London Metal Exchange and its predecessors. Earlier price data in British Pounds has been converted to US-Dollar by using historical dollar-pound exchange rates from Officer (2011b). I disinflate the data with a standard historical consumer price index from the NBER and the US Bureau of Labor Statistics (2010) as no historical world CPI index is available over this time span.
Figure 3: Historical Evolution of World GDP (percentage change), World Oil Production (percentage change) and the Real Price of Oil (logs), 1861-2009.

Notes: I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions. I have assembled the data from the following sources: World GDP: Maddison (2010); World Oil Production: Mitchell (2007), Real Price of Oil: British-Petroleum (2010).
Figure 4: Historical Evolution of World GDP (percentage change), World Tin Production (percentage change) and the Real Price of Tin (logs), 1840-2009.

Notes: I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions. I have assembled the data from the following sources: World GDP: Maddison (2010); World Tin Production: Schmitz (1979), Metallgesellschaft (1904), Metallgesellschaft (1913), German Federal Institute on Geosciences and Natural Resources (direct correspondence with the author), and International Copper Study Group (2010). Real Price of Tin: Schmitz (1979) and German Federal Institute on Geosciences and Natural Resources. The price data relates to tin traded at the London Metal Exchange and its predecessors. Earlier price data in British Pounds has been converted to US-Dollar by using historical dollar-pound exchange rates from Officer (2011b). I disinflate the data with a standard historical consumer price index from the NBER and the US Bureau of Labor Statistics (2010) as no historical world CPI index is available over this time span.
Figure 5: Historical Evolution of World GDP (percentage change), World Zinc Production (percentage change) and the Real Price of Zinc (logs), 1840-2009.

Notes: I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions. I have assembled the data from the following sources: World GDP: Maddison (2010); World Zinc Production: Schmitz (1979), Metallgesellschaft (1904), Metallgesellschaft (1913), German Federal Institute on Geosciences and Natural Resources (direct correspondence with the author), and International Copper Study Group (2010). Real Price of Zinc: Schmitz (1979) and German Federal Institute on Geosciences and Natural Resources. The price data relates to zinc traded at the London Metal Exchange and its predecessors. Earlier price data in British Pounds has been converted to US-Dollar by using historical dollar-pound exchange rates from Officer (2011b). I disinflate the data with a standard historical consumer price index from the NBER and the US Bureau of Labor Statistics (2010) as no historical world CPI index is available over this time span.
Figure 6: Historical Decomposition of the Real Price of Oil using Kilian (2009)'s original monthly dataset from 02/1973-12/2007 and his computer code.

The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual oil price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. A figure of the evolution of structural shocks, impulse response functions and estimation results are available from the author upon request.
Figure 7: Historical Decomposition of the Real Price of Oil using Kilian (2009)’s original dataset from 02/1973-12/2007 and his computer code. The data has been annualized to illustrate that his results are not due to frequency and that his identification strategy produces the same results for annual data.

The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual oil price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. A figure of the evolution of structural shocks, impulse response functions and estimation results are available from the author upon request.
Figure 8: Historical Decomposition of the Real Price of Oil using my dataset and modified computer codes from Kilian (2009) for the period 1873 to 2007.

The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual oil price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. A figure of the evolution of structural shocks, impulse response functions and estimation results are available from the author upon request.
Figure 9: Historical Evolution of the Structural Shocks for Copper.

Note: Structural residuals implied by model (1). Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 10: Historical Evolution of the Structural Shocks for Lead.

Note: Structural residuals implied by model (1) Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 11: Historical Evolution of the Structural Shocks for Oil.

Note: Structural residuals implied by model (1). Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 12: Historical Evolution of the Structural Shocks for Tin.

Note: Structural residuals implied by model (1). Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 13: Historical Evolution of the Structural Shocks for Zinc.

Note: Structural residuals implied by model (1). Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 14: Impulses to One-Standard-Deviation Structural Shocks for Copper.

Notes: Point estimates with one-standard error band based on model (1). I have constructed the confidence intervals by using a bootstrap interval according to Hall (1992).
Figure 15: Impulses to One-Standard-Deviation Structural Shocks for Lead.

Notes: Point estimates with one-standard error band based on model (1). I have constructed the confidence intervals by using a bootstrap according to Hall (1992).
Figure 16: Impulses to One-Standard-Deviation Structural Shocks for Oil.

Notes: Point estimates with one-standard error band based on model (1). I have constructed the confidence intervals by using a bootstrap according to Hall (1992).
Figure 17: Impulses to One-Standard-Deviation Structural Shocks for Tin.

Notes: Point estimates with one-standard error band based on model (1). I have constructed the confidence intervals by using a bootstrap according to Hall (1992).
Figure 18: Impulses to One-Standard-Deviation Structural Shocks for Zinc.

Notes: Point estimates with one-standard error band based on model (1). I have constructed the confidence intervals by using a bootstrap according to Hall (1992).
Figure 19: Historical Decomposition of the Real Price of Copper.

Note: Estimates derived from model (1). The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual copper price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 20: Historical Decomposition of the Real Price of Lead.

Note: Estimates derived from model (1). The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual copper price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 21: Historical Decomposition of the Real Price of Oil.

Note: Estimates derived from model (1). The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual oil price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 22: Historical Decomposition of the Real Price of Tin.

Note: Estimates derived from model (1). The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual copper price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Figure 23: Historical Decomposition of the Real Price of Zinc.

Note: Estimates derived from model (1). The historical decomposition quantifies the contribution of the three specific shocks to the deviation of the actual copper price data from its base projection. As the vertical scales are identical, the panels show not only the positive and negative effects, but also the relative importance of a given shock. Please note that I have not included data for the two World War periods and the three consecutive years due to price controls and other major market distortions.
Table 1: Estimated Coefficients of Model (1) for Copper (reduced form).

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<thead>
<tr>
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<th>$Y_t$</th>
<th>$P_t$</th>
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<td>$Q_{t-1}$</td>
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Note: t-values in brackets. $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. The Coefficients for the year dummies during the periods 1914-1921 and 1939-1948 are available from author upon request.

Table 2: Estimated Restricted A-Matrix of the Structured Version of Model (1) for Copper.

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<th>$\epsilon^P$</th>
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Table 2: Estimated Restricted A-Matrix of the Structured Version of Model (1) for Copper.

Note: $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. Bootstrap standard errors in brackets. ML estimation, Scoring Algorithm (see Amisano and Giannini (1992)).
Table 3: Estimated Coefficients of Model (1) for Lead (reduced form).

Note: t-values in brackets. $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. The Coefficients for the year dummies during the periods 1914-1921 and 1939-1948 are available from author upon request.

Table 4: Estimated Restricted A-Matrix of the Structured Version of Model (1) for Lead.

Note: $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. Bootstrap standard errors in brackets. ML estimation, Scoring Algorithm (see Amisano and Giannini (1992)).
Table 5: Estimated Coefficients of Model (1) for Oil (reduced form).

Note: t-values in brackets. $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. The Coefficients for the year dummies during the periods 1914-1921 and 1939-1948 are available from author upon request.

<table>
<thead>
<tr>
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Table 6: Estimated Restricted A-Matrix of the Structured Version of Model (1) for Oil.

Note: $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. Bootstrap standard errors in brackets. ML estimation, Scoring Algorithm (see Amisano and Giannini (1992)).
Table 7: Estimated Coefficients of Model (1) for Tin (reduced form).

<table>
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<tr>
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<th>$Q_t$</th>
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Note: t-values in brackets. $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. The Coefficients for the year dummies during the periods 1914-1921 and 1939-1948 are available from author upon request.

Table 8: Estimated Restricted A-Matrix of the Structured Version of Model (1) for Tin.

<table>
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Note: $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. Bootstrap standard errors in brackets. ML estimation, Scoring Algorithm (see Amisano and Giannini (1992)).
Table 9: Estimated Coefficients of Model (1) for Zinc (reduced form).

Note: t-values in brackets. $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. The Coefficients for the year dummies during the periods 1914-1921 and 1939-1948 are available from author upon request.

<table>
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Table 10: Estimated Restricted A-Matrix of the Structured Version of Model (1) for Zinc.

Note: $Q_t$ and $P_t$ notify the log of the annual production and the log of the average annual price of the respective mineral commodity. $Y_t$ notifies the log of annual world GDP. Bootstrap standard errors in brackets. ML estimation, Scoring Algorithm (see Amisano and Giannini (1992)).

<table>
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<tr>
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<tr>
<td>$Y_t$</td>
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<td>(0.3361)</td>
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