What drives commodity prices in the long run?*

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PRELIMINARY – COMMENTS WELCOME

Abstract

What drives commodity prices in the long run? We provide evidence on the dynamic effects of global demand shocks, commodity supply shocks, and inventory demand shocks on real commodity prices. In particular, we analyze a new data set of price and production levels for 14 agricultural, metal, and soft commodities from 1850 to 2012. We identify differences in the type of shock driving prices of the various types of commodities and relate these differences to commodity types which presumably reflect differences in long-run elasticities of supply and demand. Preliminary results show that demand shocks strongly dominate supply shocks.

JEL classification: E30, Q31, Q33, N50
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1. Introduction

Understanding the drivers of commodity prices—and thereby, their fluctuations—is of first-order importance for the global economy. On it hinges the determination of a significant portion of incomes and welfare of both commodity-consuming and commodity-producing nations (Bernanke, 2006; IMF, 2012). It also impinges upon critical issues in the distribution of incomes within particular nations as the ownership of natural resources varies widely. Necessarily, the long-run drivers of commodity prices also have serious implications for the formation and persistence of growth-enhancing—or growth-detracting—institutions (van der Ploeg, 2011). But for all this, outside spectators—whether they are academics, the general public, the investment community, or policy-makers—remain seriously divided in assigning the importance of the various forces in the determination of commodity prices.

The recent history of commodity prices are indicative of this situation. Rising from multi-decade lows in the late 1990s, real commodity prices rose for the next 10 years, culminating in the price spike of 2008 when they stood over three times their level in 1998 (Jacks, 2013). All along the way, observers battled it out, variously pointing to the respective roles of fundamentals versus speculation in driving real commodity prices to such heights. Very recent developments in the opposite direction—with real commodity prices having shed roughly 30% of their value in less than a year—have likewise generated much heat, but not so much light. Yet regardless of any particular commenter's take on the ultimate driver of commodity prices, none have doubted the question's importance.

At the same time, a fairly large academic literature has developed which follows the work of Kilian (2009) in evaluating the sources of commodity price dynamics. Here, structural vector autoregressive models are used to decompose changes in commodity prices into different types of shocks. Identification is made possible by assigning short-run (or sign) restrictions based on assumptions primarily—but not exclusively—related to inelastic short-run demand and supply curves. The upshot of much of this work has been a reversal in our understanding of the short-run determinants of commodity prices. That is, while an earlier literature implicated supply shocks as a chief source of fluctuations in commodity prices, this more recent literature finds that demand shocks are the major source of fluctuations in prices for crude oil (Kilian, 2009).[1]

Our contribution to this literature comes in being the first in providing evidence on the drivers of real commodity prices *over a broader set of commodities* and *over a broader span of time*. To this end, we assemble a new data set on the level of prices and production for 14 commodities, spanning the categories of agricultural, metal, and soft commodities from 1850 to 2012. In marked contrast to this literature which generally uses monthly data over years or perhaps decades, we use annual data over the past 165 years. This context makes it hard for us to rationalize a steep—that is, an inelastic—long-run supply curve, which is one of the basic identifying assumptions of SVARs based on short-run (or sign) restrictions. Instead, we apply Stuermer's (2014) identification scheme which is based on the idea that increases in real commodity prices induced by increases in global demand for commodities set in motion two processes: investment in new productive capacity and productivity-enhancing technological innovation. This allows us to specify three orthogonal shocks to real commodity prices based on long-run restrictions, namely a global demand shock, a commodity supply shock, and an inventory or other demand shock. Here, we emphasize that these shocks are all commodity-specific and are not to be confused with the aggregate demand and aggregate supply shocks used in much of the macroeconomic literature.

[1] See Carter et al. (2011) for a detailed summary of theories on fluctuations in commodity markets.

In particular, we assume that a global demand shock, representing an unexpected expansion in global GDP, potentially has long-run effects not only on global GDP itself but also on the production of individual commodities. We also assume that a commodity supply shock, representing a disruption in the physical production of a particular commodity, only evinces a potential long-run effect on that commodity's production but not on global GDP. Finally, we interpret the residual term, capturing all remaining uncorrelated shocks, as an inventory or other demand shock. This term is assumed to have no long-run effects on either global GDP or a commodity's global production. At its heart, this shock can be thought as to capture unexpected changes in inventory demand due to underlying changes in expectations. In combination, this identification scheme allows us to leave all short-run relationships unrestricted.

Based on the structural VAR, we derive historical decompositions for each of the relevant commodities. The historical decomposition shows the contribution of each shock in driving fluctuations in each real commodity price series over time. It serves to quantify the independent contribution of the three shocks to the deviation of each commodity price from its base projection. Our preliminary results indicate that global demand shocks and inventory or other demand shocks rather than commodity supply shocks are the primary drivers of real commodity prices. Additionally, we find that the quantitative contribution of global demand shocks to prices varies across the different commodities. At the same time, global demand shocks exhibit a common pattern with respect to their timing across all commodity markets. Third, inventory or other demand shocks are an important driver in commodity price fluctuations for most of our agricultural and soft commodities. Finally, commodity supply shocks play some role in explaining fluctuations for particular commodities, but in the main, their influence on real commodity prices is limited in its impact and transitory in nature.

The rest of the paper proceeds as follows. Section 2 sets out the underlying data while Section 3 outlines the methodology related to structural vector autoregressions. Section 4 provides the results on the contribution of various shocks on commodity price dynamics. Section 5 concludes.

2. New Data on Long-Run Prices and Production

The data used in this study represent the end result of a number of selection criteria. First, prices were drawn for all consistently-defined commodities with at least 5 billion US dollars of production in 2011 (for further discussion, see Jacks, 2013). The individual price series are expressed in US dollars and deflated by the US CPI underlying Officer (2012), supplemented by updates taken from the BLS.

Next, these prices were matched with production data for those commodities for which there is evidence of a high degree of homogeneity in the traded product (or at least, in its reference price), evidence of an integrated world market, and no evidence of significant structural changes in their marketing or use over time.[2] All told, this paper then considers the evidence on 14 individual commodity price series (barley, coffee, copper, corn, cotton, cottonseed, lead, mercury, rice, rye, steel, sugar, tin, zinc) which are drawn from three product categories—grains, metals, and soft commodities. Finally, global GDP data is based on Maddison (2010).

Figures 1 through 14 document the evolution of real commodity prices and production along with global GDP up to 2012 while Appendix I details the sources for the individual series.

[2] This last requirement precludes a consideration of natural gas and petroleum in light of the radical changes in the industrial organization of these sectors throughout the 20th century (Yergin, 1991).

3. Structural Vector Autoregression

We follow Kilian (2009) and subsequent authors in applying a structural vector autoregressive model to decompose fluctuations in commodity prices into different types of shocks. In marked contrast to this literature which generally uses monthly data over years or perhaps decades, we use annual data over the past 165 years. This context makes it hard for us to rationalize an inelastic—that is, steep—supply curve, which is one of the basic identifying assumptions of SVARs based on short-run (or sign) restrictions. Instead, we apply Stuermer's (2014) identification scheme which allows us to specify three orthogonal shocks to real commodity prices based on long-run restrictions, namely commodity-specific global demand shocks, commodity-specific supply shocks, and commodity-specific inventory or other demand shocks.

A. Identification

The identification scheme is based on the idea that increases in real commodity prices induced by increases in global demand for commodities set in motion two processes: investment in new productive capacity and productivity-enhancing technological innovation. This idea has gained considerable traction in the resource economics literature of late. For example, Anderson *et al*. (2014) show how global shocks to the demand for crude oil have induced new drilling in the United States in the last few years. Likewise, Stuermer and Schwerhoff (2013) provide stylized facts on R&D in the extractive sector and construct a growth model with a non-renewable resource stock which may be periodically augmented due to R&D investment in extraction technologies. A somewhat analogous argument has been made by earlier contributions to the literature on growth models and natural resources (Aghion and Howitt, 1998; Groth, 2007). This work basically argues that increases in factor productivity drive up total output of an economy and, thereby, productivity in the use of natural resources. Stuermer (2014) is the first to build on these insights for the purpose of identifying different shocks to commodity prices based on long-run restrictions.

We use these restrictions in the same way to identify three mutually uncorrelated shocks to real commodity prices. First, we assume that a global demand shock potentially has persistent effects on both global GDP and global production of the respective commodity. This is consistent with the logic outlined above in which unexpected changes in global GDP endogenously affect the extensive and intensive margins of commodity production in the long run.

Furthermore, we assume that a commodity supply shock potentially has a long-run effect on global production of the respective commodity, but no long-run effect on global GDP. Thus, our commodity supply shocks capture unexpected disruptions in global production of a commodity due to cartel action, inter- or intra-state conflict, strikes, weather, or the like. It might also include the unexpected opening of new mines in the case of metals or minerals or the conversion of land to the cultivation of a specific crop in the case of agricultural or soft commodities. These events are allowed to affect global GDP for quite some time as we use annual data, but ultimately, they will not affect global GDP in the long run. The reasoning here is that short-run disruptions to production are eventually eased, new mineral reserves eventually get depleted, and/or land might eventually switch back to the cultivation of agricultural or soft commodities. However, productivity shocks on the supply side for commodities are assumed to be endogenously determined by global demand shocks.

Finally, the inventory or other demand shock is a residual which captures all shocks that are not correlated with either the global demand shocks or the commodity supply shocks described above. We interpret this residual shock along the lines of Stuermer (2014) as a shock to the demand for storage of the respective commodity which potentially stems from three different sources: 1) government stocking programs, 2) commodity producers with market power who increase their inventories in an attempt to manipulate prices, and 3) shifts in the expectations of downstream commodity-processing industries or midstream commodity-trading firms about the future balance of supply and demand (on the last point, see Kilian, 2009).[3]

We assume that price changes due to these inventory or other commodity-demand shocks exhibit transitory but not long-run effects on global production of the respective commodities. They thereby only affect capacity utilization in the commodity-producing sector, but not long-run investment decisions. We consider this assumption to be plausible, in that expanding production capacity generally exhibits significant fixed costs and takes many years—and in some instances, decades—to come on-line (Radetzki, 2008; Wellmer, 1992). We furthermore assume that this type of shock does not have any potential long-run effects on global GDP. Certainly, an increase in commodity prices driven by shocks to inventory demand decreases the income of consumers in importing countries. At the same time, it increases the income of consumers in exporting countries so that there may be no net effect on global GDP via aggregate demand, even in the case of petroleum. For instance, Rasmussen and Roitman (2011) shows on a global scale that oil price shocks only exhibit small and transitory negative effects for a majority of countries.

[3] We are unable to directly include a proxy for inventories in this study due to data constraints.

B. Econometric model

Formally, we use a structural vector autoregressive system with long-run restrictions for each commodity market. The econometric model includes three endogenous variables, notably the percentage change in global GDP (ΔY), the percentage change in global production of the respective commodity (ΔQ_i), and the log of the real price of the respective commodity ($\ln(P_i)$). The matrix of deterministic terms D consists of a constant and a linear trend. These deterministic terms are designed to account for long-run trends in the costs of production, the costs of trade, and the intensity of use of the respective commodity in the global economy.

We also add annual fixed effects for World War I and the three subsequent years after its conclusion (that is, from 1914 to 1921) as well as World War II and the three subsequent years after its conclusion (that is, from 1939 to 1947). These fixed effects are meant to control for the fact that world markets for commodities during these time periods were subject to market distortions related to government policy and restrictions to trade related to the nature of the conflicts.

The structural VAR representation is

(1) $Ax_t = \alpha D_t + \beta_1^* x_{t-1} + ... + \beta_p^* x_{t-p} + B\varepsilon_t,$

where x is the vector of endogenous variables and ε is a vector of mutually and serially uncorrelated structural innovations. The reduced form coefficients are $\beta_j = A^{-1}\beta_j^*$ for $j = 1, \ldots, p$. The relation to the reduced form residuals is given by $u_t = A^{-1}B\varepsilon_t$. We impose zero restrictions on the long-run matrix of structural shocks by assuming that it is lower triangular (for technical details, see Stuermer, 2014). This leaves the contemporaneous relationships completely unrestricted. We set the number of lags (p) as four for all commodities for the benchmark regressions. We have also run the regressions allowing for a different number of lags across commodities with the number of lags being chosen according to the Akaike Information Criterion. The results remain materially unaffected, and here, we focus on the former set of results for ease of presentation.

4. Results

We present results for a set of impulse response functions for and historical decompositions of real commodity prices in the following sub-sections.

A. Impulse Responses

Figures 15 to 28 present the impulse response functions for each commodity. The impulse response functions show how the percentage change in global GDP, the percentage change in global production of the respective commodity, and the log of the respective real commodity price react to a one-standard deviation change in one of the three respective shocks through time. We make use of the accumulated impulse response functions for the shocks to global commodity production and global GDP to illustrate the long-run effects on these variables. One of the purposes of this exercise is to ensure that our method produces economically meaningful results. In particular, we expect *a priori* that:

1.) positive global demand shocks are associated with higher real global GDP, generally induce higher global commodity production, and serve to increase real commodity prices;

2.) positive commodity supply shocks have limited effects on real global GDP, generally induce persistently higher global commodity production, and serve to decrease real commodity prices; and

3.) positive inventory or demand shocks have limited effects on real global GDP, generally induce a muted response in global commodity production, and serve to increase real commodity prices.

Cumulatively, the impulse response functions demonstrate that the reaction of real prices to the different types of shocks are either in line with what one would reasonably expect or statistically insignificant. Positive global demand shocks and positive inventory or other demand shocks both serve to increase real commodity prices while positive supply shocks serve to decrease real commodity prices. On average, the effects of global demand shocks are the most persistent, with effects lingering 10 years or more. This is followed by inventory or other demand shocks which are slightly less persistent, but with effects that might last up to 10 years in some cases. Finally, the effect of commodity supply shocks is, for the most part, insignificant. As seen before, expectations are to be found in the sugar and tin markets with effects which persist up to five years.

B. Historical Decomposition

The historical decomposition shows the contribution of each shock in driving fluctuations in each real commodity price series. It serves to quantify the independent contribution of the three shocks to the deviation of each commodity price from its base projection. Figures 29 to 42 depict the historical decomposition for each commodity under consideration here. The vertical scales are identical across the three sub-panels such that the figures illustrate the relative importance of a given shock. Another way of intuitively thinking about these historical decompositions is that each of the sub-panels represents a counterfactual simulation of what the real price of a particular commodity would have been if it had only been driven by this particular shock.

For instance, take the case of global demand shocks. The collective story which emerges from our figures suggests that although the proportional contribution of the global demand shocks naturally varies across the different commodities, their accumulated effects broadly follow the same pattern with respect to timing across the 14 commodities. Thus, global demand shocks affect real commodity prices to different degrees, but they affect the real commodity prices at the same time. These results then suggest that global demand shocks have a common source.

What is more, this interpretation of the accumulated global demand shocks is in line with what economic history has to say about fluctuations in global output.[4] Thus, there is a long downturn in prices throughout the 1870s driven by the accumulated effects of negative global demand shocks during the first—but somewhat forgotten—great depression. Likewise, the early 1930s bear witness to the accumulated effects of a series of negative global commodity demand shocks which sent real prices plummeting and which are clearly attributable to the—second—Great Depression.

After World War II, positive global demand shocks led to increases in real prices in the wake of the immediate post-war efforts at re-industrialization and re-urbanization in much of Europe and Japan as well as the later economic transformation of the East Asian Tigers and Japan. From 1970, negative global demand shocks are evident in the late 1970s, the early 1980s, and the late 1990s, respectively corresponding to the global recessions of 1974 and 1981 and the Asian financial crisis of 1997. These are followed in turn by a series of positive global demand shocks emerging from the late 1990s/early 2000s due to unexpectedly strong global growth,

[4] See Stuermer (2014) for a detailed historical account.

driven by the rise of China. Finally, the lingering effects of the Global Financial Crisis are also clearly visible in the series for the accumulated effects of global demand shocks.

The historical decompositions show that inventory or other demand shocks also play an important role in driving the fluctuations in real commodity prices, particularly in the short- to medium-run. For the most part, this type of shock follows idiosyncratic patterns across the examined commodities. Detailed historical accounts for the four base-metal markets considered by Stuermer (2014) provide evidence that this type of shock can also be attributed more often than not to changes in inventories by cartels, governments, and/or private firms. However, as this "other demand shock" is, in fact, a residual term, it might also be explained by unexpected changes in the demand for specific commodities. For example, the United States introduced the copper-plated zinc penny in the 1980s which unexpectedly drove up the real price for zinc. Such events are captured by this residual demand term.

In marked contrast, the accumulated effects of commodity supply shocks do not play an important role in driving the long-run real price of most of the commodities under consideration. Generally, this type of shock is idiosyncratic in the timing of its effects and only has a transient effect on real prices. That is, they only drive short-run fluctuations. However, there are two exceptions: commodity supply shocks dominate the formation of sugar prices and it is the second most important driver for tin prices. Fairly ready explanations for these phenomena are the strong oligopolistic structure of the two markets and their long history of government intervention (c.f., Stuermer, 2014 and United States Department of Agriculture, 1971). Thus, tin has been the only base-metal market in which cartel action and international commodity agreements have prevailed for extended periods of time while sugar also has a strong history of government intervention via cartel action, international commodity agreements, and especially tariffs.

To sum up, the results for the different commodities show that the prices have basically been driven by global demand shocks and inventory or other demand shocks. These two types of shock, thus, cause an appreciable portion of the medium- and long-run fluctuations in real commodity prices. Conversely, commodity supply shocks play a rather secondary and transient role. This result is fairly consistent across agricultural, mineral, and soft commodities alike with two notable exceptions (sugar and tin) which are both strongly affected by supply shocks.

5. Conclusions and Future Prospects

This paper is the first in providing evidence on the drivers of real commodity prices in the long-run. To this end, we assemble a new data set on the level of price and production for 14 commodities, spanning the categories of agricultural, metal, and soft commodities from 1850 to 2012. Our preliminary results indicate that global demand shocks and inventory or other demand shocks rather than commodity supply shocks drive fluctuations in commodity prices.

Additionally, we find that the contribution of global demand shocks to real price varies across the different commodities. However, global demand shocks exhibit common patterns with respect to timing across the markets for agricultural, metal, and soft commodities. Inventory or other demand shocks are the most important driver in commodity price fluctuations for most of our agricultural and soft commodities. Finally, commodity supply shocks play some role in explaining fluctuations for particular commodities, but in the main, their influence on real commodity prices is limited in impact and transitory in duration.

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Appendix I

This appendix details the sources of the real commodity prices and production used throughout this paper.

Prices

As such, there are a few key sources of data: the annual Sauerbeck/*Statist* (SS) series dating from 1850 to 1950; the annual Grilli and Yang (GY) series dating from 1900 to 1986; the annual unit values of mineral production provided by the United States Geographical Survey (USGS) dating from 1900; the annual Pfaffenzeller, Newbold, and Rayner (PNR) update to Grilli and Yang's series dating from 1987 to 2010; and the monthly International Monetary Fund (IMF), United Nations Conference on Trade and Development (UNCTAD), and World Bank (WB) series dating variously from 1960 and 1980. The relevant references are:

Grilli, E.R. and M.C. Yang (1988), "Primary Commodity Prices, Manufactured Goods Prices, and the Terms of Trade of Developing Countries: What the Long Run Shows." *World Bank Economic Review* 2(1): 1-47.

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"Wholesale Prices in 1950." *Journal of the Royal Statistical Society* 114(3): 408-422.

A more detailed enumeration of the sources for each individual series is as follows.

Barley: 1850-1869, SS; 1870-1959, Manthy, R.S. (1974), *Natural Resource Commodities - A Century of Statistics*. Baltimore and London: Johns Hopkins Press; 1960-2013, WB.

Coffee: 1850-1959, Global Financial Data; 1960-2013, WB.

Copper:

Corn: 1850-1851, Cole, A.H. (1938), *Wholesale Commodity Prices in the United States, 1700-1861: Statistical Supplement*. Cambridge: Harvard University Press; 1852-1859; Bezanson, A. (1954), *Wholesale Prices in Philadelphia 1852-1896*. Philadelphia: University of Pennsylvania Press; 1860-1999, Global Financial Data; 2000-2013, United States Department of Agriculture National Agricultural Statistics Service.

Cotton: 1850-1899, SS; 1900-1959, GY; 1960-2013, WB.

Cottonseed: 1874-1972, Manthy, R.S. (1974), *Natural Resource Commodities - A Century of*

Statistics. Baltimore and London: Johns Hopkins Press; 1973-2013, National Agricultural Statistics Service.

Lead:

Mercury:

Rice: 1850-1899, SS; 1900-1956, GY; 1957-1979, Global Financial Data; 1980-2013, IMF.

Rye: 1850-1851, Cole, A.H. (1938), *Wholesale Commodity Prices in the United States, 1700-1861: Statistical Supplement*. Cambridge: Harvard University Press; 1852-1869, Bezanson, A. (1954), *Wholesale Prices in Philadelphia 1852-1896*. Philadelphia: University of Pennsylvania Press; 1870-1970, Manthy, R.S. (1974), *Natural Resource Commodities - A Century of Statistics*. Baltimore and London: Johns Hopkins Press; 1971-2013, National Agricultural Statistics Service.

Steel: 1897-1998, USGS; 1999-2013, WB.

Sugar: 1850-1899, SS; 1900-1959, GY; 1960-2013, WB.

Tin:

Zinc:

Production

Figure 1: The Long-Run Evolution of Barley Prices, Barley Production, and World GDP

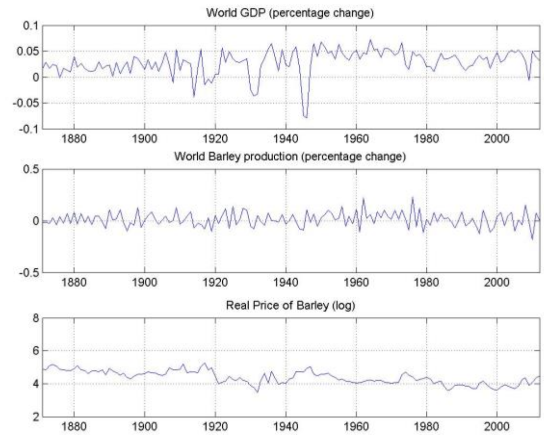

Figure 2: The Long-Run Evolution of Corn Prices, Corn Production, and World GDP

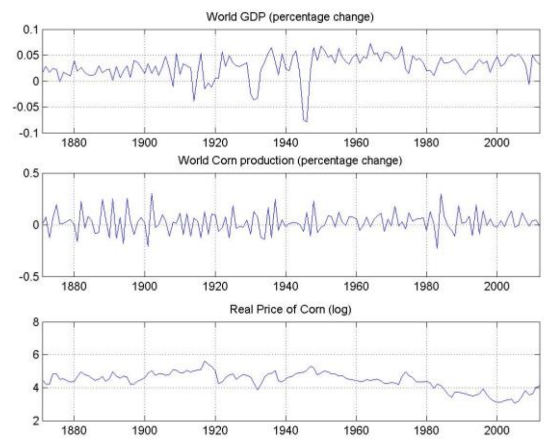

Figure 3: The Long-Run Evolution of Rice Prices, Rice Production, and World GDP

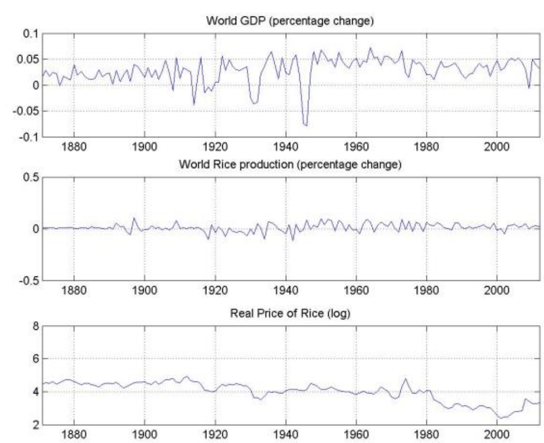

Figure 4: The Long-Run Evolution of Rye Prices, Rye Production, and World GDP

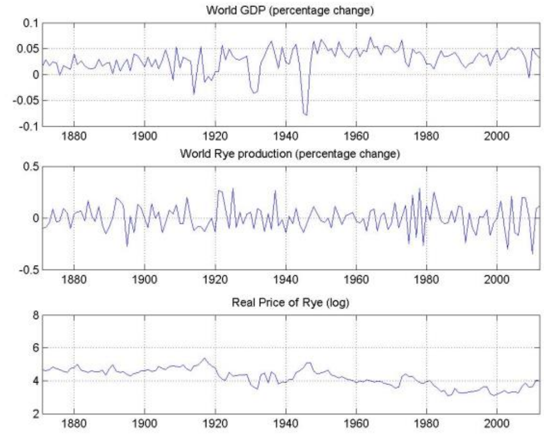

Figure 5: The Long-Run Evolution of Copper Prices, Copper Production, and World GDP

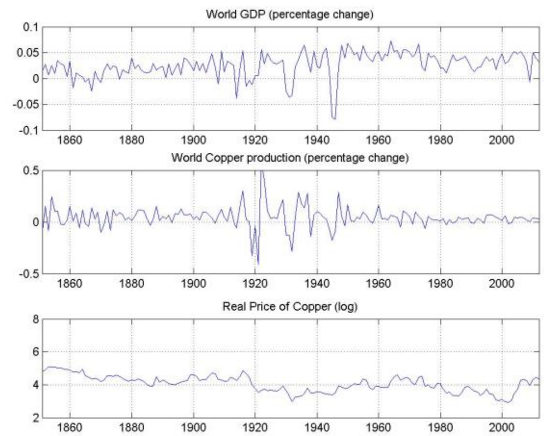

Figure 6: The Long-Run Evolution of Lead Prices, Lead Production, and World GDP

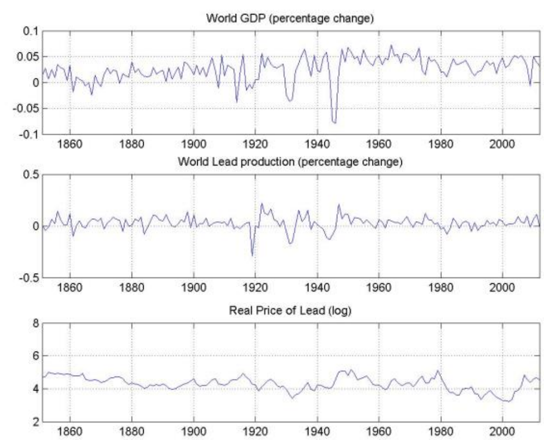

Figure 7: The Long-Run Evolution of Mercury Prices, Mercury Production, and World GDP

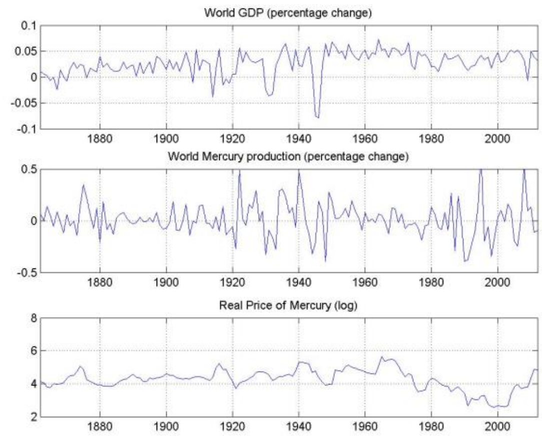

Figure 8: The Long-Run Evolution of Steel Prices, Steel Production, and World GDP

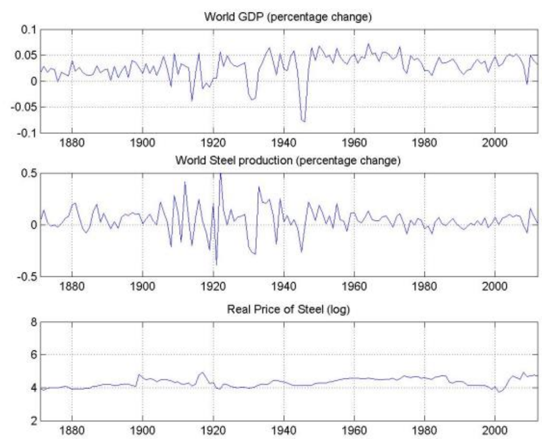

Figure 9: The Long-Run Evolution of Tin Prices, Tin Production, and World GDP

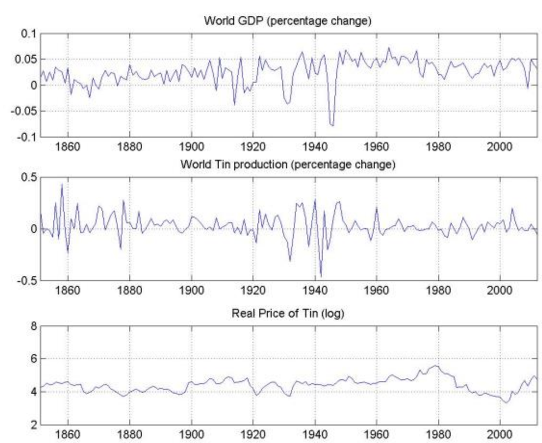

Figure 10: The Long-Run Evolution of Zinc Prices, Zinc Production, and World GDP

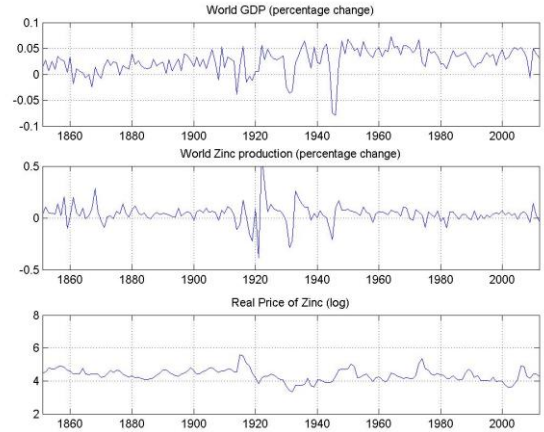

Figure 11: The Long-Run Evolution of Coffee Prices, Coffee Production, and World GDP

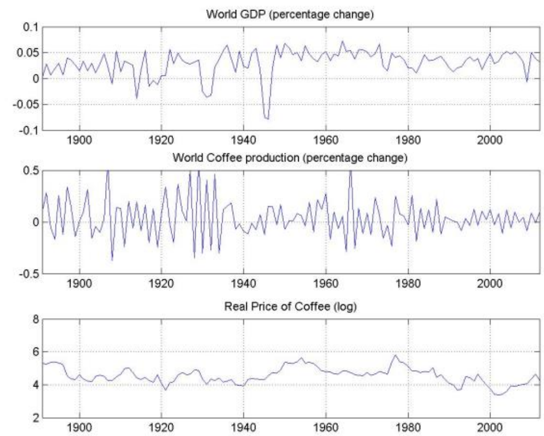

Figure 12: The Long-Run Evolution of Cotton Prices, Cotton Production, and World GDP

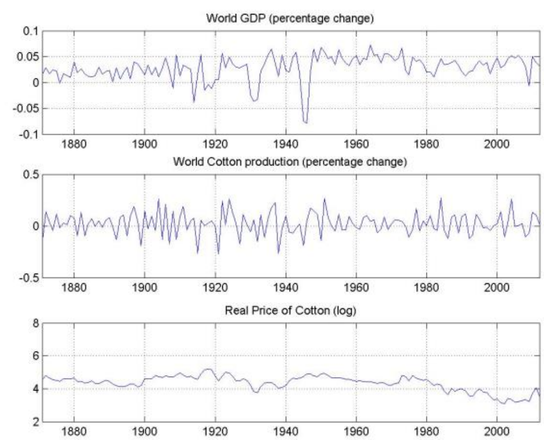

Figure 13: The Long-Run Evolution of Cottonseed Prices, Cottonseed Production, and World GDP

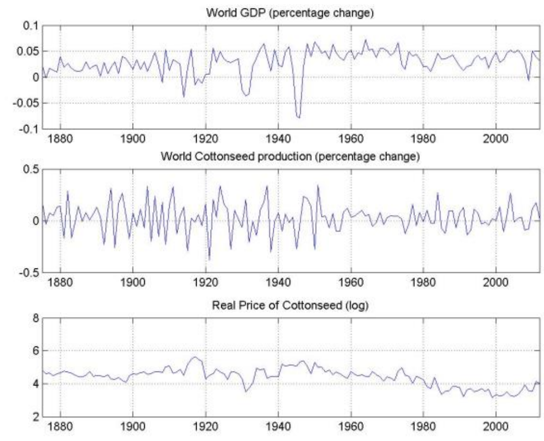

Figure 14: The Long-Run Evolution of Sugar Prices, Sugar Production, and World GDP

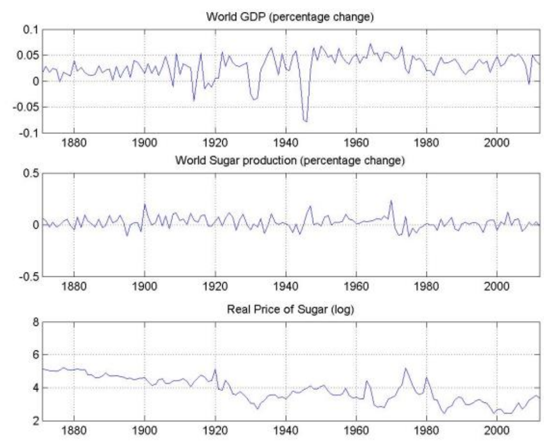

Figure 15: Impulse Response Function for Barley

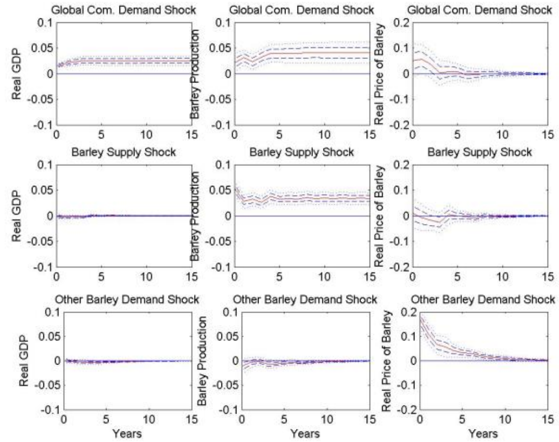

Figure 16: Impulse Response Function for Corn

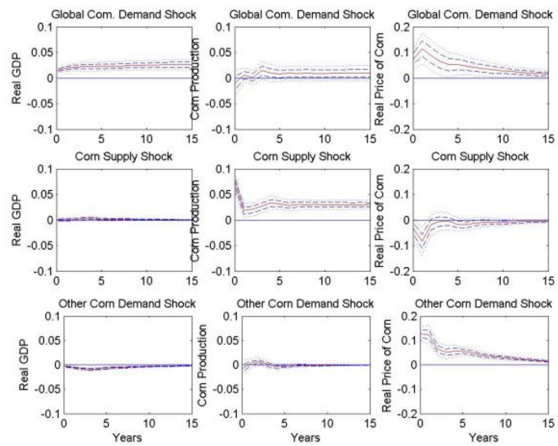

Figure 17: Impulse Response Function for Rice

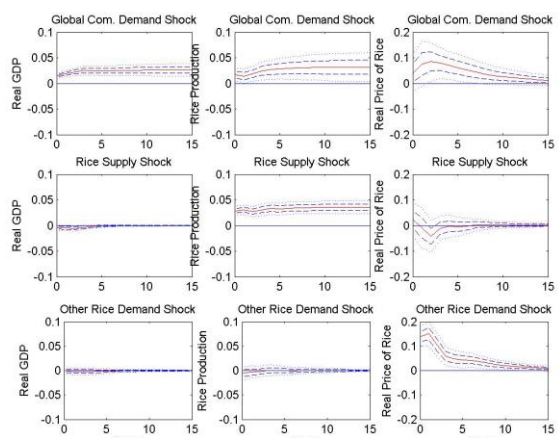

Figure 18: Impulse Response Function for Rye

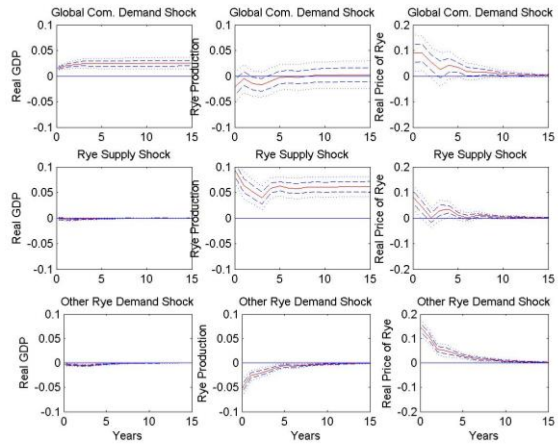

Figure 19: Impulse Response Function for Copper

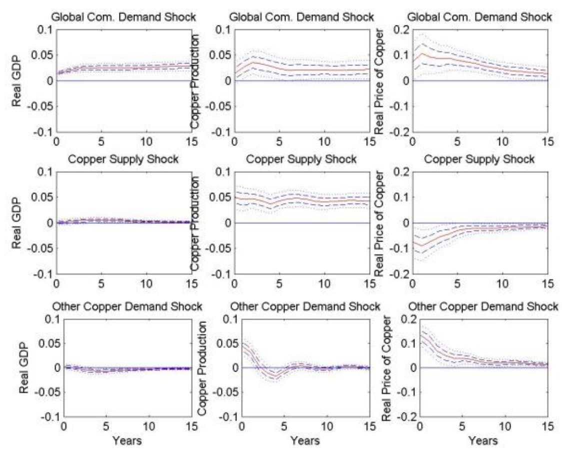

Figure 20: Impulse Response Function for Lead

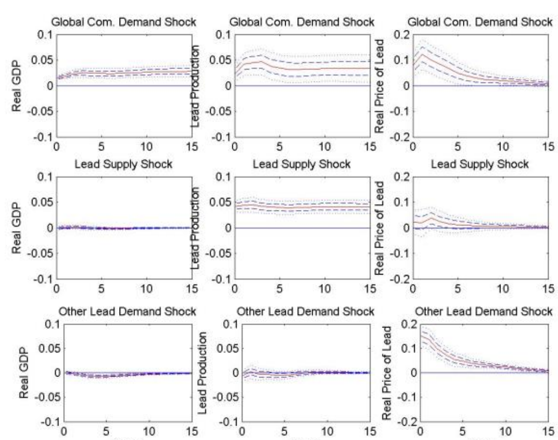

Figure 21: Impulse Response Function for Mercury

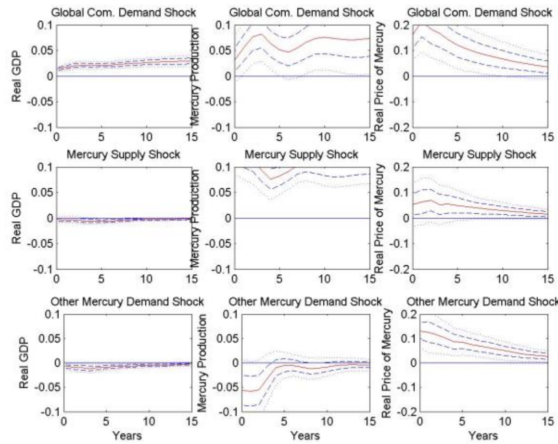

Figure 22: Impulse Response Function for Steel

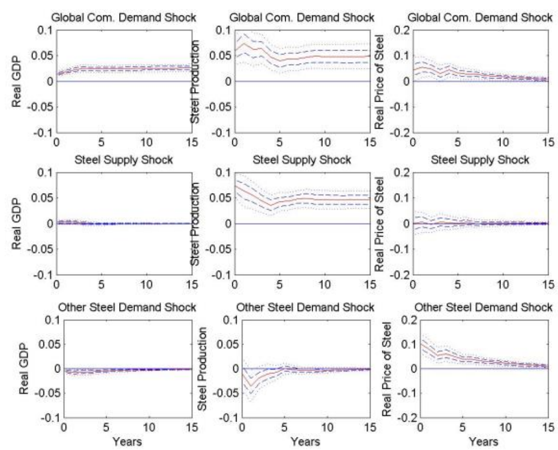

Figure 23: Impulse Response Function for Tin

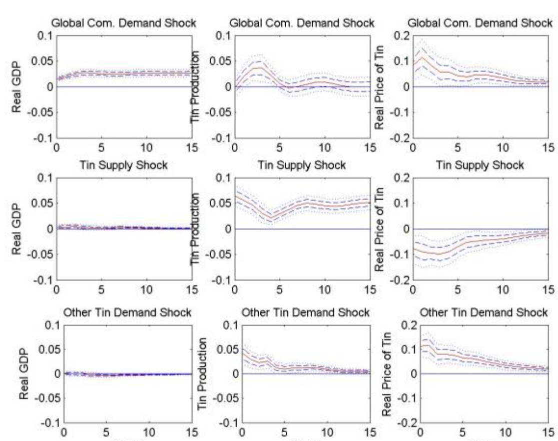

Figure 24: Impulse Response Function for Zinc

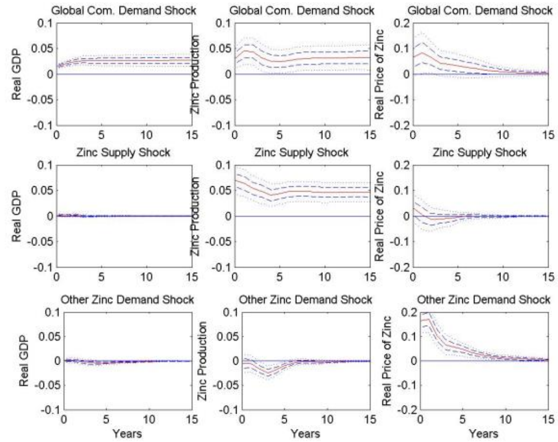

Figure 25: Impulse Response Function for Coffee

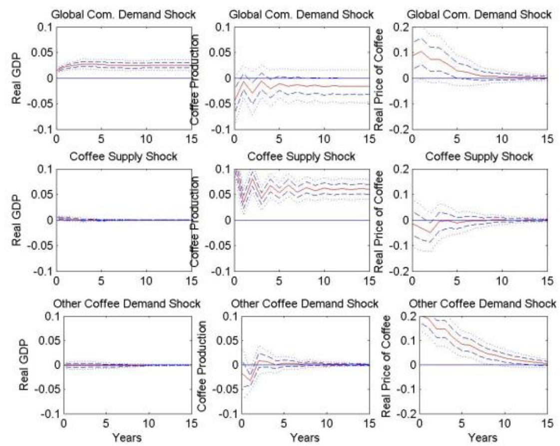

Figure 26: Impulse Response Function for Cotton

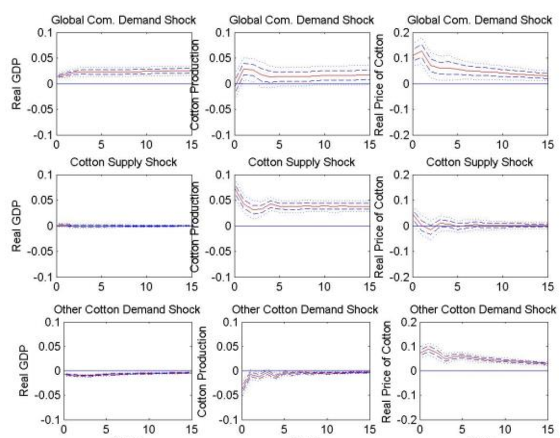

Figure 27: Impulse Response Function for Cottonseed

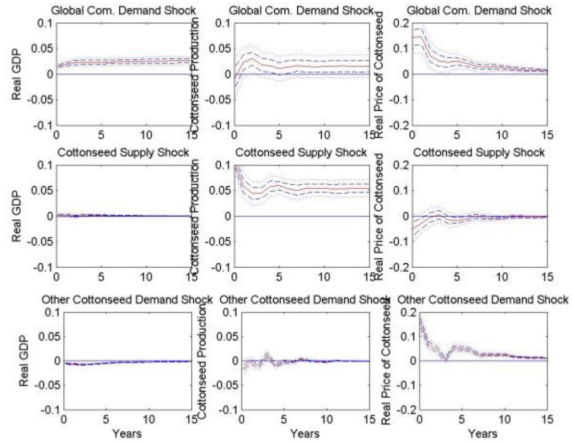

Figure 28: Impulse Response Function for Sugar

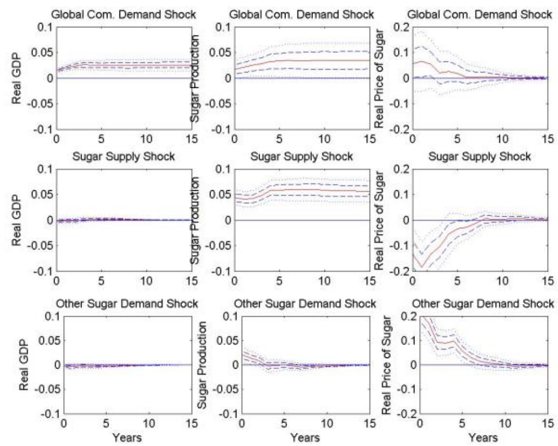

Figure 29: Historical Decomposition of Real Barley Prices

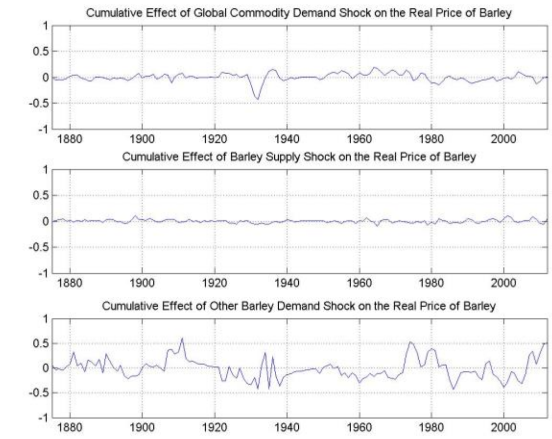

Figure 30: Historical Decomposition of Real Corn Prices

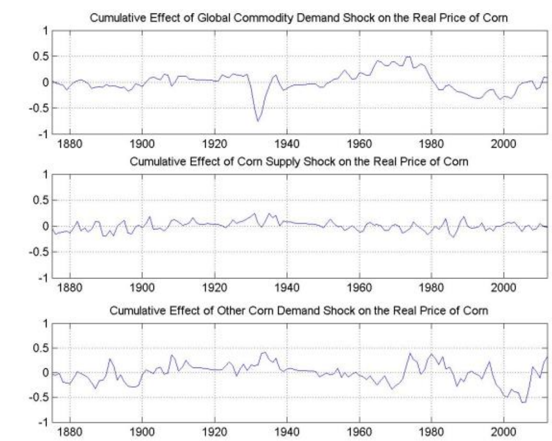

Figure 31: Historical Decomposition of Real Rice Prices

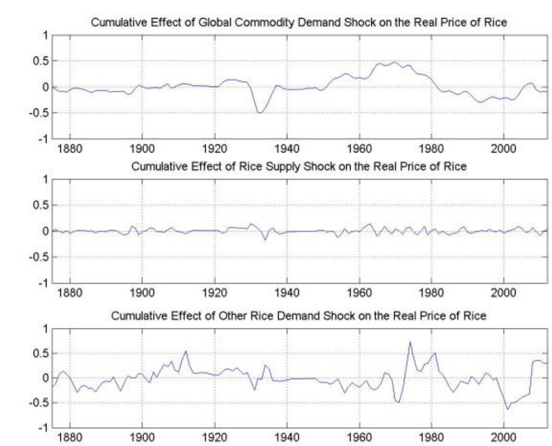

Figure 32: Historical Decomposition of Real Rye Prices

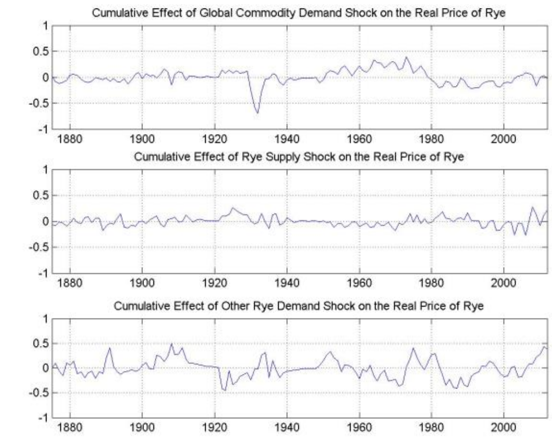

Figure 33: Historical Decomposition of Real Copper Prices

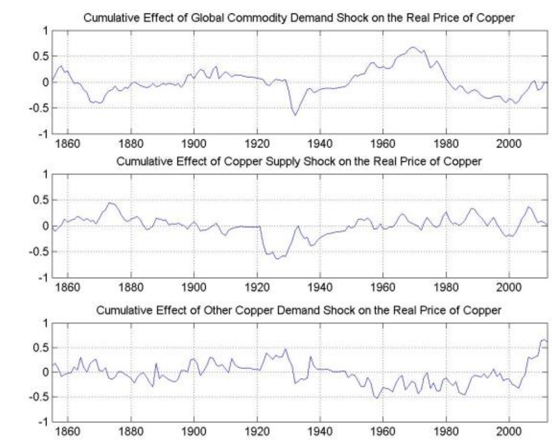

Figure 34: Historical Decomposition of Real Lead Prices

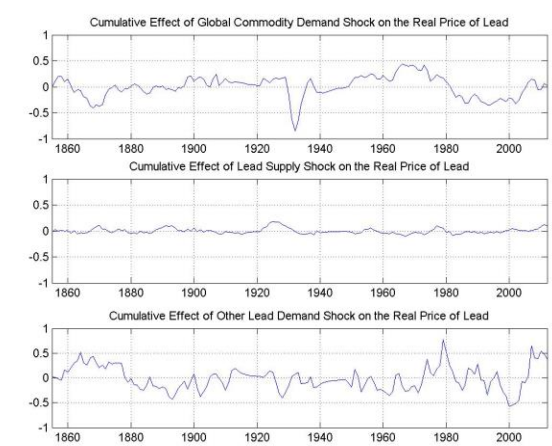

Figure 35: Historical Decomposition of Real Mercury Prices

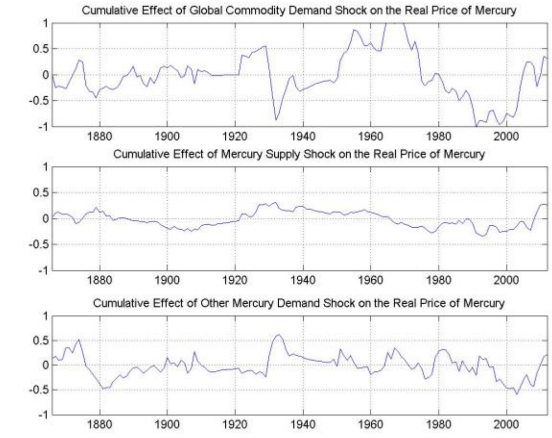

Figure 36: Historical Decomposition of Real Steel Prices

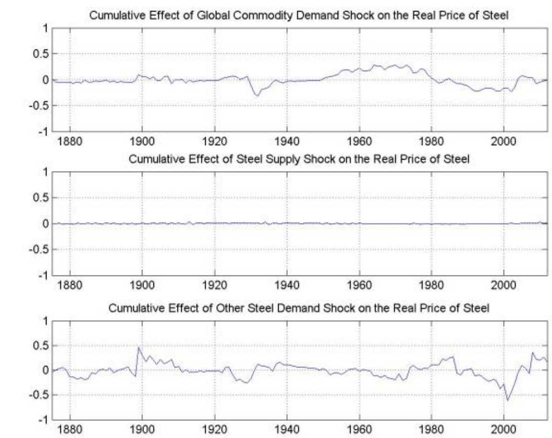

Figure 37: Historical Decomposition of Real Tin Prices

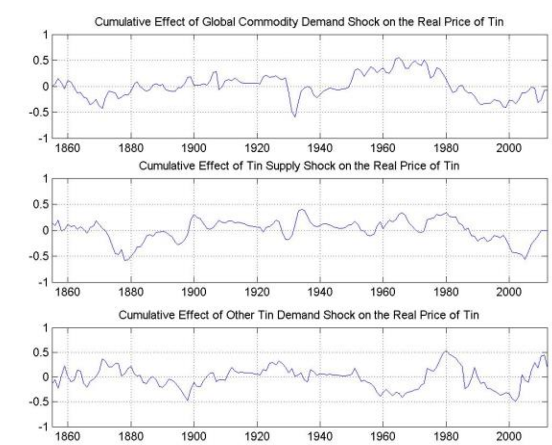

Figure 38: Historical Decomposition of Real Zinc Prices

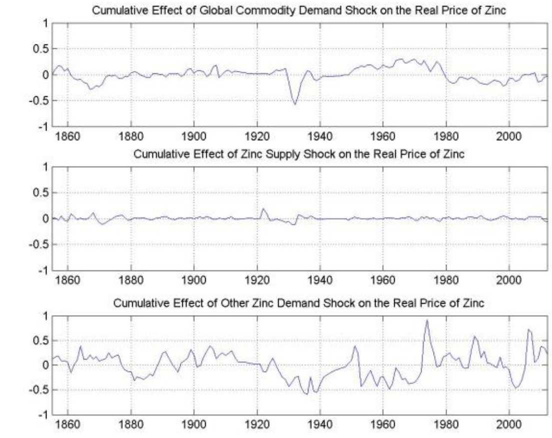

Figure 39: Historical Decomposition of Real Coffee Prices

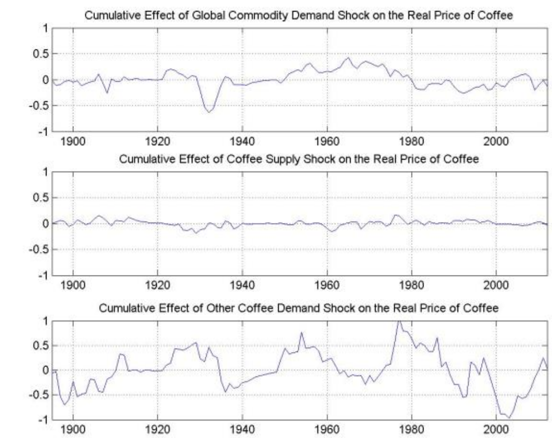

Figure 40: Historical Decomposition of Real Cotton Prices

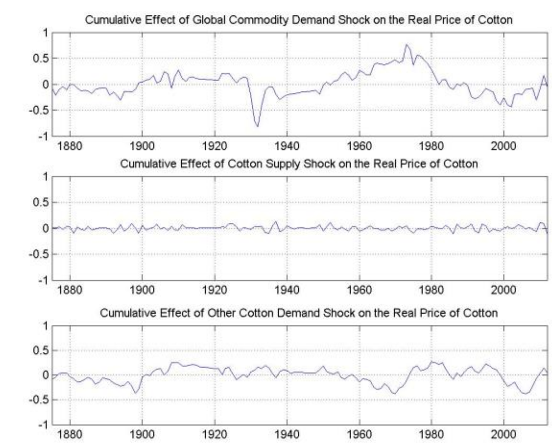

Figure 41: Historical Decomposition of Real Cottonseed Prices

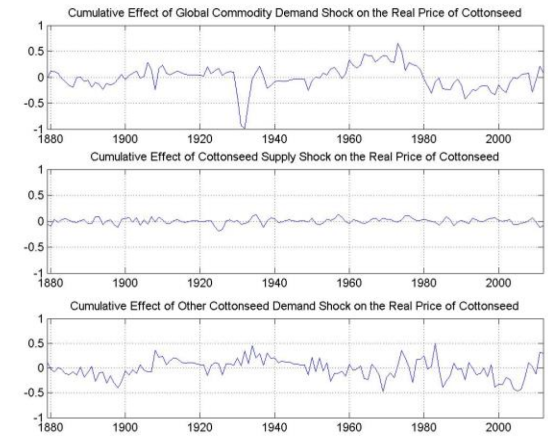

Figure 42: Historical Decomposition of Real Sugar Prices