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What Drives Commodity Price Booms and Busts?*

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Abstract

We provide evidence on the dynamic effects of aggregate commodity demand shocks, commodity supply shocks, and storage or other commodity-specific demand shocks on real commodity prices. We analyze a new dataset of price and production levels from 1870 to 2015 for 15 grains, metals, and soft commodities, representing nearly $2.5 trillion in annual gross value of production. We establish that commodity demand shocks strongly dominate commodity supply shocks in driving prices over a broad set of commodities and over a long period of time. Furthermore, while commodity demand shocks have increased in importance over time, commodity supply shocks have become less relevant.

Keywords: Commodity prices, natural resources, structural VAR
JEL Classification: E30, N50, Q31

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1. Introduction

Understanding the drivers of commodity price booms and busts is of first-order importance for the global economy. A significant portion of income and welfare in both commodity-consuming and commodity-producing nations hinges upon these prices (Bernanke, 2006; IMF, 2012). They also vitally affect the distribution of income within particular nations as the ownership of natural resources varies widely. What is more, the long-run drivers of commodity prices also have serious implications for the formation and persistence of both growth-detracting and growth-enhancing 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 various forces in the determination of commodity price booms and busts.

The recent history of commodity prices is indicative of this situation. 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 at 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 (Irwin, 2009; Fattouh, Kilian, and Mahadeva, 2013). Recent developments in the opposite direction—with real commodity prices having shed roughly 50% of their value in the past few years—have likewise generated much heat, but not so much light.[1] Yet regardless of any particular commenter's take on the ultimate driver of commodity price booms and busts, 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 crude oil price dynamics since the 1970s. Here,

[1] An exception is the literature on crude oil prices. Recent work by Baumeister and Kilian (2016) and Kilian (2017), in particular, provides a decomposition of the determinants of the decline in the real price of oil from 2014 to 2016.

structural vector autoregressive models are used to decompose changes in real crude oil prices into different types of shocks. Identification is made possible by assigning short-run exclusion 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 crude oil prices. That is, while an earlier literature implicated oil supply shocks as a chief source of variation in crude oil prices (see e.g. Hamilton, 2008), this more recent literature finds that demand shocks are the major source of variation in prices for crude oil (Kilian, 2009; Kilian and Murphy, 2014).[2]

However, it is not clear whether this evidence is specific to the crude oil market, or whether developments from the 1970s are representative for longer time periods. Policymakers are also naturally concerned whether the recent boom and bust in commodity markets are a new phenomenon or are a recurring feature of the global economy. 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 longer span of time.[3] To this end, we assemble a new dataset on the level of prices and production for 15 commodities, representing roughly \$2.5 trillion in gross value of production and spanning the categories of grains, metals, and soft commodities from 1870 to 2015.[4] In marked contrast to the literature on crude oil prices which

[2] See Carter, Rausser, and Smith (2011) for a detailed summary of theories on commodity price booms and busts.

[3] Erten and Ocampo (2013) extract so-called "commodity super cycles" from various commodity price indices over the time period 1865 to 2010 and attribute them to changes in global real GDP. Our paper goes beyond this as we are able to identify the contribution of different commodity demand and supply shocks and to quantify the persistence of their effects on the real price of commodities. This is made possible by our new data-set on commodity production and by relying on a substantially different methodology.

[4] We recognize that crude oil is arguably the most important commodity, in particular, in the period from 1950. Ideally, we would include crude oil in our analysis. However, the crude oil market experienced several structural changes and periods of strong market interventions which unfortunately makes this type of exercise infeasible over such a long period of time. Alquist, Kilian, and Vigfusson (2011), Dvir and Rogoff (2009), Hamilton (2011), and Yergin (1991) all point to strong changes in the access to supply and in the role of its active management, first by the Texan Railway Commission and then later by OPEC.

Furthermore, crude oil was mainly used for the production of kerosene for lighting during the late 19th and early 20th centuries and then rapidly as a source of energy for automobiles (Yergin, 2009), causing a strong generally uses monthly data over several decades, we use annual data over the past century and a half. This context makes it hard for us to rationalize a steep—that is, an inelastic—short-run supply curve which is one of the basic identifying assumptions of SVARs based on short-run restrictions (e.g., Kilian, 2009) or to impose bounds on the short-run price elasticity of supply as used in models with sign restrictions (e.g., Kilian and Murphy, 2014).

Instead, we build on Stuermer's (2018) identification scheme which is based on the idea that booms 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. We thereby specify three orthogonal shocks to real commodity prices based on long-run restrictions, namely an aggregate commodity demand shock, a commodity supply shock, and a storage or other commodity-specific demand shock. We emphasize that these shocks are specifically related to commodity markets and are not to be confused with the aggregate demand and aggregate supply shocks used in the macroeconomic literature.

We allow aggregate commodity demand shocks, representing an unexpected expansion in global GDP as in periods of rapid industrialization and urbanization, to have long-run effects not only on global GDP itself but also on the production of individual commodities. The idea is that

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structural change in its use from the 1920s. Finally, to our knowledge, there is no empirical evidence regarding the historical integration of the oil market. However, a close reading of the secondary literature suggests that petroleum markets were highly fragmented early in our period while we know that crude oil markets are highly integrated from at least the 1980s, suggesting another potential source of structural change.

Bearing these caveats in mind, Stuermer (2018) uses data for the crude oil market in a structural VAR for the period from 1861 to 2014 (reported in the online appendix). The results were not robust with respect to different sub-periods, and the impulse response functions were not well behaved presumably due to the structural changes in the market highlighted above. Running regressions for different sub-periods is not sensible due to the small number of observations available in any annual data set. Appendix III presents a similar set of results for quarterly data on petroleum prices and production from 1973 to 2015.

Regardless, we believe that our results have important implications for energy markets in that:
(1) many agricultural goods are also important inputs to the production of fuels (e.g., corn and sugar);
(2) the commodities examined here have long had characteristics such as homogeneity (or at least, reference pricing) and highly integrated markets which make them good benchmarks for crude oil and other energy markets;
(3) our results are a broad confirmation drawn from many different commodities of Kilian's (2009) empirical findings for the crude oil market that variation in prices is mainly driven by shocks to demand.

an increase in price due to a shift in commodity demand for all commodities triggers not only technological change but also investment in new productive capacity such as the discovery of new mineral deposits or the expansion of arable land. In contrast, we assume that commodity supply shocks, which we interpret as a disruption in the physical production of a particular commodity through cartel action, natural disasters, or strikes, only affect global GDP temporarily. This is also consistent with robust evidence that oil supply shocks have only short-lived effects on real GDP (Kilian, 2009). Finally, we label the residual term, capturing all remaining uncorrelated shocks, as a storage or other commodity-specific demand shock (see Kilian and Murphy, 2014). This term is assumed to have no long-run effects on either global GDP or a particular commodity's global production. In combination, this identification scheme allows us to leave all short-run relationships unrestricted.

Based on the structural VAR model, we compute structural impulse responses and historical decompositions for each of the 15 commodity markets. The historical decomposition shows the cumulative contribution at each point in time of each of the three structural shocks in driving booms and busts in commodity prices. It serves to quantify the independent contribution of the three shocks to the deviation of each commodity price from its base projection after accounting for long-run trends in real commodity prices.

Our results indicate that aggregate commodity demand shocks strongly dominate commodity supply shocks as drivers of commodity price booms and busts over a broad set of commodities and over a long period of time. Over the entire period, the average share of aggregate commodity demand shocks in explaining price changes is 31% while the average share of commodity supply shocks is 20%. The most important shocks are storage or other commodity-specific demand shocks which on average drive 49% of price changes. Furthermore, aggregate commodity demand shocks and storage or other commodity-specific demand shocks affect prices up to 10 years while commodity supply shocks affect prices for only up to 5 years.

Additionally, we find that for the period from 1949 to 2015 the contribution of aggregate commodity demand shocks to price changes varies across the different commodities with the largest contribution to soft commodities (35% on average) and to a lesser extent to grains (32% on average) and metals (34% on average). At the same time, aggregate commodity demand shocks exhibit a common pattern with respect to their timing across all commodity markets. Likewise, storage or other commodity-specific demand shocks have stronger effects on commodity prices in the markets for soft commodities than for grains and metals. Commodity supply shocks play some role in explaining variation in particular commodities, but in the main, their influence on real commodity prices is limited. Finally, we find evidence that the importance of commodity supply shocks has decreased over time while aggregate commodity demand shocks have become more important.

The rest of the paper proceeds as follows. Section 2 describes the underlying data while Section 3 outlines the methodology related to structural vector auto-regressions. Section 4 quantifies the contribution of various shocks on commodity price dynamics. Section 5 concludes.

2. New Data on Long-Run Real Prices and Production

The data used in this study represent the end result of a number of selection criteria. First, real prices were drawn for all consistently-defined commodities with at least three billion U.S. dollars of production in 2015 (for further discussion, see Jacks, 2013). The individual real price series are expressed in U.S. dollars and deflated by the U.S. Consumer Price Index underlying Officer (2012), supplemented by updates taken from the U.S. Bureau of Labor Statistics.

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, sharp structural changes in their marketing or global use over time.[5] All told, we consider 15 individual commodity price series (barley, coffee, copper, corn, cotton, cottonseed, lead, rice, rye, steel, sugar, tin, tobacco, wheat, and zinc) which are drawn from three product categories—grains, metals, and soft commodities. Table 1 reveals that these goods represent a non-trivial amount of global commodity production with nearly $2.5 trillion in aggregate gross value of production in 2015. Finally, global real GDP data is based on Maddison (2010) and extensions of Stuermer (2018).

Figure 1 documents the evolution of global real GDP in percentage terms from 1870 to 2015 while Figures 2 through 4 document the evolution of real commodity prices and production for the same years. Appendix I details the sources for the individual series.

3. Structural Vector Autoregression

We follow Kilian (2009) and subsequent authors in applying a structural vector autoregressive model to decompose changes in the real price of a given commodity into components driven by different types of shocks. Unlike these earlier studies, however, we build on the identification scheme proposed by Stuermer (2018). This identification scheme allows us to specify three orthogonal shocks to real commodity prices based on long-run restrictions, namely an aggregate commodity demand shock, a commodity supply shock, and an storage or other commodity-specific demand shock.

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

3.1 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, Kellogg, and Salant (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, 2015) provide stylized facts on R&D in the extractive sector and construct a growth model with a non-renewable resource stock which may be augmented due to R&D investment in extraction technologies. A related argument has been made by earlier contributions to the literature on endogenous 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 (2018) 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 allow aggregate commodity demand shocks to have persistent effects on both global GDP and global production of individual commodities (see Panel A of Table 2). 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 may potentially have long-run effects on global production of a particular commodity, but no long-run effects on global GDP.

Thus, we interpret this shock as capturing unexpected disruptions in global production of a commodity due to cartel action, inter- or intra-state conflict, labor action, weather, or the like. 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. This is also consistent with the robust evidence that oil supply shocks have only short-lived effects on real GDP (Kilian, 2009; Kilian and Murphy, 2014).

Finally, the storage or other commodity-specific demand shock is a residual which captures all shocks that are not correlated with either the aggregate commodity demand shocks or the commodity supply shocks described above. We interpret this residual shock as a shock to the demand for storage of a particular 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 (see Rausser and Stuermer, 2015); 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 and Murphy, 2014).[6] However, this residual shock may also encompass unexpected changes in a commodity's intensity of use with regard to global GDP (Kilian, 2009). As these processes are rather gradual and long-term on a global scale (Pindyck, 1980), we assume that they are primarily captured in the deterministic trend in the regression.

We assume that price changes due to this storage or other commodity-specific demand shock exhibit transitory but no 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 permanently expanding production capacity generally exhibits significant fixed costs and takes

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

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 storage 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. For instance, Rasmussen and Roitman (2011) show on a global scale that even oil price shocks only exhibit small and transitory negative effects for the majority of countries. Table 2 summarizes our assumptions on the persistent and transitory effects of the three orthogonal shocks discussed above.

3.2 Econometric model

Formally, we use a structural vector autoregressive system with long-run restrictions for each commodity market. That is, the individual commodities are considered on a one-by-one basis. The econometric model for each commodity market 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.[7] 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 1948). These fixed effects are meant to control for the fact that world markets for commodities during these time periods were subject to market

[7] Results for alternative specifications including nonlinear trend specifications are summarized in section 4.3 below.

distortions related to government policy and restrictions to trade related to the nature of the conflicts and their aftermath.

The structural VAR representation is

$$Ax_t = \Pi D_t + \Gamma_1^* x_{t-1} + ... + \Gamma_1^* x_{t-p} + B\varepsilon_t \ (1)$$

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 $\Gamma_j = A^{-1}\Gamma_j^*$ for $j = 1, \ldots, p$ and $\Pi = A^{-1}\Pi^*$. A and B are $K \times K$ matrices. The number of endogenous variables is denominated by K. The relation to the reduced form residuals is given by $u_t = A^{-1}B\varepsilon_t$.

We compute the structurally identified impulse response by first setting $A = I_K$, with I equal to a $K \times K$ identity matrix. We then estimate the matrix of contemporaneous effects $C = A^{-1}B$ by $\hat{C} = \hat{\Phi}^{-1}\ \hat{\Psi} = \hat{\Phi}^{-1}\text{chol}[\hat{\Phi}\ \hat{\Sigma}_u\ \hat{\Phi}']$, where Φ is the matrix of accumulated effects of the impulses and Ψ is the matrix of long-run effects. We assume that Ψ is lower triangular to identify the three structural shocks. Doing so means that we place zero restrictions on the upper-right corner of the long-run matrix, thereby, leaving the contemporaneous relationships completely unrestricted. That is, shocks to the global of supply of the respective commodity and the storage or other commodity-specific demand shock affect global GDP in the short-, but not the long-run. Furthermore, the storage or other commodity-specific demand shock exhibit only transitory effects on global commodity production. Finally, the Cholesky decomposition of the matrix $\hat{\Phi}\ \hat{\Sigma}_u\ \hat{\Phi}'$ provides us with an estimate of the matrix of long-run effects Ψ (see Lütkepohl and Krätzig, 2004).

We follow Goncalves and Kilian (2004) and use a recursive-design wild bootstrap with 2,000 replications for inference. 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

4.1 Impulse Response Functions

Figure 5 presents the impulse response functions for all commodity markets. For purposes of making the picture as clear as possible, we have done so with no confidence bands depicted. The interested reader may consult Figures 6 to 8 which present the impulse response functions for each commodity separately along with their respective confidence bands.

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

(2) positive commodity supply shocks have limited effects on global GDP, generally

induce persistently higher global commodity production, and serve to decrease real commodity prices; and

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

In the main, 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 aggregate commodity demand shocks and positive storage or other commodity-specific demand shocks both serve to increase real commodity prices while positive commodity supply shocks serve to decrease real commodity prices. On average, the effects of aggregate commodity demand shocks are the most persistent with effects lingering up to 10 years. This is followed by storage or other commodity-specific demand shocks which are slightly less persistent, but with effects that also last up to 10 years in some cases. Finally, the effect of commodity supply shocks is, for the most part, insignificant. However, a few exceptions to this general result are to be found in the sugar and tin markets with effects which persist up to five years.

4.2 Historical Decompositions

The historical decompositions show the contribution of each shock in driving variation in each real commodity price series. They serve to quantify the independent contribution of the three shocks to the deviation of each commodity price from its base projection. Thus, Figures 9 to 11 depict the historical decomposition of booms and busts 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 aggregate commodity demand shocks. The collective story which emerges from our figures suggests that although the proportional contribution of the aggregate commodity demand shocks naturally varies across the different commodities, their accumulated effects broadly follow the same pattern with respect to timing across the 15 commodities (see Figure 12, in particular). Thus, aggregate commodity 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 aggregate commodity demand shocks have a common source. This finding is consistent with the arguments in Barsky and Kilian (2002) that there is a common business cycle component in commodity prices. The latter idea has also been exploited in the forecasting literature (e.g., Alquist, Kilian, and Vigfusson, 2013).

What is more, this interpretation of the accumulated aggregate commodity demand shocks is in line with what economic history has to say about variation in global output.[8] The historical decompositions start in 1875 when prices were depressed due to the negative accumulated effects of aggregate commodity demand shocks on prices during the first—but somewhat forgotten—great depression. Afterwards, the effects of aggregate commodity demand shocks are in line with our historical knowledge about the business cycles in major economies at the time. For example, the effects of the large negative aggregate commodity demand shock in

[8] See also Stuermer (2017), who establishes that periods of industrialization affect the derived demand for metals in individual countries using a data-set of five base-metals and 12 countries that over the time period 1840 to 2010.

1907 can be associated to the so-called Panic of 1907. Likewise, in the early 1930s real prices plummeted, as the (second) Great Depression reduced global demand for commodities.

After World War II, aggregate positive commodity demand shocks led to increases in real commodity 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 aggregate commodity 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 aggregate commodity demand shocks emerging from the late 1990s and early 2000s due to unexpectedly strong global growth, driven by the industrialization and urbanization of China. Finally, the lingering effects of the Global Financial Crisis are also clearly visible in the series for the accumulated effects of aggregate commodity demand shocks.

The historical decompositions show that storage or other commodity-specific demand shocks also play an important role in driving variation 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 base-metal markets 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 (Stuermer, 2017). However, as this 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 naturally captured by this residual demand term.

In marked contrast, the accumulated effects of commodity supply shocks play a less important role in driving deviations in long-run real prices from their underlying trend for 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 as mentioned previously. 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, 2018 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.

Likewise, Table 3 numerically summarizes the contribution of each shock by commodity category and period. Thus, for the full period from 1871 to 2015 (Table 3, Panel A), aggregate commodity demand shocks explain 29-32% (across the three types of commodities examined here) of the variation in real commodity prices while storage or other commodity-specific demand shocks explain 47-52%. These two types of shock, thus, cause an appreciable portion (76-84%) of the medium- and long-run variation in real commodity prices. Conversely, commodity supply shocks play a rather secondary and transient role, explaining only 15-24% of the variation. This result is fairly consistent across grains, metals, and soft commodities alike.

Averages for three sub-periods based on the full sample (see Table 3, Panels B to D) show that supply shocks have lost importance over time, as their average share declined from 24% during the interwar period to 18% in the period after World War II. At the same time, the average share of aggregate commodity demand shocks has increased from 27% in the pre-World War I period to 30% during the interwar period and to 34% in the post-World War II period. While there are several potential explanations for this phenomenon, we leave their exploration to further research.

4.3 Robustness

Our results are robust to a number of different approaches to the data and econometric modelling. First, we have allowed for the possibility of non-linear trends in real commodity prices. De-trended real commodity prices were derived via the Christiano-Fitzgerald asymmetric band-pass filter used in Jacks (2013). No material differences in our results were forthcoming.

Second, we have used a shorter sample from 1900 to 2015 to reflect concerns about the quality of data, in particular, that for production in the nineteenth century. Again, the results are not qualitatively different than those presented here.

Third, the results are by-and-large not sensitive to sub-period regressions for the time periods 1871-1938 and 1922-2015. It is not possible to consider even shorter sub-periods both because our identification relies on long-run identifying restrictions and because the sample becomes too small to estimate the model.

Finally, we allowed 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. Details on the sensitivity tests are available from the authors upon request.

4.4 Extensions

Up to this point, our results speak to the phenomena of commodity price booms and busts at the individual good level. However, an often remarked feature of real commodity prices is their tendency to rise and fall in a synchronous fashion from time to time, giving rise to the popular notion of a "commodity price super-cycle". Therefore, it may be informative to consider the commodities in our sample collectively, rather than individually. To this end, Appendix II presents equivalent exercises for two commodity price and production indices, one unweighted and one weighted by the current value of production on a year-by-year basis. The results are highly consistent with the main themes presented here, namely that aggregate commodity demand and inventory or other commodity demand shocks strongly dominate while supply shocks contribute only a small share in explaining variation in real commodity prices.

5. Conclusions

This paper is the first in providing evidence on the drivers of real commodity prices in the long-run across different types of commodities. To this end, we assemble a new data set on the level of price and production for 15 commodities, spanning the categories of grains, metals, and soft commodities from 1870 to 2015. We establish that aggregate commodity demand shocks and storage or other commodity-specific demand shocks strongly dominate commodity supply shocks in driving the fluctuation in real commodity prices over a broad set of commodities and over a long period of time.

Additionally, we find that the contribution of aggregate commodity demand shocks to real prices varies across the different commodities. However, aggregate commodity demand shocks exhibit common patterns with respect to timing across the markets for grains, metals, and soft commodities. Storage or other commodity-specific demand shocks are the most important driver in commodity price variation for most of our commodities. Commodity supply shocks play some role in explaining variation for particular commodities, but in the main, their influence on real commodity prices is limited in impact and transitory in duration.

There are significant differences in the persistence across the different types of shocks. While commodity demand and storage or other commodity-specific demand shocks affect prices up to 10 years, supply shocks only have an effect for up to 5 years. Finally, aggregate commodity demand shocks have increased in importance over time while commodity supply shocks have become less relevant.

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Appendix I

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

Prices

There are a few key sources of price 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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The Statist (1930), "Wholesale Prices of Commodities in 1929." *Journal of the Royal Statistical Society* 93(2): 271-87.

"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: 1870-1959, Manthy, R.S. (1974), *Natural Resource Commodities - A Century of Statistics*. Baltimore and London: Johns Hopkins Press; 1960-2015, WB.

Coffee: 1870-1959, Global Financial Data; 1960-2015, WB.

Copper: 1870-2015, Stuermer.

Corn: 1870-1999, Global Financial Data; 2000-2015, United States Department of Agriculture National Agricultural Statistics Service.

Cotton: 1870-1899, SS; 1900-1959, GY; 1960-2015, WB.

Cottonseed: 1874-1972, Manthy, R.S. (1974), *Natural Resource Commodities*. Baltimore and London: Johns Hopkins Press; 1973-2015, National Agricultural Statistics Service.

Lead: 1870-2015, Stuermer.

Rice: 1870-1899, SS; 1900-1956, GY; 1957-1979, Global Financial Data; 1980-2015, IMF.

Rye: 1870-1970, Manthy, R.S. (1974), *Natural Resource Commodities.* Baltimore and London: Johns Hopkins Press; 1971-2015, National Agricultural Statistics Service.
Steel: 1897-1998, USGS; 1999-2015, WB.
Sugar: 1870-1899, SS; 1900-1959, GY; 1960-2015, WB.
Tin: 1870-2015, Stuermer.
Tobacco: 1870-1899, Carter, S. et al. (2006), *Historical Statistics of the United States, Millennial Edition*. Cambridge: Cambridge University Press; 1900-1959, GY; 1960-2015, WB.
Wheat: 1870-1999, Global Financial Data; 2000-2015, United States Department of Agriculture National Agricultural Statistics Service.
Zinc: 1870-2015, Stuermer.

Production

There are a few key sources of production data: the annual FAOSTAT (FAO) series for global production dating from 1961 to 2015; the annual Mitchell (MIT) series for country-level production dating from 1870 to 2010.

The relevant references are:

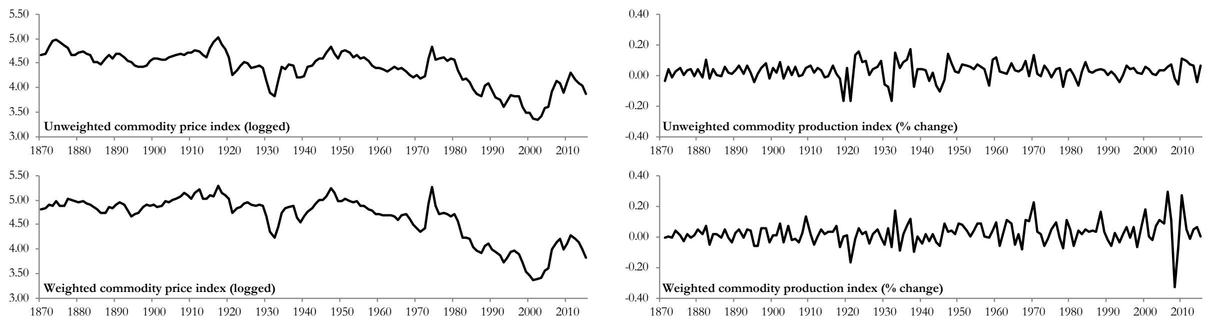
Food and Agricultural Administration of the United Nations Statistics, http://faostat3.fao.org/home/E
Mitchell, B.R. (2015), *International Historical Statistics, 1750-2010*, http://www.palgraveconnect.com/pc/archives/ihs.html.
Stuermer, M. (forthcoming), "150 Years of Boom and Bust: What Drives Mineral Commodity Prices?" *Macroeconomic Dynamics*.

Barley: 1870-1961, MIT; 1962-2015, FAO.
Coffee: 1870-1924, Wickizer, V.D. (1943), The World Coffee Economy. Stanford: Food Research Institute; 1925-1934, *The Commodity Yearbook*, Commodity Research Bureau, various years; 1935-1974, World Bank (1975), "Structure and Prospects of the World Coffee Economy." *World Bank Staff Working Paper no. 208*; 1975-2015, FAO.
Copper: 1870-2015, Stuermer.
Corn: 1870-1961, MIT; 1962-2015, FAO.
Cotton: 1870-1961, MIT; 1962-2015, FAO.
Cottonseed: 1870-1961, MIT; 1962-2015, FAO.
Lead: 1870-2015, Stuermer.
Rice: 1870-1961, MIT; 1962-2015, FAO.
Rye: 1870-1961, MIT; 1962-2015, FAO.
Steel: 1870-1920, Verein Deutscher Eisenhuettenleute (1950), *Weltstatistik der Erzeugung von Roheisen und Rohstahl sowie der Herstellung von Walzwerksfertigerzeugnissen 1870-1948*. Duesseldorf; 1921-2007, Bundesvereinigung Stahl (personal communication); 2008-2015, USGS.
Sugar: 1870-1961, MIT; 1962-2015, FAO.
Tin: 1870-2015, Stuermer.
Tobacco: 1870-1961, MIT; 1962-2015, FAO.
Wheat: 1870-1961, MIT; 1962-2015, FAO.
Zinc: 1870-2015, Stuermer.

Appendix II

This appendix replicates the exercise conducted in the main body of the text, but this time with a view towards the collective performance of the 15 underlying commodities. An often remarked feature of real commodity prices is their tendency to rise and fall in a synchronous fashion from time to time, giving rise to the popular notion of a "commodity price super-cycle". To this end, we have estimated the model using two commodity price and production indices, one unweighted and one weighted by the current value of production on a year-by-year basis. Figure A1 charts the evolution of these unweighted and weighted real price and production indices from 1870.

Figure A1: Evolution of Real Commodity Price and Production Indices



Figures A2 and A4 provide the impulse response functions and historical decompositions for the unweighted real price index while Figures A3 and A5 do the same for the weighted versions. Even a causal glance at the series reveals that the results are highly consistent with the themes discussed in the main text, namely that aggregate commodity demand and inventory or other commodity demand shocks strongly dominate while supply shocks contribute only a small share in explaining variation in real commodity prices.

Figure A2: Impulse Response Functions for the Unweighted Real Commodity Price Index

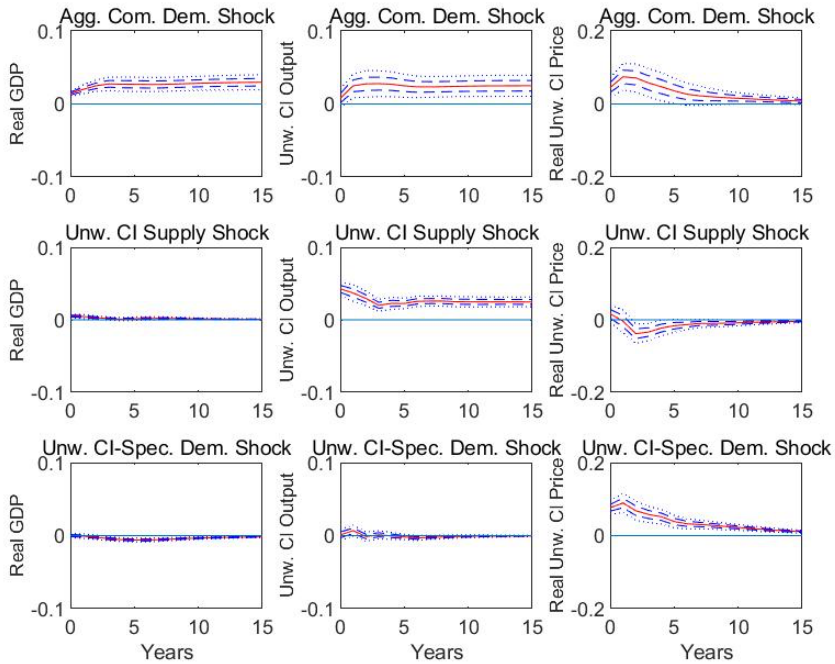


Figure A3: Impulse Response Functions for the Weighted Real Commodity Price Index

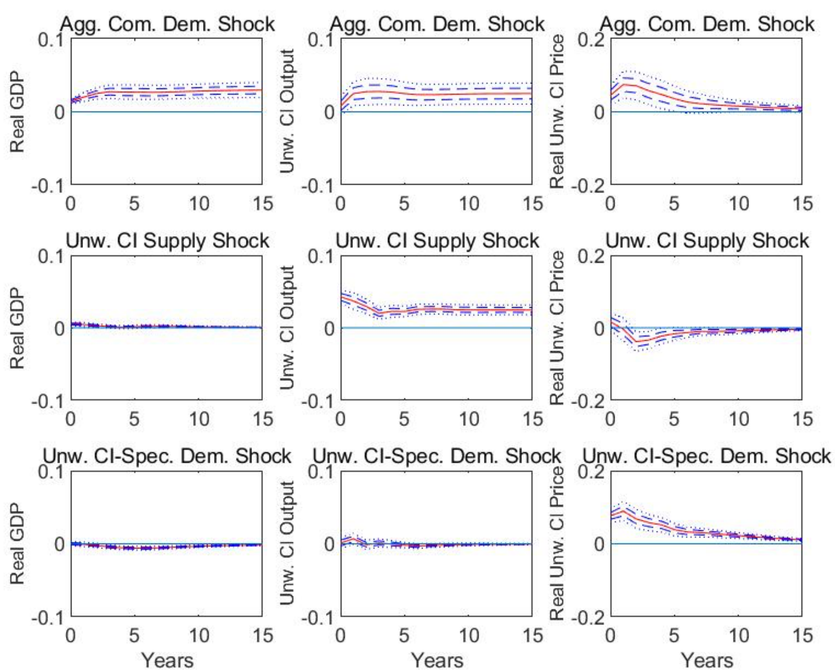


Figure A4: Historical Decompositions of the Unweighted Real Commodity Price Index

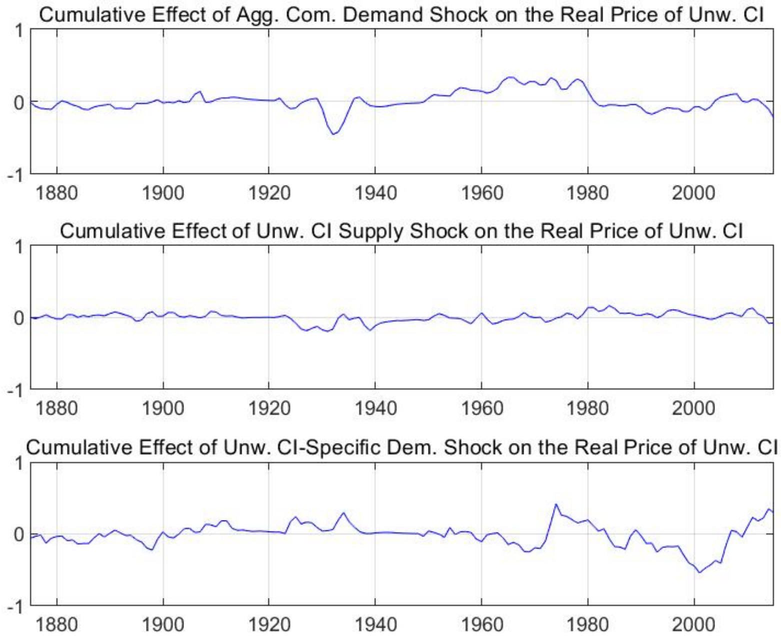
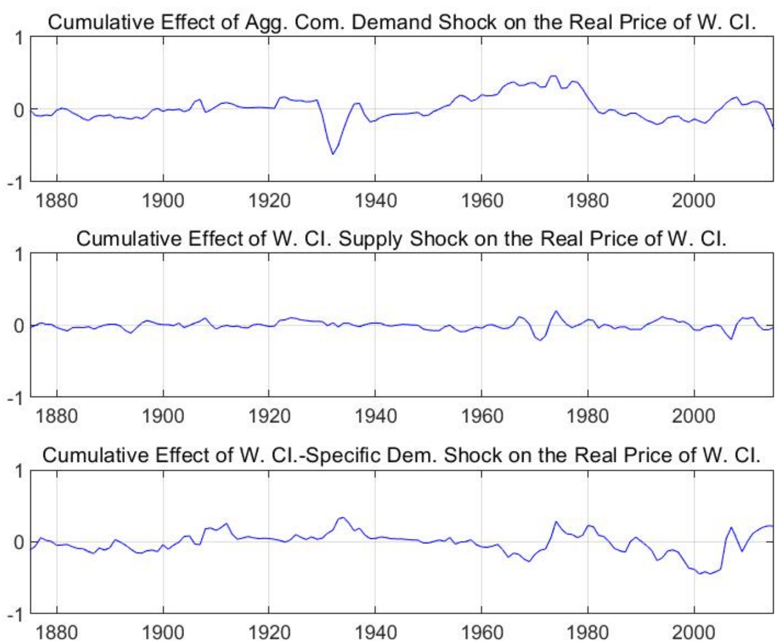


Figure A5: Historical Decompositions of the Weighted Real Commodity Price Index



Appendix III

As stated in the text, we recognize that crude oil is arguably the most important commodity, in particular, in the period from 1950. Thus, we would ideally include crude oil in our analysis.

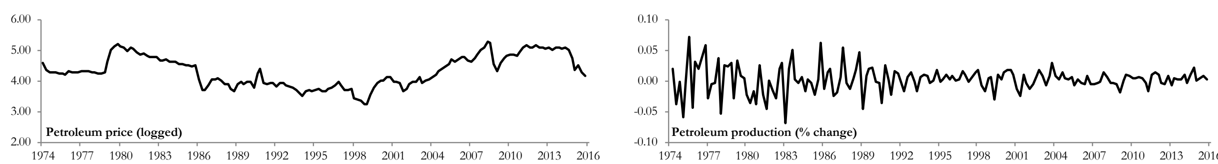
However, the crude oil market experienced several structural changes and periods of strong market interventions which unfortunately makes this type of exercise infeasible over such a long period of time. Alquist, Kilian, and Vigfusson (2011), Dvir and Rogoff (2009), Hamilton (2011), and Yergin (1991) all point to strong changes in the access to supply and in the role of its active management, first by the Texan Railway Commission and then later by OPEC.

Furthermore, crude oil was mainly used for the production of kerosene for lighting during the late 19th and early 20th centuries and then rapidly as a source of energy for automobiles (Yergin, 2009), causing a strong structural change in its use from the 1920s. Finally, to our knowledge, there is no empirical evidence regarding the historical integration of the oil market. However, a close reading of the secondary literature suggests that petroleum markets were highly fragmented early in our period while we know that crude oil markets are highly integrated from at least the 1980s, suggesting another potential source of structural change.

Bearing these caveats in mind, Stuermer (2018) uses data for the crude oil market in a structural VAR for the period from 1861 to 2014 (reported in the online appendix). The results were not robust with respect to different sub-periods, and the impulse response functions were not well behaved presumably due to the structural changes in the market highlighted above.

As a further means of addressing this issue, we have collected quarterly data on real petroleum prices and production from the IMF and US EIA. Figure A6 charts the evolution of quarterly petroleum prices and production from the first quarter of 1974 to the fourth quarter of 2015.

Figure A6: Evolution of Real Petroleum Prices and Production



A similar pattern as in Stuermer (2018) emerges in Figure A7: positive aggregate demand shocks are associated with a negative and significant change in real petroleum prices. Given this counterintuitive result, we, therefore, put little stock in the historical decomposition given in Figure A8, suggesting potential limits to the model in being brought to the data.

Figure A7: Impulse Response Functions for Petroleum

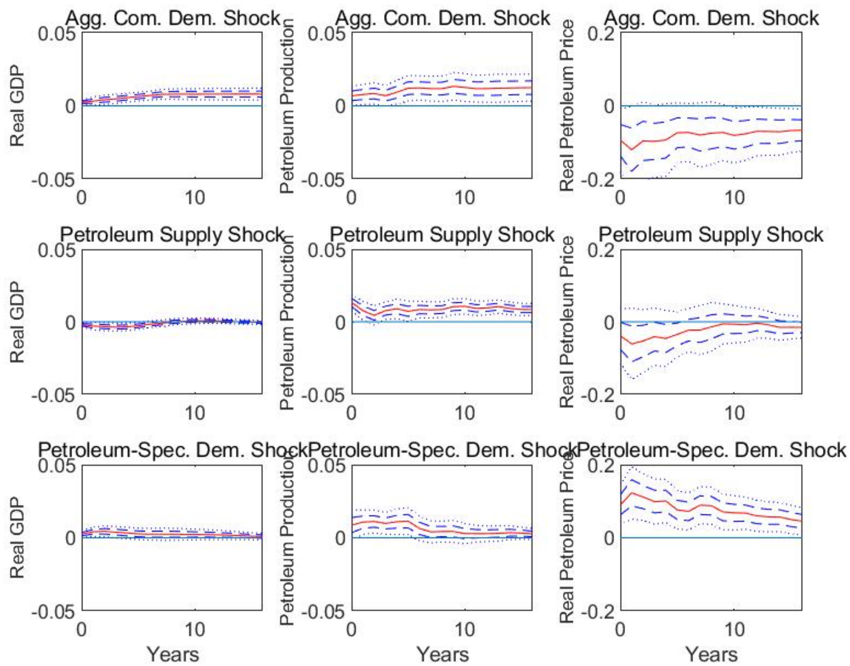


Figure A8: Historical Decompositions of Real Petroleum Prices

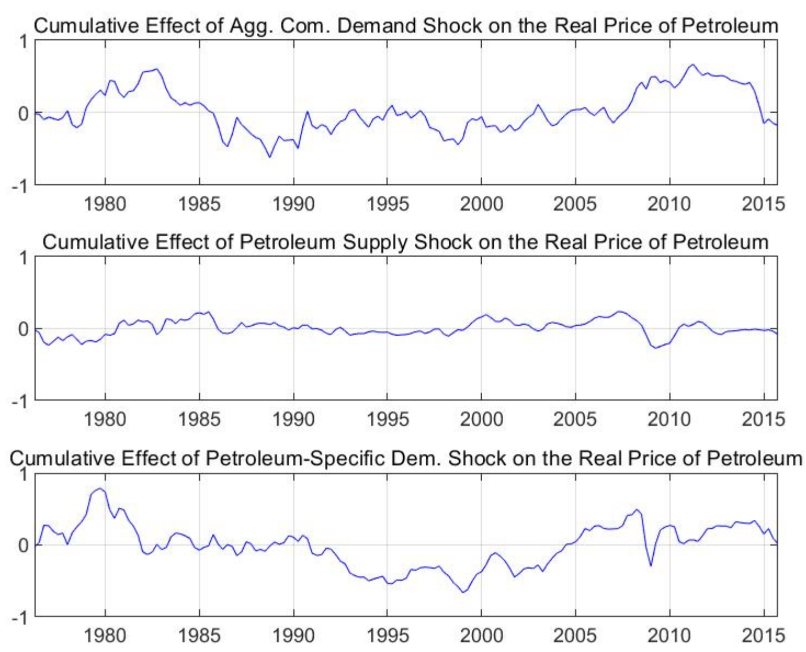


Table 1: Value of Production Across Commodities in 2015 (b USD)

Commodity	Production in 2015	Units of measurement	Value of production
Grains			**584.84**
Barley	148.46	Million tonnes	18.01
Corn	1010.61	Million tonnes	145.53
Rice	740.08	Million tonnes	281.27
Rye	13.00	Million tonnes	3.33
Wheat	736.98	Million tonnes	136.70
Metals			**1745.13**
Copper	21.54	Million tonnes	122.62
Lead	9.43	Million tonnes	16.74
Steel	1620.00	Million tonnes	1576.00
Tin	294.00	Thousand tonnes	4.97
Zinc	12.80	Million tonnes	24.80
Soft commodities			**163.00**
Coffee	7.19	Million tonnes	25.34
Cotton	25.22	Million tonnes	39.14
Cottonseed	43.41	Million tonnes	10.72
Sugar	180.62	Million tonnes	53.51
Tobacco	6.99	Million tonnes	34.29

Figure 1: Evolution of Real Global GDP, 1870-2015

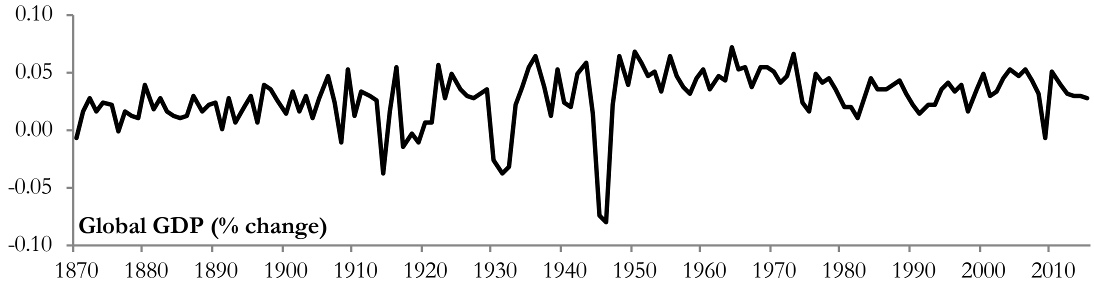


Figure 2: Evolution of Real Grain Prices and Production

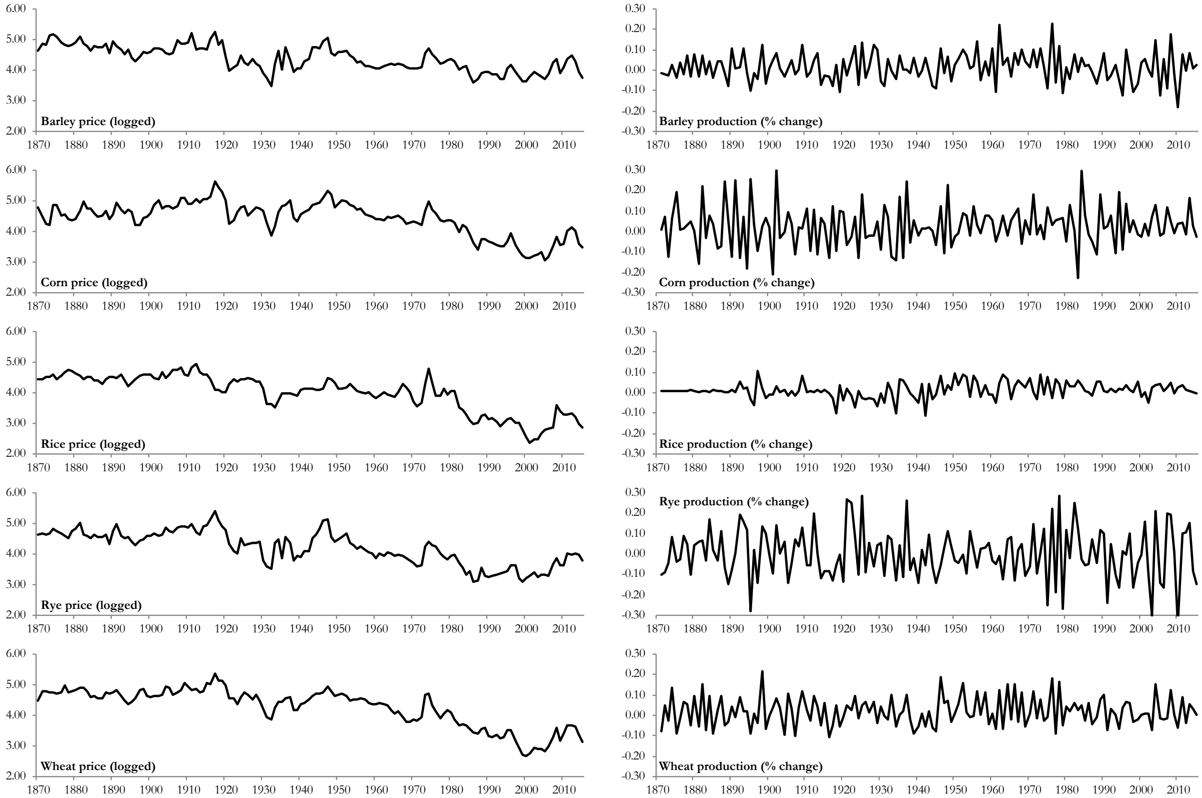


Figure 3: Evolution of Real Metal Prices and Production

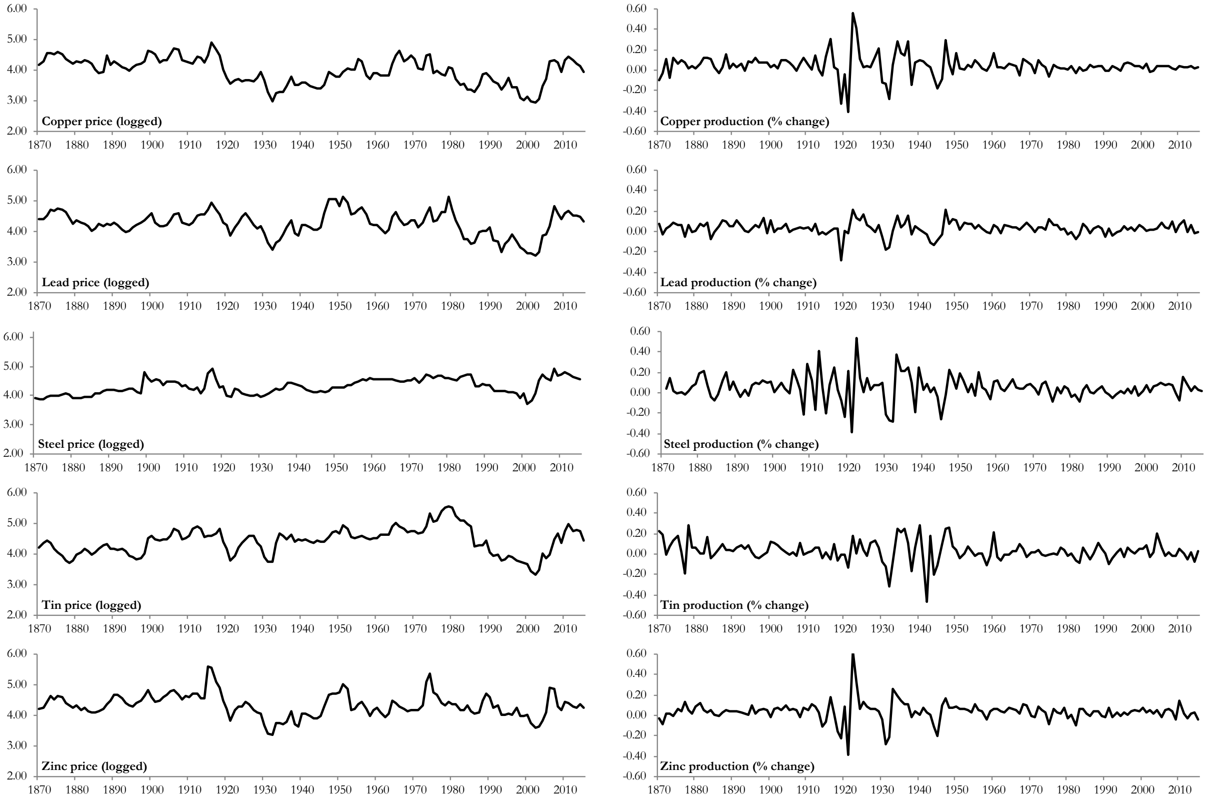


Figure 4: Evolution of Real Soft Commodity Prices and Production

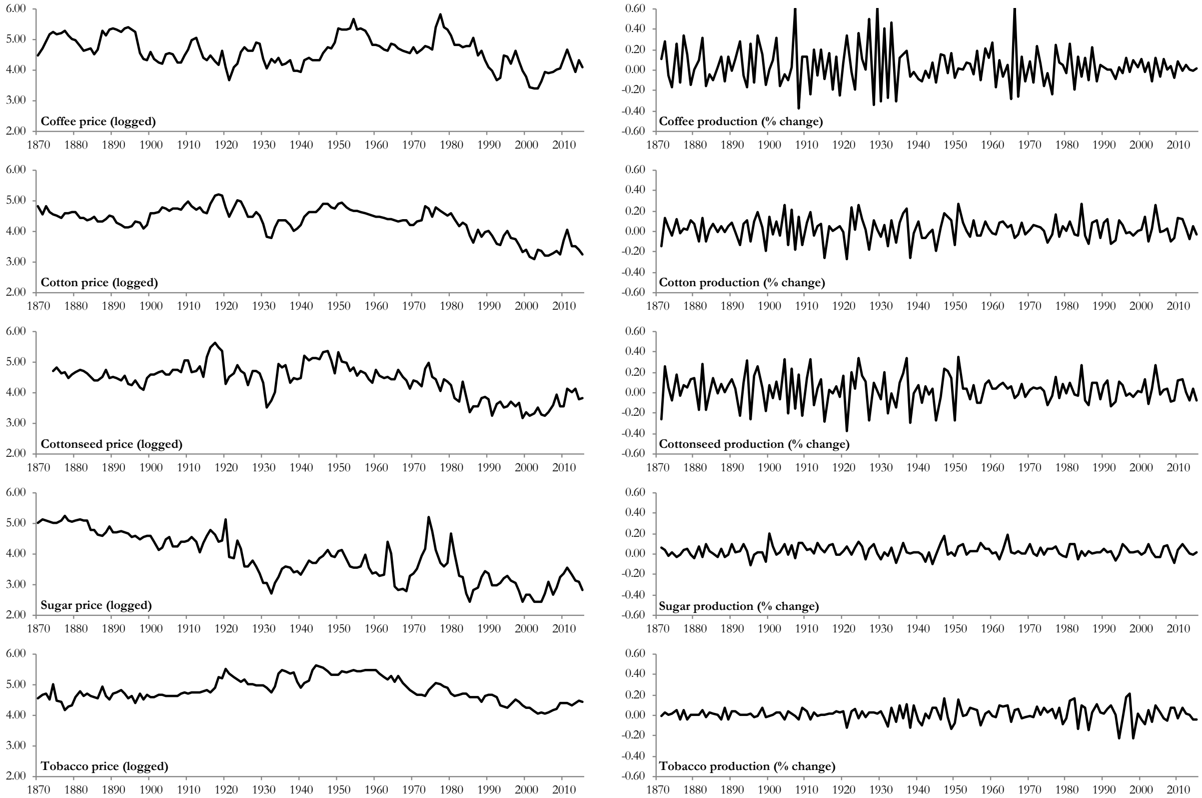


Table 2: Assumptions on Possible Effects of Three Orthogonal Shocks on Three Endogenous Variables

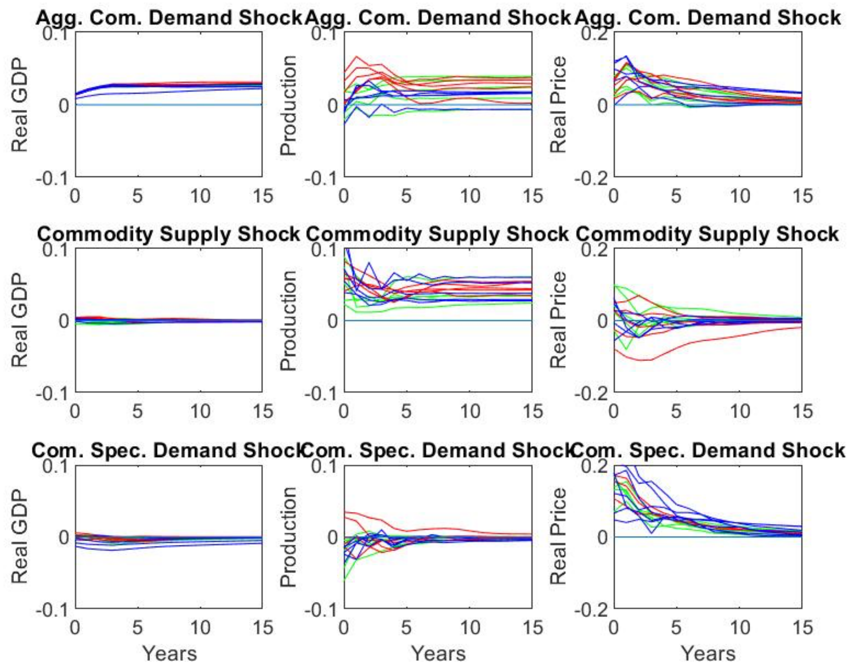
A. Persistent Effects

	Global GDP	Production	Price
Commodity Demand Shock	YES	YES	YES
Commodity Supply Shock	NO	YES	YES
Commodity-Specific Demand Shock	NO	NO	YES

B. Transitory Effects

	Global GDP	Production	Price
Commodity Demand Shock	YES	YES	YES
Commodity Supply Shock	YES	YES	YES
Commodity-Specific Demand Shock	YES	YES	YES

Figure 5: Impulse Response Functions for all 15 Commodity Markets



NB: Green: grains; Red: metals; Blue: soft commodities.

Figure 6: Impulse Response Functions for Grains

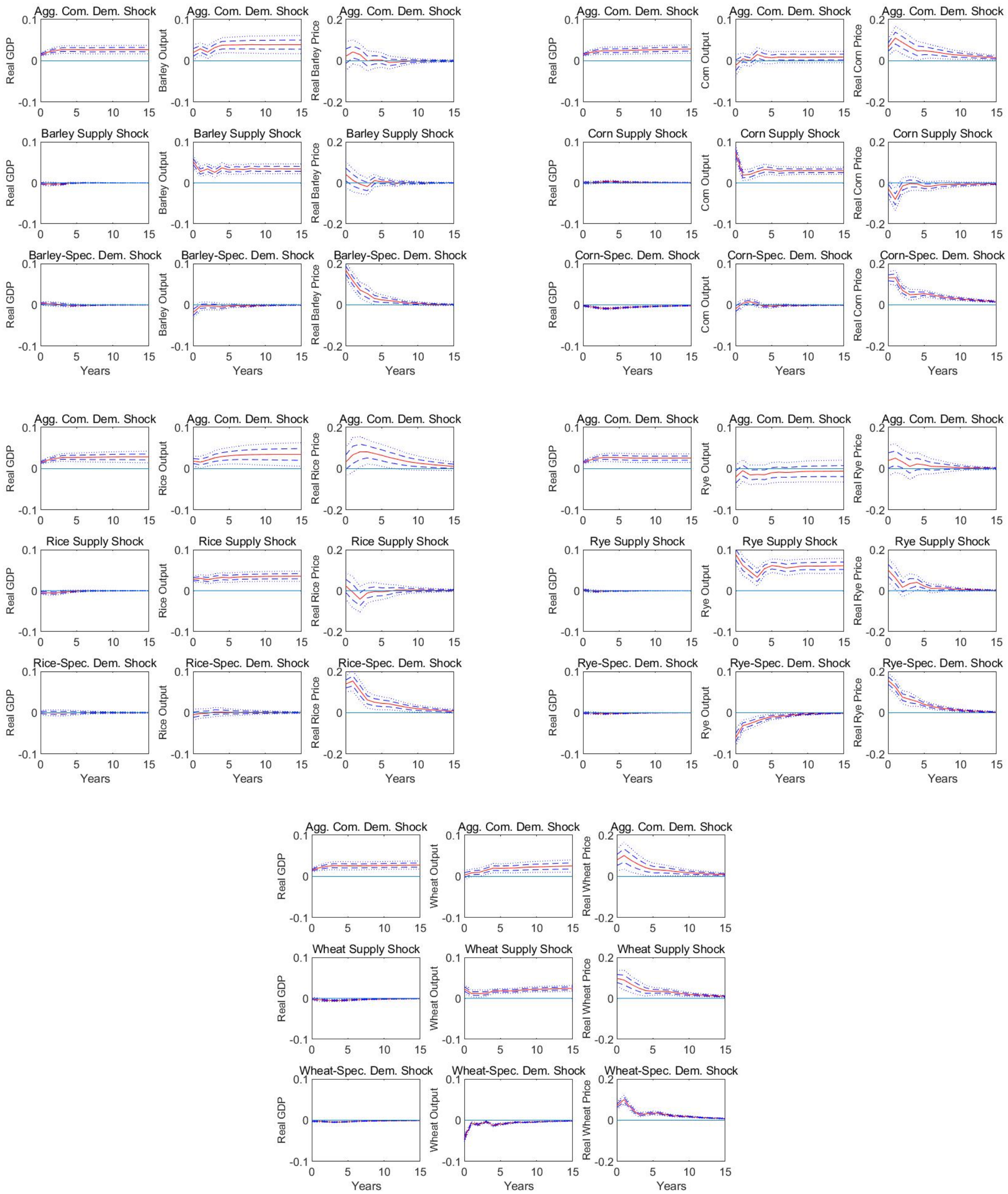


Figure 7: Impulse Response Functions for Metals

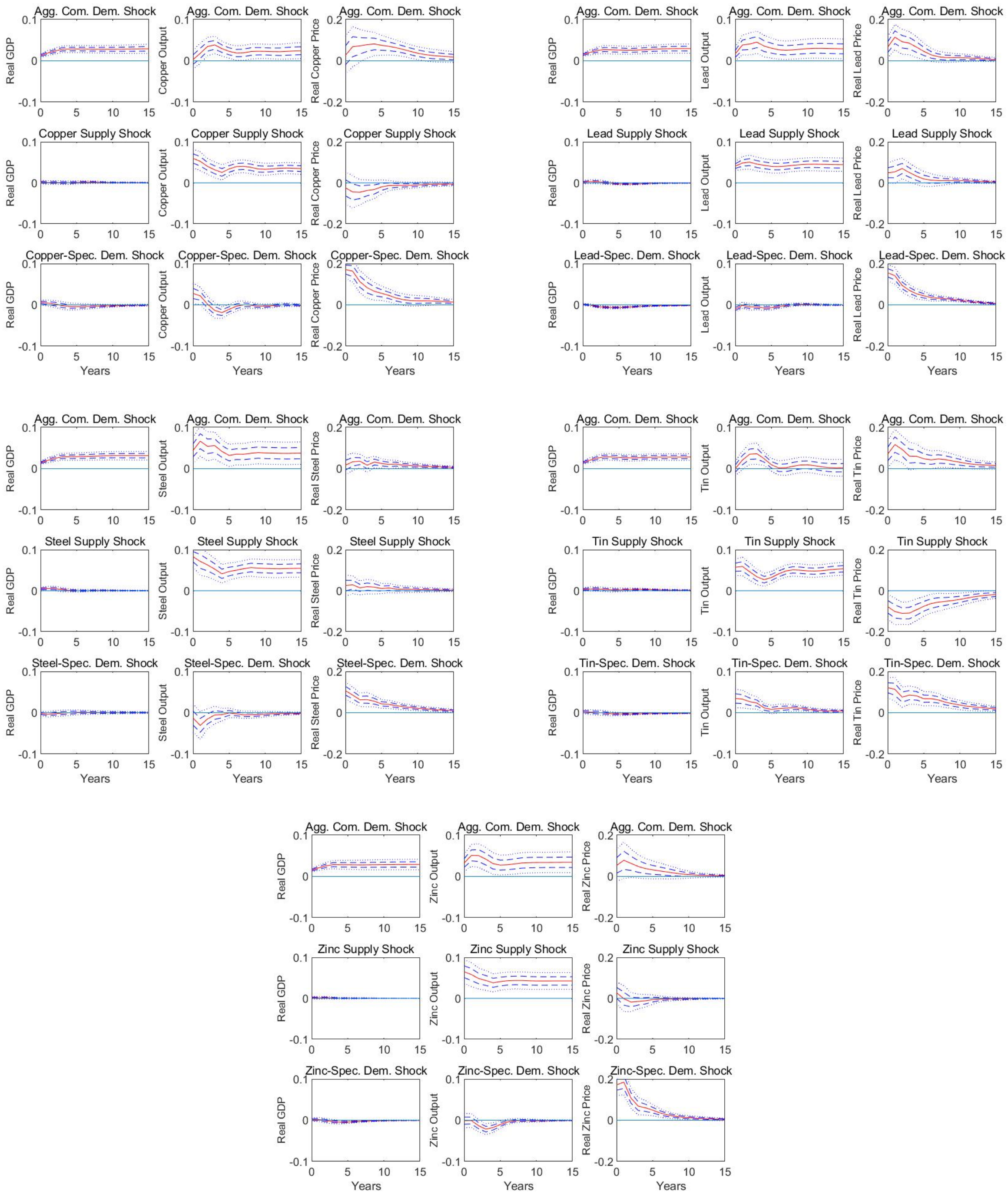


Figure 8: Impulse Response Functions for Soft Commodities

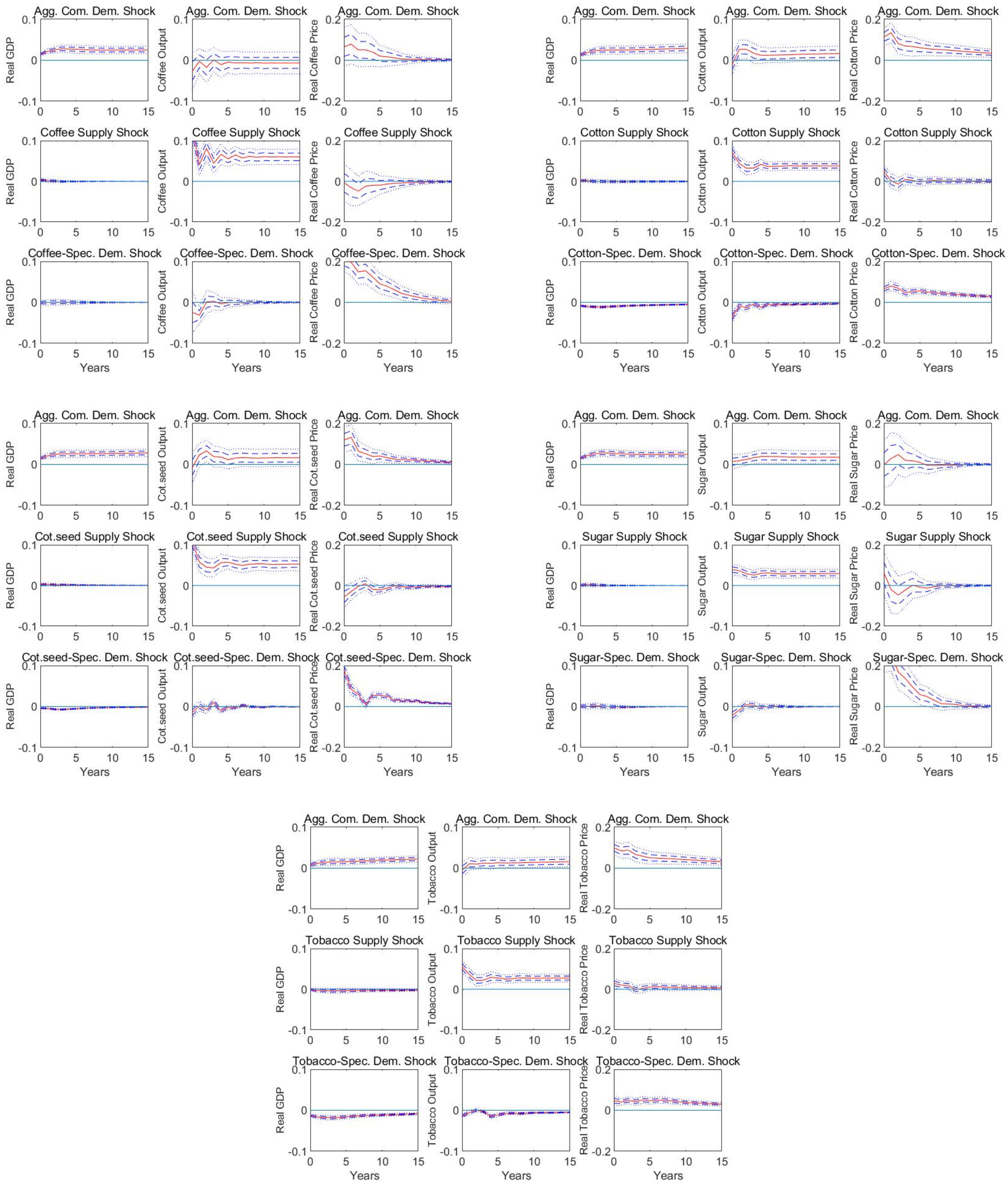


Figure 9: Historical Decompositions of Real Grain Prices

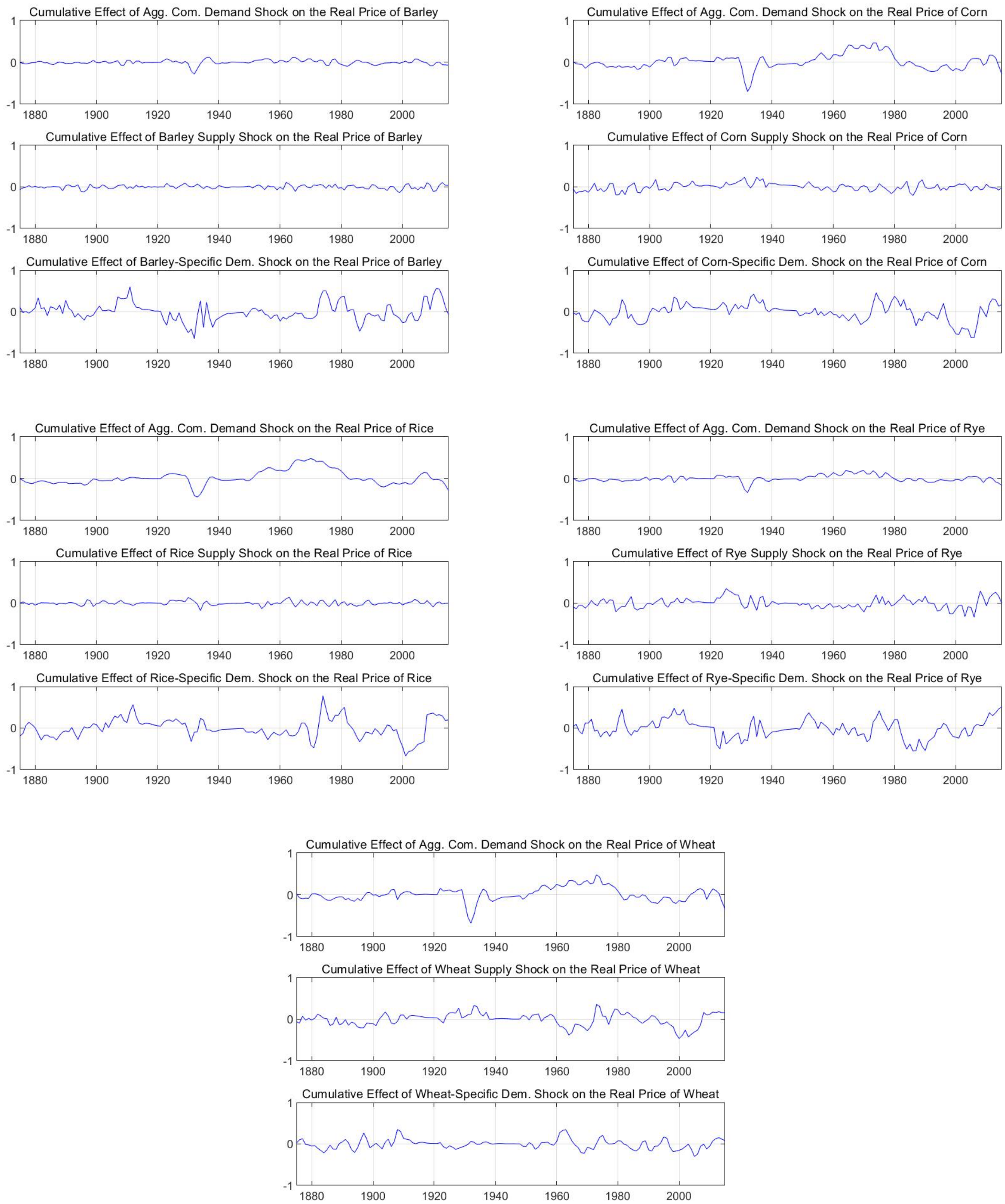


Figure 10: Historical Decompositions of Real Metal Prices

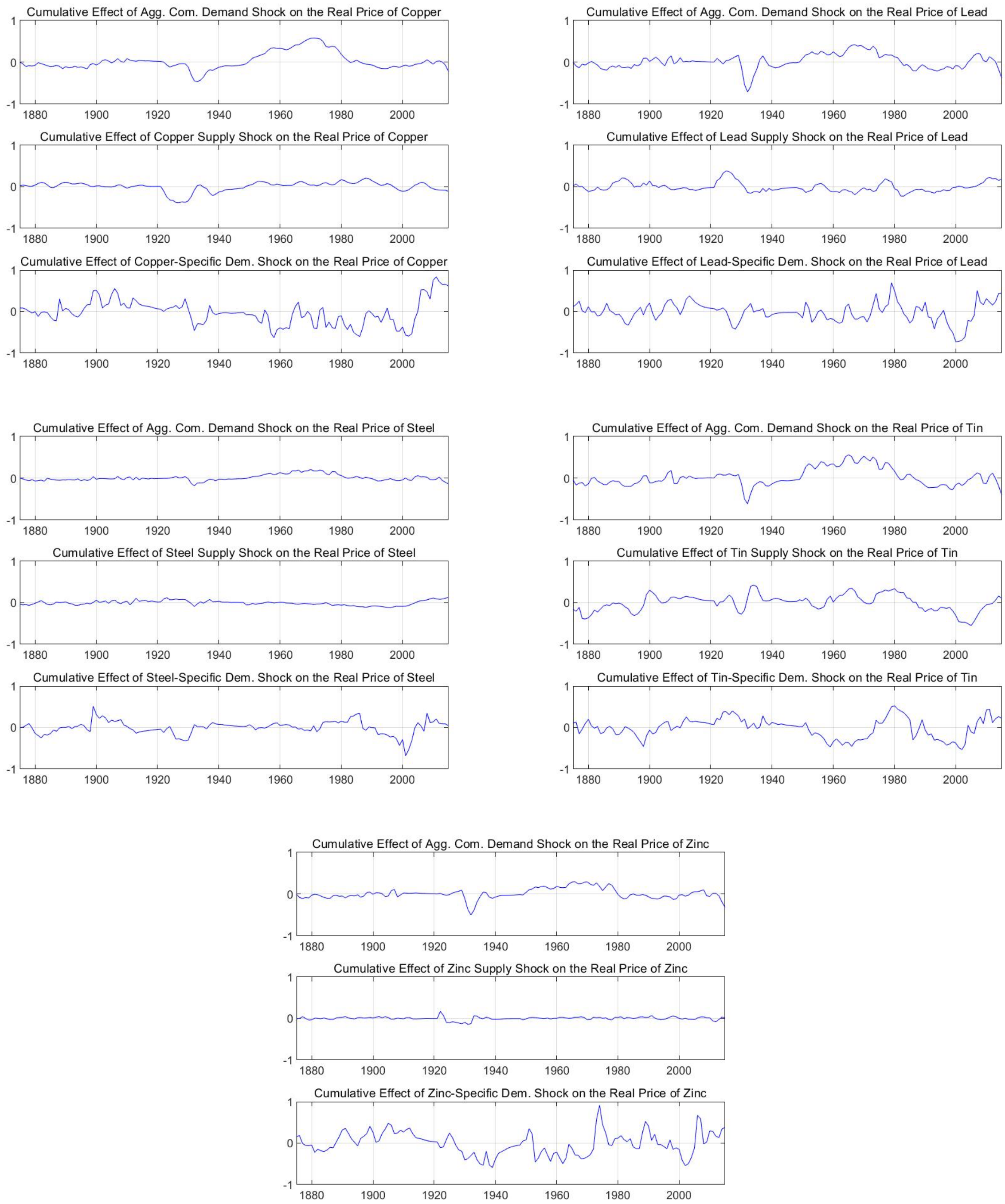


Figure 11: Historical Decompositions of Real Soft Commodity Prices

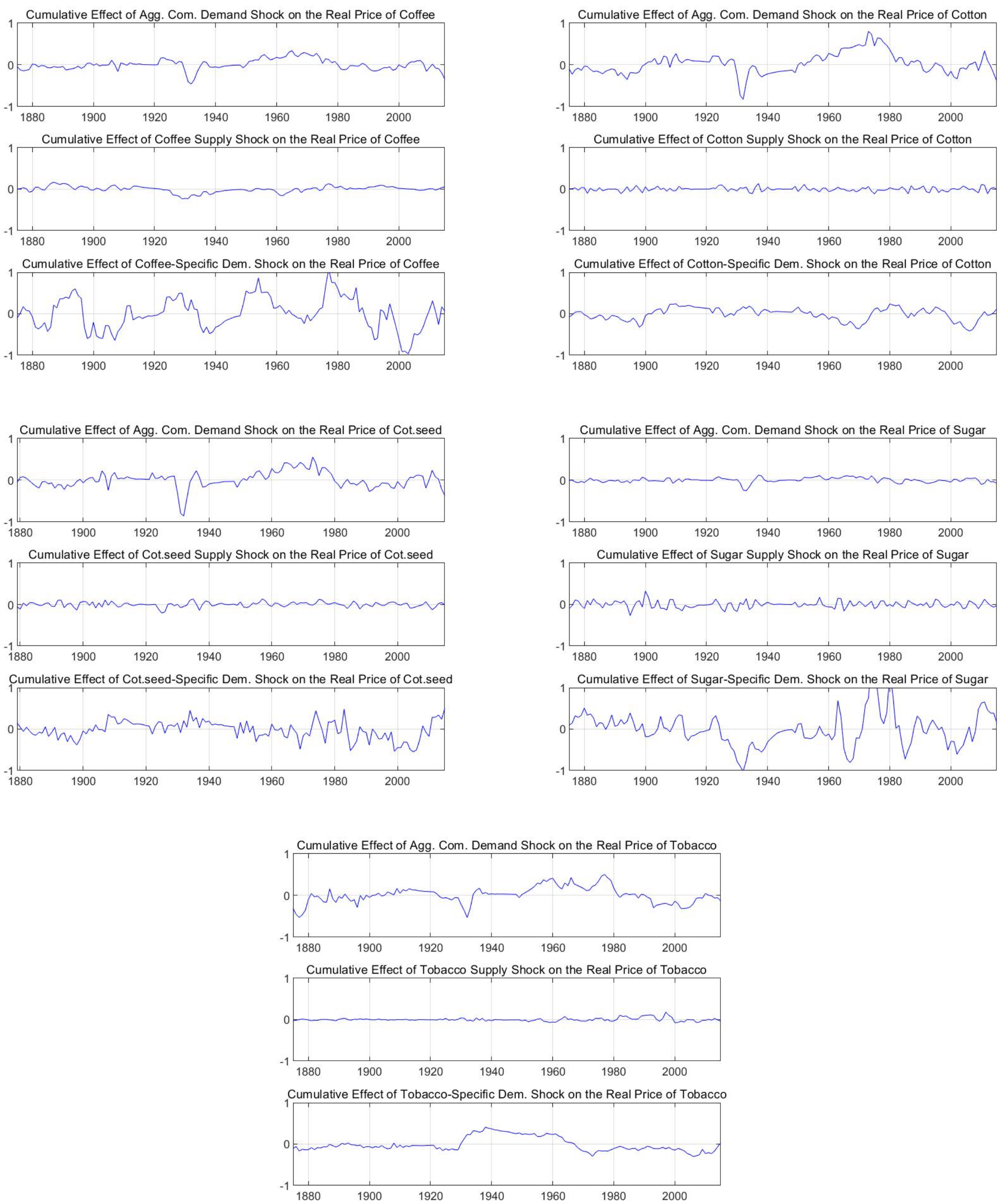
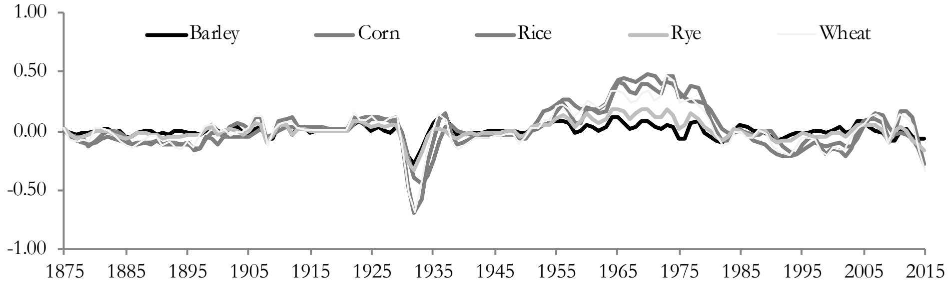
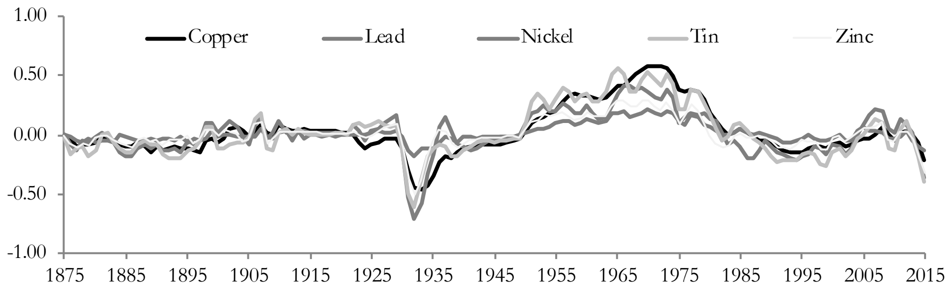


Figure 12: Cumulative Effects of Aggregate Commodity Demand Shocks

A. Grains



B. Metals



C. Soft Commodities

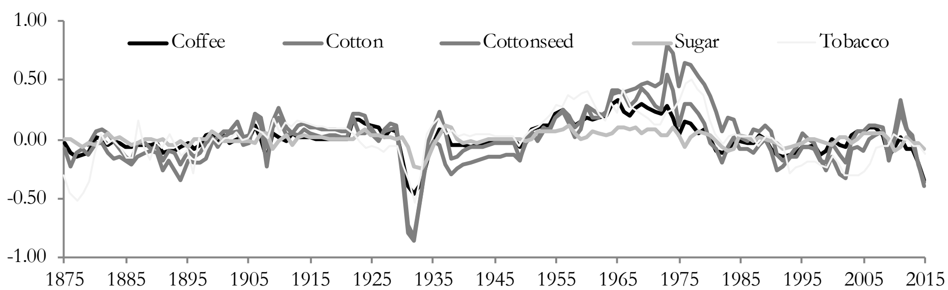


Table 3: Shares of Shocks in Explaining Commodity Price Booms and Busts by Period

	Commodity demand shock	Commodity supply shock	Commodity-specific demand shock
Panel A: 1871-2015			
Grains	0.29	0.24	0.47
Metals	0.28	0.21	0.51
Softs	0.32	0.15	0.52
Total	0.31	0.20	0.49
Panel B: 1871-1914			
Grains	0.23	0.27	0.50
Metals	0.28	0.23	0.49
Softs	0.32	0.18	0.50
Total	0.27	0.23	0.50
Panel C: 1919-1939			
Grains	0.29	0.25	0.46
Metals	0.26	0.31	0.43
Softs	0.32	0.17	0.52
Total	0.30	0.24	0.47
Panel D: 1949-2015			
Grains	0.32	0.22	0.45
Metals	0.34	0.20	0.46
Softs	0.35	0.14	0.52
Total	0.34	0.18	0.48