Energy Economics 85 (2020) 104035

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

What drives commodity price booms and busts?☆

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ARTICLE INFO

Article history:
Received 19 December 2017
Received in revised form 3 May 2018
Accepted 10 May 2018
Available online 26 May 2018

JEL classification:
E30
Q31
Q33
N50

Keywords:
Commodity prices
Natural resources
Structural VAR

ABSTRACT

We provide evidence on the dynamic effects of aggregate commodity demand shocks, commodity supply shocks, and storage demand or other commodity-specific demand shocks on real commodity prices. We analyze a new data set of price and production levels for 12 agricultural goods, metals, and soft commodities from 1870 to 2013. 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. While commodity demand shocks have gained importance over time, commodity supply shocks have become less relevant.

Published by Elsevier B.V.

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 et al., 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, structural vector autoregressive models are used to decompose changes in real crude oil prices into different types of shocks. Identification is made

☆ The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. Jacks gratefully acknowledges the Hong Kong Institute for Monetary Research and the Social Science and Humanities Research Council of Canada for research support. We are grateful for comments and suggestions from Michele Cavallo, Lutz Kilian, Alexander Chudik, Mine Yucel, Christiane Baumeister, Hilde Bjornland, Reid Stevens, Colin Carter, Francesco Furlanetto, Tatevik Sekhposyan, MIchael Plante, Soojin Jo and participants at the 2017 American Economic Association annual meetings, the International Commodities Symposium hosted by the J.P. Morgan Center for Commodities at the University of Colorado Denver Business School, the 2016 Association of Environmental and Resource Economists summer meetings, the 2015 Bank of Canada and Federal Reserve Bank of Dallas joint conference on commodity price cycles, the 2016 Federal Reserve System Macro Meeting, the 2015 Norges Bank/CAMP workshop, and seminars at the Bundesbank, the European Central Bank, the Hong Kong Monetary Authority, and Texas A&M University.

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[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.

https://doi.org/10.1016/j.eneco.2018.05.023
0140-9883/Published by Elsevier B.V.

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 fluctuations in crude oil prices (see e.g. Hamilton, 2008; Caldara et al., 2016), this more recent literature finds that aggregate demand shocks are the major source of fluctuations in prices for crude oil (Kilian, 2009; Kilian and Murphy, 2014; Baumeister and Hamilton, 2015).[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 data set on the level of prices and production for 12 commodities, spanning the categories of agricultural goods, metals, and soft commodities from 1870 to 2013.[4] In marked contrast to the literature on crude oil prices which 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 demand 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 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 demand 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 twelve 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. The average share of aggregate commodity demand shocks in explaining price changes is 35% while the average share of commodity supply shocks is 20%. The most important shocks are storage demand or other commodity-specific demand shocks which on average drive 46% of price changes. Furthermore, aggregate commodity demand shocks and storage demand 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 the contribution of aggregate commodity demand shocks to price changes varies across the different commodities with the largest contribution to metals (38% on average) and to a lesser extent to agricultural goods (32% on average) and soft commodities (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 demand or other commodity-specific demand shocks have stronger effects on commodity prices in the markets for agricultural goods and soft commodities than for metals. Commodity supply shocks play some role in explaining fluctuations for 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 5 billion U.S. dollars of production in 2011 (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

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

[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 et al. (2013), 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. Running regressions for different sub-periods is not sensible due to the small number of observations available in any annual data set.

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 12 individual commodity price series (barley, coffee, copper, corn, cotton, cottonseed, lead, rice, rye, sugar, tin, and zinc) which are drawn from three product categories—agricultural goods, metals, and soft commodities. Finally, global real GDP data is based on Maddison (2010) and extensions of Stuermer (2018).

Fig. 1 in the online-Appendix documents the evolution of global real GDP in percentage terms from 1870 to 2013 while Figs. 2 through 4 in the online-Appendix document the evolution of real commodity prices and production for the same years. Appendix A 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 a storage demand or other commodity-specific demand shock.

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 et al. (2018) 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 periodically augmented due to R&D investment in extraction technologies. A similar 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 1). 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).

Table 1
Assumptions on possible effects of three orthogonal shocks on three endogenous variables.

	World GDP	Commodity production	Price
A. Persistent effects			
Aggregate commodity demand shock	Yes	Yes	Yes
Commodity supply shock	No	Yes	Yes
Commodity-specific demand shock	No	No	Yes
B. Transitory effects			
Aggregate commodity demand shock	Yes	Yes	Yes
Commodity supply shock	Yes	Yes	Yes
Commodity-specific demand shock	Yes	Yes	Yes

Finally, the storage demand 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; 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 demand 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 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 1 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

[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).

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

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

The structural VAR representation is

$$Ax_t = \Pi D_t + \Gamma_1^* x_{t-1} + \ldots + \Gamma_1^* x_{t-p} + B\varepsilon_t \tag{1}$$

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 $\hat{C} = \hat{\Phi}^{-1}\hat{\Psi} = \hat{\Phi}^{-1}\mathrm{chol}[\hat{\Phi}\ \hat{\Sigma}_u\ \hat{\Phi}']$, 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. 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. This leaves the contemporaneous relationships completely unrestricted (for further exposition, see Stuermer, 2018).

We follow Goncalves and Kilian (2004) and use a recursive-design wild bootstrap with 2000 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

Fig. 1 presents the impulse response functions for all commodity markets. The reader is referred to the online-Appendix for separate impulse response functions for each market, which also include 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 demand 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.

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 aggregate commodity demand shocks and positive storage demand 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 demand 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 fluctuations 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, Figs. 17 to 28 in the online-Appendix 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 12 commodities (see Fig. 2). 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 et al., 2013).

What is more, this interpretation of the accumulated aggregate commodity demand shocks is in line with what economic history has to say about fluctuations 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 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

[7] Results for alternative trend specifications including nonlinear trend specifications are summarized at the end of Section 4.

[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.

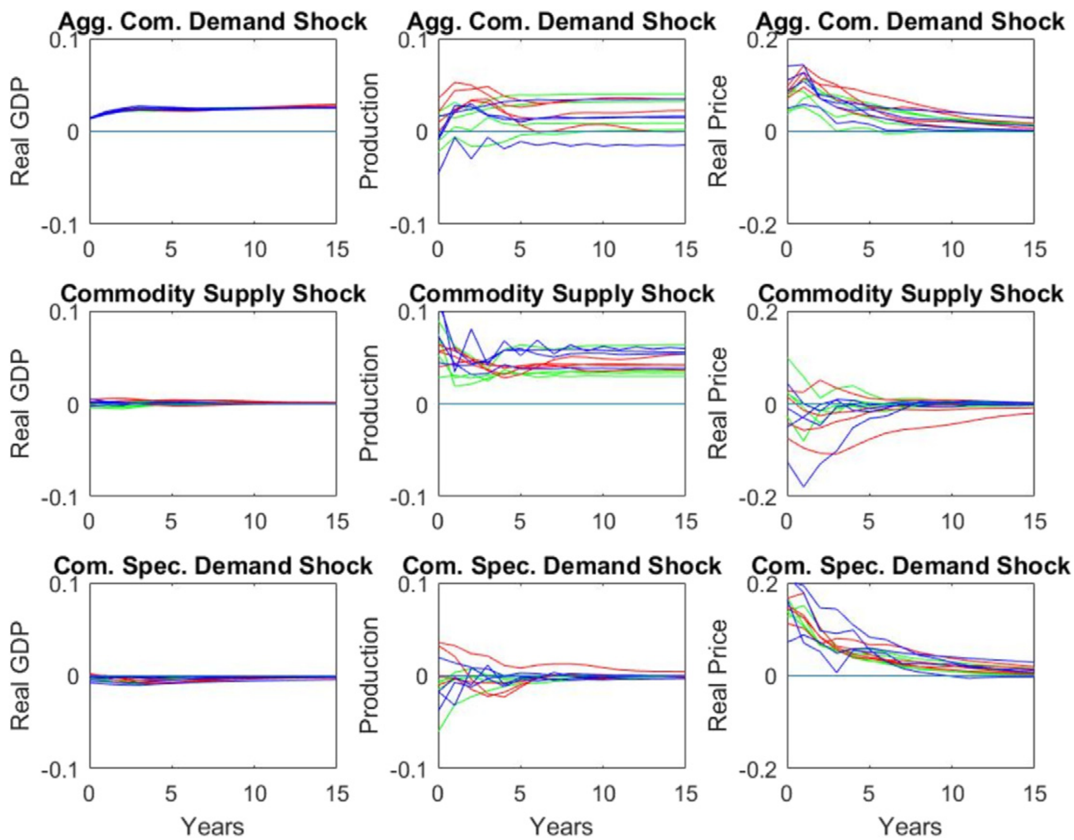

Fig. 1. Impulse response functions for all 12 commodity markets. Green: agricultural goods; red: metals; blue: soft commodities.

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 demand or other commodity-specific demand shocks also play an important role in driving 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 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, 2018). 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 2 numerically summarizes the contribution of each shock by commodity category and period. Thus, for the full period from 1871 to 2013 (Table 2, Panel A), aggregate commodity demand shocks explain 32–38% (across the three types of commodities examined here) of the variation in real commodity prices while storage demand or other commodity-specific demand shocks explain 42–50%. These two types of shock, thus, cause an appreciable portion (74–82%) of the medium- and long-run fluctuations in real commodity prices. Conversely, commodity supply shocks play a rather secondary and transient role, explaining only 18–20% of the variation. This result is fairly consistent across agricultural goods, metals, and soft commodities alike.

Averages for three sub-periods based on the full sample (see Table 2, Panels B to D) show that supply shocks have lost importance over time, as their average share declined from 24% in the period before World War I to 23% during the interwar period, and finally down to 16% in the period after World War II. At the same time, the average share of aggregate commodity demand shocks has increased from 29% in the pre-World War I period to 34% during the interwar period and up to 38% in the post-World War II period. While there are several potential explanations for this phenomenon, we leave their exploration to further research.

Results are robust to a number of different approaches to the data and econometric modelling. First, we have allowed for the possibility

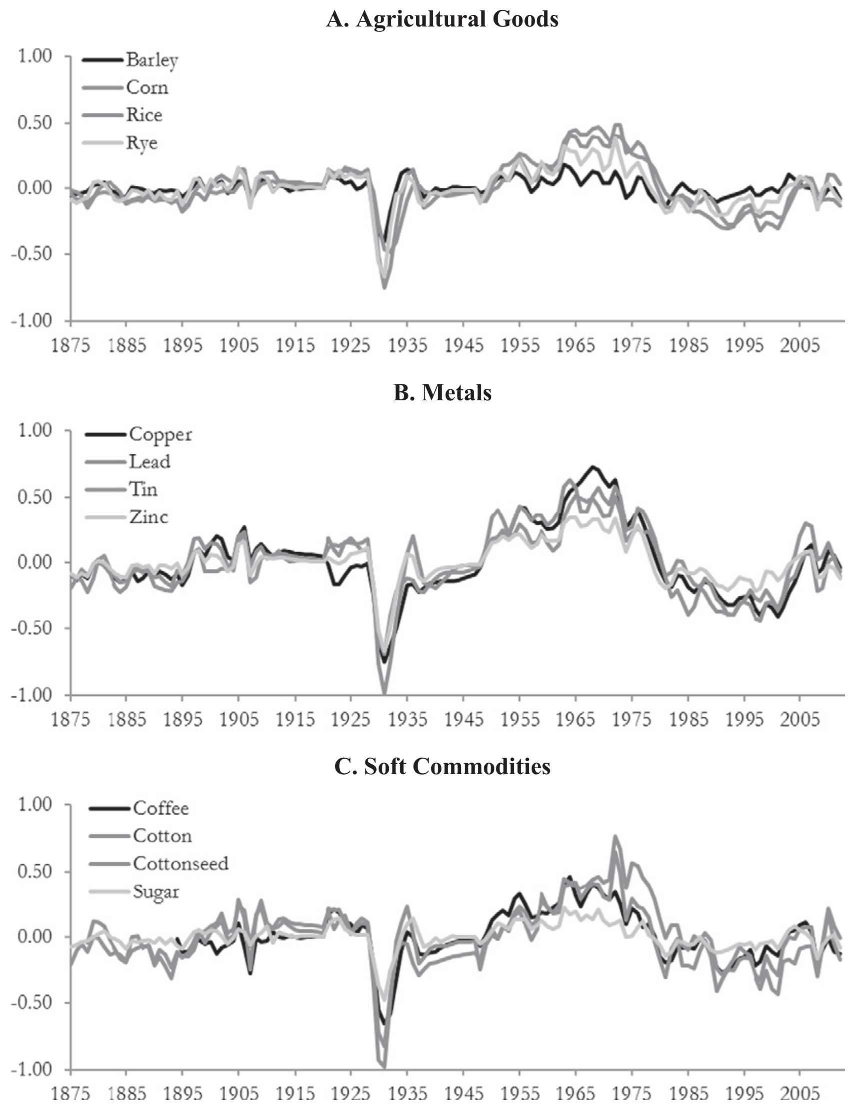

Fig. 2. Cumulative effects of aggregate commodity demand shocks on real commodity prices.

Table 2
Shares of shocks in explaining commodity price booms and busts by period.

	Commodity demand shock	Commodity supply shock	Commodity-specific demand shock
Panel A: 1871–2013			
Grains	0.32	0.18	0.50
Metals	0.38	0.20	0.42
Softs	0.34	0.20	0.44
Total	0.35	0.20	0.46
Panel B: 1871–1913			
Grains	0.26	0.23	0.52
Metals	0.33	0.24	0.44
Softs	0.27	0.24	0.48
Total	0.29	0.24	0.47
Panel C: 1919–1939			
Grains	0.32	0.19	0.49
Metals	0.34	0.27	0.38
Softs	0.35	0.19	0.46
Total	0.34	0.23	0.45
Panel D: 1949–2013			
Grains	0.37	0.16	0.47
Metals	0.42	0.16	0.42
Softs	0.38	0.18	0.45
Total	0.38	0.16	0.46

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 2013 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 1922–2013. 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.

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 12 commodities, spanning the categories of agricultural goods, metals, and soft commodities from 1870 to 2013. We establish that aggregate commodity demand shocks and storage demand 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 agricultural goods, metals, and soft commodities. Storage demand or other commodity-specific demand shocks are the most important driver in commodity price fluctuations for most of our agricultural goods and soft commodities. 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.

There are significant differences in the persistence across the different types of shocks. While commodity demand and storage demand 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 gained importance over time; commodity supply shocks have become less relevant.

Appendix A

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

A.1. 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.

Pfaffenzeller, S., P. Newbold, and A. Rayner (2007), "A Short Note on Updating the Grilli and Yang Commodity Price Index." *World Bank Economic Review* 21(1): 151–163.

Sauerbeck, A. (1886), "Prices of Commodities and the Precious Metals." *Journal of the Statistical Society of London* 49(3): 581–648.

Sauerbeck, A. (1893), "Prices of Commodities During the Last Seven Years." *Journal of the Royal Statistical Society* 56(2): 215–54.

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Stuermer, M. (2018), "150 Years of Boom and Bust: What Drives Mineral Commodity Prices?" *Macroeconomic Dynamics*, vol. 22, pp. 702–717.

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; 1960–2013, WB. *Coffee*: 1870–1959, Global Financial Data; 1960–2013, WB.

Copper: 1870–2013, Stuermer.

Corn: 1870–1999, Global Financial Data; 2000–2013, United States Department of Agriculture National Agricultural Statistics Service.

Cotton: 1870–1899, 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: 1870–2013, Stuermer.

Rice: 1870–1899, SS; 1900–1956, GY; 1957–1979, Global Financial Data; 1980–2013, IMF.

Rye: 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.

Sugar: 1870–1899, SS; 1900–1959, GY; 1960–2013, WB.

Tin: 1870–2013, Stuermer.

Zinc: 1870–2013, Stuermer.

A.2. Production

There are a few key sources of production data: the annual FAOSTAT (FAO) series for global production dating from 1961 to 2013; 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. (2013), *International Historical Statistics*, *1750–2010*, http://www.palgraveconnect.com/pc/archives/ihs.html.

Barley: 1870–1961, MIT; 1962–2013, 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*; 1975–2013, FAO.

Copper: 1870–2013, Stuermer.

Corn: 1870–1961, MIT; 1962–2013, FAO.

Cotton: 1870–1961, MIT; 1962–2013, FAO.

Cottonseed: 1870–1961, MIT; 1962–2013, FAO.

Lead: 1870–2013, Stuermer.

Rice: 1870–1961, MIT; 1962–2013, FAO.

Rye: 1870–1961, MIT; 1962–2013, FAO.

Sugar: 1870–1961, MIT; 1962–2013, FAO.

Tin: 1870–2013, Stuermer.

Zinc: 1870–2013, Stuermer.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.05.023.

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