Commodity Price Cycles: Commonalities, Heterogeneities, and Drivers*

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Abstract

This paper studies commodity price cycles and their underlying drivers using a dynamic factor model from a sample of 39 monthly commodity prices for the period 1970:01–2019:12. We identity global and group specific cycles in commodity markets and include them in a structural VAR model together with measures of global economic activity and global inflation to disentangle their response to global demand, global supply and commodity market-specific shocks. We find the following main results: (i) There exists a global cycle in commodity markets that accounts for an increasing fraction of comovement in commodity prices over the past two decades, particularly for energy, metals, and precious metals; (ii) Results are heterogeneous across groups of commodities with group-specific commodity cycles existing for grains and precious metals over the full sample period, 1970–2019. Metal and energy prices exhibit within-group synchronization for the period 1970–1999; however, in recent years, their movements have become increasingly aligned with the global business cycle; (iii) Since 2000, the global commodity cycle is largely driven by global supply shocks, such as rapid productivity growth in emerging markets and developing economies, which increase demand for commodities; (iv) The large price spikes observed during the two most prominent commodity market boom-bust episodes of the past half-century (i.e., 1972–74 and 2006–08) are driven additionally by shocks orthogonal to global economic activity such as shifts in speculative demand for commodities.

Keywords: Commodity price comovement, dynamic factor model, global business cycle, speculative demand. **JEL Classification:** C51, E53, Q02

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1 Introduction

International commodity markets experienced a major boom-bust cycle starting early 2000s. This episode was striking in terms of the breadth of commodities that were affected. Commodities ranging from base metals to energy to grains experienced a synchronized surge and collapse in prices over this period, exhibiting a common cycle across multiple commodity sectors (Baffes & Haniotis, 2010; C. A. Carter, Rausser, & Smith, 2011; Helbling, 2012). In particular, over the period 2006-08, the prices, for example, for copper, crude oil, and wheat increased by 75%, 104% and 110%, respectively. This upswing in prices was disrupted by the global financial crisis, with prices declining to early 2006 levels by the end of 2008.[1] However, the common movement in commodity markets observed during this period is a phenomenon that is not unprecedented in recent history. The post World War II era has experienced at least two other periods of broad-based boom-bust episodes in commodity prices, namely the 1950–51 and the 1972–74 commodity price cycles.[2] In both of these periods, a widespread increase in prices resulted in commodity price indices more than doubling in a short span of time, but they subsequently fell almost equally rapidly (Cooper & Lawrence, 1975; Radetzki, 2006).

A number of studies have examined common cycles in commodity markets and their underlying causes. In particular, plausible narratives can be constructed by focusing on microeconomic forces driving individual commodities—a "perfect storm," thus, generated by the concurrence of these independent forces. However, Cooper & Lawrence (1975) state that, "these stories are intriguing and sometimes significant, [but] they do not fill the need for some general explanation—a common cause, or strong linkages among the commodities affected." A popular view in the literature that attempts to provide a macroeconomic explanation for this phenomenon is that the common component of commodity price fluctuations is simply a surrogate for ebbs and flows in global economic activity (see, for example, Chiaie, Ferrara, & Giannone, 2017). However, this view ignores the concerns that episodes such as the 2006-08 spike in commodity prices are difficult to rationalize on the basis of economic growth alone (Frankel, 2008).

The purpose of this paper is to investigate the existence and drivers of common cycles in commodities. Do common price cycles exist across multiple commodity markets? If yes, what drives this joint variation? In particular, are historical episodes of extraordinary booms and busts in commodity prices fully accounted for by unexpected changes in economic growth? Or are the widespread,

[1] Our analysis is focused on higher frequency movements in commodity prices. Thus, we are able to evaluate shorter-term cycles within the long-term cycle in commodity markets (or the so-called 2000–2014 commodity supercycle) over this period. For a discussion on the latter, see Erten & Ocampo (2013), Jacks (2019), and Baffes & Kabundi (2020).

[2] See Radetzki (2006) for a discussion of the three major commodity price booms since the World War II era.

synchronized fluctuations partly driven by shocks orthogonal to global economic activity such as "speculative" demand for commodities?

We address these questions with a two-step approach. The first step employs a dynamic factor model to estimate common global and group components (or factors), alongside idiosyncratic disturbances in a panel of 39 commodity prices from 1970:01–2019:12. We identify the common factors as global and group cycles in commodity markets. The second step incorporates the estimated common factors into a factor-augmented VAR (FAVAR) model alongside measures of global economic activity and global inflation to assess the impact of three structural shocks on common commodity cycles. In particular, we identify a global demand shock, a global supply shock and a commodity market-specific shock through a combination of sign and elasticity restrictions. Examples of positive global demand shocks include shifts in consumer preferences related to consumption of commodity-intensive goods or an unanticipated fiscal stimulus that increases overall commodity demand. Whereas, positive global supply shocks can include productivity gains (for example, due to technological progress) that increase the marginal product of all inputs, including commodities and, thus, increase demand for commodities. Commodity market-specific shocks, on the other hand, are designed to account for innovation in commodity prices due to residual shocks such as unanticipated changes in speculative or precautionary demand for commodities.

The paper makes three main contributions. First, in a unified framework, it identifies both global and group cycles for a broad set of commodity prices and evaluates their underlying drivers. This contrasts with earlier literature that has focused on a subset of commodities (see, for example, Lombardi, Osbat, & Schnatz, 2010; Chen, Jackson, Kim, & Resiandini, 2013; Byrne, Sakemoto, & Xu, 2017). In analyzing common cycles, it is important to study all commodity markets simultaneously—limiting the analysis to a subset of commodity prices can generate commonalities that appear to be specific to a particular group when in fact they belong to a much larger set of commodities. A few recent studies address this issue by estimating common factors for a large sample of commodities, however they do not study the underlying drivers of the estimated factors (see Yin & Han, 2015; Chiaie, Ferrara, & Giannone, 2017; Bilgin & Ellwanger, 2017). Second, the paper extends beyond a general impulse response analysis, and investigates the role played by structural shocks during two most pronounced boom-bust episodes in international commodity markets of the past half-century, (i.e., the 1972–74 and the 2006–08 commodity price cycles). In particular, our analysis disentangles the contribution of speculative demand shifts from other shocks in driving the common surge in commodity prices during these periods. Third, we account for heterogeneity in commodity markets by evaluating the drivers of different group commodity cycles. By imposing appropriate elasticity restrictions in the FAVAR framework, we are able to assess the impact of unanticipated changes in global economic activity on group cycles—an issue that has not been explored formally in previous studies (see Bilgin & Ellwanger, 2017, for a general discussion).

We find that the global factor captures, on average, 11.2 percent of the variation in commodity prices for the full sample period 1970–2019. However, there is significant heterogeneity in its contribution across commodity groups. For example, on average, it accounts for much more variation for metals and precious metals (20 and 20.1 percent, respectively) than for grains and raw materials (11.7 and 11.5 percent, respectively). We also find that commodity price comovement has increased considerably since the early 2000s. The global factor captures, on average, 17.9 percent of the variation in commodity prices between 2000–2019, versus 8.7 percent in the earlier sample period, 1970 - 1999. Moreover, we find broad-based within-group commodity price comovement for only two commodity groups (precious metals and grains) over both subsample periods, 1970–1999 and 2000–2019, and for four commodity groups (energy, metals, precious metals and grains) for the subsample period, 1970–1999.

The results from the FAVAR estimation suggest that since 2000, the global commodity cycle is largely driven by global supply shocks such as rapid productivity growth in emerging markets and developing economies, particularly China. Moreover, the joint fluctuations in commodity prices are driven not only by unanticipated changes in global demand and global supply but also by shocks orthogonal to them. In particular, for the two periods of extraordinary commodity price booms (1972–1974 and 2006–2008), we find that the large spikes in commodity prices (such as those during late 1973 to early 1974 and late 2007 to mid-2008) are additionally attributed to commodity market-specific shocks that we interpret as unexpected shifts in speculative demand for commodities. Finally, we confirm that group commodity factors are driven by shocks particular to these markets while the role of unanticipated changes in global economic activity (as captured by global demand and global supply shocks) in driving group commodity cycles is small.

2 Literature Review

The paper broadly relates to the significant body of empirical work that has examined the idea of common movements in commodity prices. In their seminal work, Pindyck & Rotemberg (1990) study comovement in prices of largely unrelated commodities. Their results suggest strong commonalities in price fluctuations of commodities that exhibit low cross-price elasticities of demand and supply. Moreover, the joint behavior of commodity prices exceeds what can be explained by common macroeconomic shocks. They dubbed this phenomenon “excess” comovement. The joint upswing in commodity prices in early 2000s rekindled interest in this area. The literature since then has adopted different methodologies and frameworks to investigate the existence and drivers of common price cycles in commodity markets (see, amongst others, Ai et al., 2006; Cuddington &

Jerrett, 2008; Lescaroux, 2009; Alquist et al., 2020; Baffes & Kabundi, 2020).

A growing number of studies have employed factor models to study commonalities in commodity price movements. Factor models can be used to extract a small number of unobserved factors from a large sample of commodity prices. The estimated factors represent common variation in commodity price data. Together with the factor loadings, the factors can be used to evaluate the extent of synchronization in commodity price fluctuations. This approach is useful in today's data-rich environment to systematically analyze information in large datasets (see Stock & Watson, 1998; Bernanke & Boivin, 2001). Moreover, if a large panel of data can be arranged into groups, multi-level (or hierarchal) dynamic factor models can be used to model covariations that are specific to a particular subset of the data, in addition to overall comovement. Kose, Otrok, & Whiteman (2003) employ a multi-level dynamic factor model to investigate business-cycle fluctuations across 60 countries and 7 regions of the world. Exploiting the block structure of the data, they interpret the estimated factors as world, region-specific and country-specific.[3] Multi-level dynamic factor models are particularly relevant for evaluating common price fluctuations in commodity markets since commodities can be organized into distinct sectors (for example, energy, metals, grains etc.). Thus, the structure of the data can be used to assess both overall and within-group comovement in commodity prices.

Few studies have employed multi-level dynamic factor models to account for sectoral heterogeneity in commodity price comovement. Yin & Han (2015) use a monthly dataset of 24 commodities over the period 1991–2014 to decompose commodity price variation into global, sectoral and idiosyncratic factors. Their results, based on the Bayesian estimation approach of Kose et al. (2003), indicate that global and group factors account for, on average, 16.9 and 32.6 percent of variation in commodity prices, respectively. Moreover, they find that the global factor has increased in importance since 2004. Similarly, Chiaie, Ferrara, & Giannone (2017) extract global and block-specific factors from a dataset of 52 commodities for a monthly sample from 1980–2015. They find that the bulk of the variation in commodity prices is well summarized by one global factor. Their findings also indicate increased synchronization of commodity prices since 2002.

A related strand of this literature has explored the drivers of common fluctuations in commodity prices. Byrne, Sakemoto, & Xu (2017) estimate global and sector-specific factors using a hierarchal factor model from a quarterly sample of 38 non-energy commodity prices from 1974–2014. They include the estimated factors in a set of FAVAR models with selected macroeconomic variables to evaluate how different shocks impact commonalities in non-energy commodity prices. Their results indicate that common variation in commodity prices responds significantly to innovations in

[3] For other applications of multi-level dynamic factor models, see, for example, Jackson et al. (2015), Miranda-Agrippino & Rey (2015), Sarno, Tsiakas, & Ulloa (2015), and Ha et al. (2017).

the global business cycle, real interest rates and uncertainty, with heterogenous responses observed across different sectors.[4] Similarly, Bilgin & Ellwanger (2017) estimate global and block-specific factors in a sample of 42 commodity prices series from 1981–2017. In line with Chiaie et al. (2017), they evaluate reduced-form correlations between the global factor and two measures of global economic activity (i.e., Baltic Dry Index and global industrial production) to assess drivers of common fluctuations in commodity prices. Their results suggest strong positive correlation between the global factor and global economic activity.

The remainder of the paper is structured as follows. Section 3 describes the dataset and lays out the empirical framework. In particular, we introduce the dynamic factor model and the FAVAR methodologies, which allow us to identify commodity cycles and disentangle the underlying shocks driving them. In addition, it discusses the estimation strategy. Section 4 reports the results. We begin by presenting the estimated global and group commodity factors and their importance in accounting for commodity price variation. The contribution of global demand, global supply and commodity market-specific shocks in driving commodity cycles are discussed thereafter. The concluding comments are in Section 5.

3 Data and Methodology

This section describes the empirical framework we employ to investigate common fluctuations in commodity prices and their determinants.

3.1 Data

The dataset includes monthly series of commodity prices, global economic activity and global inflation for the period 1970:01 - 2019:12. The commodity price data is obtained from the World Bank's Commodity Price database (henceforth, the *Pink Sheet*). The Pink Sheet contains data on 55 commodity prices and indices. We exclude series that are either aggregates or close substitutes of other series to avoid introducing price comovement by construction.[5] This leaves us with 39 commodities, which are divided into 9 distinct groups based on the Pink Sheet's classification. The

[4] A number of other studies use a similar framework to examine determinants of commonalities in commodity prices. However, they focus on a single common factor, typically extracted from a subset of commodity price data (see, amongst others, Vansteenkiste, 2009; Lombardi, Osbat, & Schnatz, 2010; Byrne, Fazio, & Fiess, 2013; Poncela, Senra, & Sierra, 2014).

[5] For example, we include 'Logs, Malaysian' but exclude 'Sawnwood, Malaysian' since the latter is produced by cutting the logs longitudinally. Therefore, these two commodities are close substitutes and any changes in the price of sawnwood will closely follow the fluctuations in the price of logs. Thus, including both series will generate price comovement by construction. Similarly, we keep one monthly price series for each of the following: crude oil, natural gas, coffee, tea, soybeans, sugar, and phosphate.

groups include energy, metals, precious metals, fertilizers, grains, food oils, other foods, beverages, and raw materials.[6] Each group contains a minimum of three price series. All series are deflated using the U.S. Consumer Price Index for all urban consumers (CPI) published monthly by the Bureau of Labor Statistics (BLS) and transformed by taking first differences of logs. We measure global economic activity based on the world industrial production index developed by Baumeister & Hamilton (2019). The global inflation rate is proxied by the OECD inflation rate.

3.2 Dynamic Factor Model

Consider a panel of N commodity price series, each of length T, which can be categorized into R distinct commodity groups. Our goal is to model common movements across all series and common movements within specific commodity groups. Suppose $y_{i,t}$ represents the growth rate of the price of commodity i at time period t. We assume that $y_{i,t}$ can be decomposed into three components: (1) a common global component (or global factor, $f_{g,t}$) that affects all commodity price series, (2) a common group component (or group factor, $f_{r,t}$) that affects only commodity prices within group r, and (3) an idiosyncratic disturbance, $\epsilon_{i,t}$, that only affects an individual commodity price series i.

The growth rate of commodity price series i at time period t can, thus, be written as

$$y_{i,t} = b_{0,i} + b_{g,i} f_{g,t} + b_{r,i} f_{r,t} + \epsilon_{i,t}, \tag{1}$$

where $i = 1, \ldots, N$, $r = 1, \ldots, R$ with $R < N$ and $t = 1, \ldots, T$. The coefficients $b_{g,i}$ and $b_{r,i}$ are factor loadings that reflect the degree to which fluctuations in $y_{i,t}$ can be accounted for by the global and group-specific factors, respectively. The idiosyncratic disturbance, $\epsilon_{i,t}$, follows an $AR(q)$ process

$$\epsilon_{i,t} = \psi_i(L)\epsilon_{i,t-1} + \zeta_{i,t} \tag{2}$$

where $\psi_i(L)$ is a lag polynomial operator, $\zeta_{i,t} \sim N(0, \sigma_i^2)$ and $E(\zeta_{it}\zeta_{jt}) = 0$ for all $i \neq j$.

The global and group-specific factors can be collected in the vector $F_t = [f_{g,t}, f_{1,t}, \ldots, f_{r,t}]$. F_t follows an $AR(p)$ process such that

$$\mathbf{F_t} = \Phi(L)\mathbf{F_{t-1}} + v_t, \tag{3}$$

where $\Phi(L)$ is a diagonal lag polynomial matrix, $v_t \sim N(0, \sigma_r^2 \mathbf{I}_{R+1})$ with σ_r^2 normalized to 1 and $E(\zeta_{it} v_{rt}) = 0$. Since $\Phi(L)$ is a diagonal matrix, there are no spillovers among factors. Also, since

[6] See Table 2 for all commodities and their respective groups.

innovations u_{it} and v_{rt} are contemporaneously uncorrelated, all comovement is accounted by the factors.

Identification of Global and Group-specific factors

The factor loadings can be collected in an $N \times K$ matrix, $\mathbf{B}$. We impose zero-restrictions on $\mathbf{B}$ to identify global and group-specific factors. For instance, in a 2-commodity case ($\{i, j\} = \{Crude\ Oil, Copper\}$), where each commodity belongs to a distinct commodity sector, zero restrictions on the loading matrix can be expressed as follows:

$$\begin{bmatrix} b_{g,i} & b_{Energy,i} & 0 \\ b_{g,j} & 0 & b_{Metals,j} \end{bmatrix},$$

where $b_{g,i}$ and $b_{g,j}$ are the loadings for the growth rates in commodity prices for commodities i and j on the global factor, respectively. On the other hand, $b_{Energy,i}$ and $b_{Metals,j}$ are the loadings for price growth rates of commodity i and commodity j on group-specific factors, respectively. Thus, the growth rate of each commodity price is driven by a global factor that affects all commodity prices, group factors that affect commodity prices within their respective groups, and an idiosyncratic disturbance.

Variance decompositions

In order to find the relative contributions of the global and group commodity factors to the fluctuations in different commodity prices, the variance of each observed variable can be decomposed as follows:

$$\mathrm{var}\left(y_{i,t}\right) = \left(b_{g,i}\right)^2 \mathrm{var}\left(f_{g,t}\right) + \left(b_{r,i}\right)^2 \mathrm{var}(f_{r,t}) + \mathrm{var}\left(\epsilon_{i,t}\right). \tag{4}$$

Thus, the share of fluctuation in, for example, copper price growth due to the global commodity factor and the metals factor is given by $\frac{\left(b_{g,Copper}\right)^2 \mathrm{var}\left(f_{g,t}\right)}{\mathrm{var}\left(y_{\mathrm{Copper},t}\right)}$ and $\frac{\left(b_{metals,Copper}\right)^2 \mathrm{var}\left(f_{metals,t}\right)}{\mathrm{var}\left(y_{\mathrm{Copper},t}\right)}$, respectively.

3.3 Factor-Augmented VAR Model

In this section we lay out a framework for the factor-augmented VAR analysis. We estimate two types of FAVAR models, which differ only in terms of the variables included. The objective is to examine the drivers of both the global and group-specific commodity factors estimated by the DFM described by equations (1) - (3). The first model includes three endogenous variables: (1) an index of world industrial production, q_t, developed by Baumeister & Hamilton (2019), (2) a measure of global inflation, π_t, proxied by aggregate OECD inflation rate, and (3) the global commodity price factor. In the second model, we replace the global commodity factor with a group-specific commodity factor, while keeping the world industrial production and global inflation variables. Thus, for the second type of model, we estimate a set of FAVARs, one for each group factor that is quantitatively important for within-group comovement.[7]

We employ the following general form of a structural FAVAR model

$$\mathbf{B_0 y_t} = \sum_{i=1}^{p} \mathbf{B_i y_{t-i}} + \mathbf{w_t}, \tag{5}$$

where $\mathbf{y_t}$ is a $K \times 1$ vector that contains the endogenous model variables, $\mathbf{w_t}$ is the $K \times 1$ vector of mutually uncorrelated structural shocks, $\mathbf{B_0}$ is the structural impact multiplier matrix that provides a description of the contemporaneous relationships among the model variables, $\mathbf{B_i}$ is the matrix of coefficients and p is the lag length. The reduced form errors can be written as $\mathbf{u_t} = \mathbf{B_0^{-1} w_t}$, where

$$\mathbf{u_t} = \mathbf{y_t} - \sum_{i=1}^{p} \mathbf{A_i y_{t-i}}, \tag{6}$$

$\mathbf{A_i} = \mathbf{B_0^{-1} B_i}$ and $E(\mathbf{u_t u_t}') = \Sigma_u$ is the $K \times K$ reduced form variance-covariance matrix. Thus, given the structural impact multiplier matrix, $\mathbf{B_0}$, we can represent the reduced-form innovations as weighted averages of the mutually uncorrelated structural shocks, $\mathbf{w_t}$. However, since the model parameters are not uniquely identified, we require further identifying restrictions to estimate $\mathbf{B_0}$.

Identification of shocks

We employ a combination of sign restrictions and elasticity bounds on the matrix $\mathbf{B_0}$, to identify a global demand shock, a global supply shock and a commodity-specific shock. The baseline sign restrictions can be described as following

$$\mathbf{u_t} = \begin{pmatrix} u_t^q \\ u_t^\pi \\ u_t^f \end{pmatrix} = \begin{bmatrix} + & + & - \\ + & - & + \\ + & + & + \end{bmatrix} \begin{pmatrix} w_t^{\text{Global Demand}} \\ w_t^{\text{Global Supply}} \\ w_t^{\text{Commodity-specific}} \end{pmatrix} = \mathbf{B_0^{-1} w_t},$$

where signs are imposed on the elements of the inverse of the structural impact multiplier matrix, $\mathbf{B_0^{-1}}$, and all shocks are normalized to increase the commodity price factor.

The impact sign restrictions on $\mathbf{B_0}$ are in line with theoretical predictions and other empirical

[7] To assess the importance of each group factor we rely on the variance decompositions as discussed in Section 3.2.

studies.[8] For example, positive global demand shocks are characterized by positive comovement in the global industrial production index, global inflation, and the common commodity price factor. Examples of positive global demand shocks include an unexpected fiscal stimulus focusing on commodity-intensive investment that increases overall demand for commodities. A positive global supply shock, on the other hand, increases global output, decreases global inflation and increases commodity prices. Global supply shocks include, for example, technological innovation that raises total factor productivity. This would also include productivity-boosting economic reforms such as trade liberalization and privatization measures. An increase in productivity would raise the marginal product of all commodities and increase their overall demand and prices. A positive commodity-specific shock decreases output, increases global inflation, and increases commodity prices. Commodity-specific shocks are designed to account for innovations to commodity prices that are orthogonal to global demand and global supply shocks such as unexpected shifts in speculative or precautionary demand for commodities. These can be due to financialization of commodity markets or geopolitical tensions (see Kilian, 2009; Tang & Xiong, 2012).

A closer look at the above examples for each positive structural shock indicates that all three shocks (i.e., global demand, global supply, and commodity market-specific) increase demand for commodities. This is consistent with the view that a synchronized increase in commodity prices should, typically, be a result of shifts in commodity demand rather than commodity supply (Bilgin & Ellwanger, 2017). Commodity supply shifts are generally more idiosyncratic and only affect individual commodities. For example, a labor disruption that curtails steel production, may not impact mine output for aluminum. An exception is disruptions in supply of crude oil. Since crude oil is used in producing other commodities, crude oil supply disruptions can increase price of oil and, consequently, cost of production for other commodities. Thus, a commodity market-specific supply disruption through this channel can result in a joint surge in commodity prices. In our framework, this effect would be captured as a commodity market-specific shock. However, the timing and direction of the impact of these shocks as documented in Section 4.2.1 (e.g., in the latter half of the 1972-74 and the 2006-08 commodity price boom and bust) provide reasons to believe that these shocks effectively reflect exogenous shifts in speculative demand for commodities. The nature of speculative demand, however, has likely changed over time (see Baffes & Haniotis, 2010; C. A. Carter et al., 2011).

For the set of FAVAR models where we substitute the global factor with a group factor, we additionally impose elasticity bounds on the element $\mathbf{B_{0,(1,3)}}$ of matrix $\mathbf{B_0}$. The elasticity bound

[8] Charnavoki & Dolado (2014) identify global demand, global supply and commodity market shocks to examine their effects on macroeconomic aggregates of a small commodity-exporting economy. Ha, Kose, & Ohnsorge (2018) employ a similar identification scheme to investigate the drivers of global inflation.

is based on the assumption that the short-run elasticity of the global industrial production to a commodity group-specific shock is small. We follow the approach of Kilian & Murphy (2012) and Charnavoki & Dolado (2014), to shrink the set of admissible structural models based on the pure sign restrictions. In particular, we bound the negative impact response of global activity to commodity group-specific shocks to be not more than 10 percent. This translates into imposing a lower bound on element $\mathbf{B}_{\mathbf{0},(\mathbf{1},\mathbf{3})}$ of the structural impact multiplier matrix of -0.1.[9]

3.4 Estimation

Dynamic Factor Model. The equations (1) – (3) comprise a state-space system where equation (1) corresponds to an observation equation and equations (2) and (3) correspond to the transition equation. The estimation of this system follows the Bayesian state-space approach of Kim & Nelson (1998).[10] The estimation objective is to infer from the observed data: (1) the path of common factors F_t and (2) all unknown parameters of the model. The Bayesian approach views these as two vectors of random variables. Inference in the Bayesian framework is based on obtaining the joint and marginal distribution of these given the historical data on commodity prices i.e., obtaining the joint and marginal posterior distributions of all factors and model parameters. However, since the joint posterior distribution of these vectors is not analytically obtainable; therefore, Gibbs sampling is used to sample from the posterior.

We can collect the observed data series in the vector $\mathbf{Y_t}$. The Gibbs sampling proceeds by taking a drawing from the conditional distribution of the model parameters given the data $\mathbf{Y_t}$ and the factor $\mathbf{F_t}$ and then drawing from the conditional distribution of the factor $\mathbf{F_t}$ given data $\mathbf{Y_t}$ and the prior drawing of the model parameters. The estimation of the model parameters given the factors, $\mathbf{F_t}$, is straightforward. Notice that by treating $\mathbf{F_t}$ as a set of data, generating the unknown parameters of the observation and state transition equations ($\mathbf{B},\ \Psi(L),\ \Phi(L),\ \Omega,\ I_K$) is a standard application of Bayesian linear regression.[11] However, sampling from the posterior of the AR coefficients is not

[9] Structural models with $a_{13} < -0.1$ in our analysis typically exhibit a large within one month response of global industrial production to group-specific shocks, which is unlikely given the relatively small share of each commodity group in global real activity. For example, the GDP-share of oil for the United States is argued to be close to 2 percent over the Great Moderation period, 1986 - 2015 (see Soytaş & Sari, 2020). Similarly, the share of other commodities in global economic activity should be small.

[10] The classical approach to state-space modeling, which is based on maximizing the likelihood function with respect to all parameters, can be computationally inefficient in large scale models. The Bayesian approach based on Gibbs sampling works with smaller components of the model by drawing from conditional distributions of the parameters (Blake & Mumtaz, 2012). Another approach is the non-parametric Principal Component Analysis (PCA), which is computationally faster and commonly used. However, the parametric state space approach to estimating factor models gives more accurate variance decomposition estimates compared to PCA-based methods. For a comparison of different estimation methods, see Jackson, Kose, Otrok, & Owyang (2015).

[11] Note that we collect the AR coefficients from the observation equation in (1) in the diagonal lag polynomial matrix $\Psi(L)$ and the error term variance-covariance matrix as $E(\zeta_t \zeta_t') = \Omega$. The remaining notation follows from

simple since the conditional distributions of $\Psi(L)$ and $\Phi(L)$ are unknown. Therefore, we sample the AR coefficients using a Metropolis-Hastings algorithm (see Chib & Greenberg, 1994; Otrok & Whiteman, 1998). The latter step involving the generation of the vector, $\mathbf{F_t}$, is based on the multimove Gibbs-sampling (or the forward-backward) algorithm as described by C. K. Carter & Kohn (1994). This procedure allows us to generate the whole vector $\mathbf{F_t}$ from the joint distribution $p(F_1, F_2, \ldots, F_T|\mathbf{Y_t})$.[12] Using the Markov property of the state equation, the joint posterior of $\mathbf{F_t}$ can be factorized into $p(F_T|\mathbf{Y_t})$ and $p(F_s|F_{s+1}, \mathbf{Y_t})$ for all $s = 1, \ldots, T-1$. Since these two components are normally distributed given that error terms in the observation and state transition equations are normally distributed, we can draw from distributions by computing their mean and variance. The Kalman filter is used to compute the mean and variance of $p(F_T|\mathbf{Y_t})$ and a backward recursion provides the mean and variance of $p(F_t|F_{t+1}, \mathbf{Y_t})$. Thus, the C. K. Carter & Kohn (1994) forward-backward algorithm delivers a draw of $\mathbf{F_t}$.[13] The estimation procedure can be summarized in the following four steps:

1. Conditional on $\mathbf{F_t}$, sample $\mathbf{B}$ and Ω from their posterior distributions.

2. Conditional on $\mathbf{F_t}$, sample $\Phi(L)$ and I_K from their posterior distributions.

3. Conditional on the parameters of the state space, $\mathbf{B}$, Ω, $\Phi(L)$ and I_K, sample F_t from its posterior distribution as discussed above.

4. Repeat steps 1 to 3 until convergence.

The prior distribution for each model parameter is specified by the mean and the standard deviation. However, the priors are weak except that stationarity is imposed on the AR coefficients in equations (2) and (3). The priors for the autoregressive coefficients in equations (2) and (3) are $N(0, 10)$ and $N(0, 10)$. The prior is specified over the roots of the polynomial for the variance terms and then translated into priors for the coefficients. The prior on all factor loadings coefficients in equation (1) is $N(0, 1)$ where the zero restrictions are appropriately applied. For the prior on the innovation variances in equation (1), $IG(8, 0.25^2)$ is used, where $IG()$ denotes inverse-gamma distribution.[14] The AR parameters for equations (2) and (3) are constrained to be stationary. The model is estimated for each commodity over 10,000 draws after a burn-in of 5000 draws.

Section 3.2.

[12] Note that singlemove Gibbs sampling generates elements of $\mathbf{F_t}$ one at a time from the conditional distribution $p(F_t|\mathbf{F_{\neq t}}, \mathbf{Y_t})$. The multimove Gibbs sampling procedure is computationally faster and more efficient (Kim & Nelson, 1999).

[13] For a detailed exposition, see Kim & Nelson (1999), Blake & Mumtaz (2012) and Jackson et al. (2015).

[14] Note that the priors are loose, and experimenting with tighter priors suggests that results are not sensitive to these changes.

FAVAR estimation with sign restrictions. In order to generate the structural impulse response functions, we follow the procedure of Rubio-Ramírez, Waggoner, & Zha (2010). This is done by first drawing a $K \times K$ matrix $\mathbf{X}$ of independent $N(0,1)$ values. Then the QR decomposition of $\mathbf{X}$ is generated such that $\mathbf{X} = \mathbf{QR}$ and $\mathbf{QQ}' = \mathbf{I}$. The candidate solution, $\tilde{\mathbf{B}}$, can be obtained as $\mathbf{PQ}$, where $\mathbf{P}$ is the Choleksy decomposition of the reduced form residuals. The candidate solution is used to construct impulse responses that are checked against the maintained sign restrictions. These steps are repeated many times (in our case, 1.5 million times) and the results are recorded accordingly.[15]

4 Results

4.1 Common Commodity Cycles

Figure 1 plots the 33-, 50- and 66-percent quantiles of the posterior distribution of the global commodity factor, $f_{g,t}$, estimated from the DFM (1) - (3) over the period 1970 - 2019.[16] As discussed in Section 3.2, the global factor captures all common variation in our panel of commodity prices. However, since the global factor itself is unobserved and we only recover the factor estimate based on its tentative relationship with the observable commodity price data, particular attention is required to evaluate what it represents.

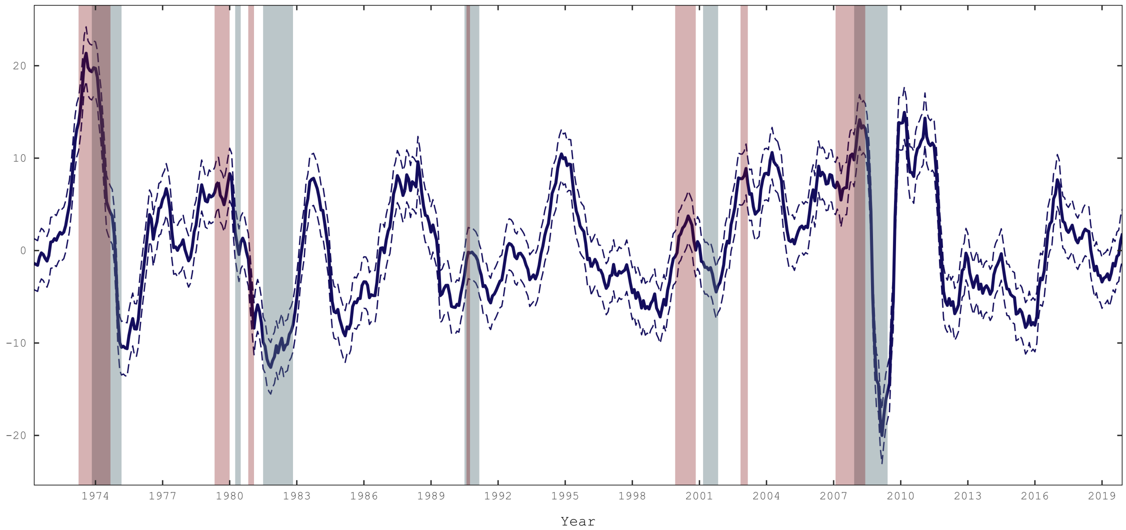
Recent literature has paid considerable attention to the association between the global business cycle and common variation in commodity prices. Joint fluctuations in commodity prices can be driven by unexpected changes in aggregate economic activity. For example, an increase in aggregate economic activity results in an increase in demand for all commodities and, consequently, their prices since commodities are used to produce final goods (Kilian, 2009; Chiaie et al., 2017; Alquist et al., 2020). In fact, a casual inspection of Figure 1 shows that the estimated global commodity factor captures some important historical business cycle episodes.[17] For example, it registers a decrease during the 1973 - 1975 recession, following the early 1970s commodity price boom. It also records a decline during the global economic recession of the early 1980s that affected a number of advanced economies. Similarly, it increases during the 2003 - 2007 economic expansion, which was accompanied by a surge in commodity prices, registers a sharp fall during the global financial crisis, and picks up during the subsequent recovery. Thus, is the global factor simply tracking changes

[15] Note that since sign identified structural VARs are set identified, we follow the median target method to report impulse responses (see Fry & Pagan, 2011).

[16] The dispersion of the posterior distribution reflects the uncertainty in our estimation. Given that the 33% and 66% quantiles are narrow, the results suggest that the global commodity factor is estimated precisely.

[17] See Kose, Sugawara, & Terrones (2020) for an identification and analysis for turning points of the global business cycle.

Figure 1: Global Commodity Price Factor: 1971:M1 - 2019:M12



Note: Solid line: Global Commodity Price factor estimated using DFM (1) - (3), alongside 33- and 66-percent quantiles (dashed line). Pink-shaded bars depict periods of oil price spikes as identified in Hamilton (2009). Grey bars show recession periods, from NBER. *Source:* Authors' calculations.

in global economic activity? A closer look, however, shows that the global factor does not always align with US recessions as depicted by the grey bars in Figure 1.[18] For example, the global factor increases during the early 1990s recession while its decline during the mid-1970s recession and the 2007-09 global financial crisis is observed with a lag.[19] To be more precise, the correlations between the global factor and two measures of global economic activity, namely, the Kilian index and the world industrial production, are 0.52 and 0.66, respectively.[20] Thus while changes in global economic activity are a key source of shocks to commodity markets, understanding common fluctuations in commodity prices (especially during short-term boom-bust episodes that are characterized by high volatility) requires going beyond changes in global economic activity.

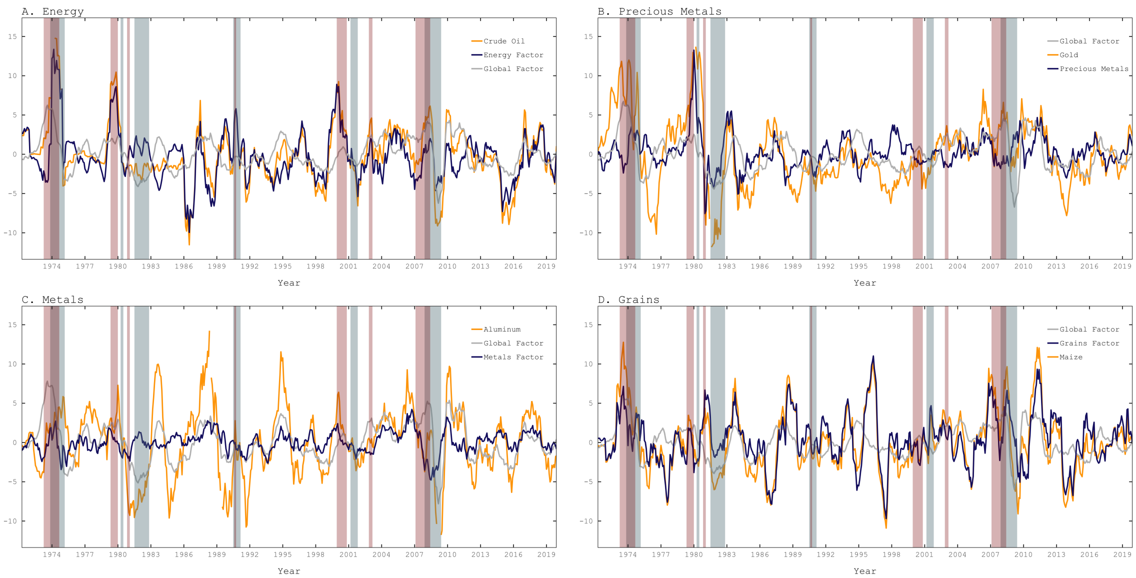
Figure 1 also shows that some of the biggest peaks in the global commodity factor occur during episodes of large oil price spikes. Since oil is an important input in the production of other commodities, idiosyncratic changes in oil prices can spillover across commodity markets to generate simultaneous commodity price variation (Baffes, 2007; Bilgin & Ellwanger, 2017; Alquist et al., 2020). Moreover, since we identify the global factor by a positive factor loading on crude oil prices,

[18] Note that we use US recessions as a proxy for slowdowns in global growth.

[19] For example, while global growth slowed down during 2007-08, Frankel (2008) observed that "commodity prices have found their second wind over precisely this period! Up some 25% or more since August 2007, by a number of indices. So much for the growth explanation."

[20] See Kilian (2009) for details regarding the Kilian index; world industrial production index is from Baumeister & Hamilton (2019). The correlations are reported for year-over-year growth rates.

Figure 2: Group Commodity Price Factors: 1971:M1 - 2019:M12



Note: Solid line: Group Commodity Price factors (blue) alongside the global factor (grey) and the most traded commodity in each group (orange). Pink-shaded bars depict periods of oil price spikes as identified in Hamilton (2009). Grey bars show recession periods, from NBER. *Source:* Authors' calculations.

an oil price spike would imply an upward movement in the global commodity factor. However, the magnitude of the factor loading for crude oil (0.30) indicates that the association between oil prices and the global factor is not particularly strong when compared to other commodities.[21]

The estimated group factors are presented in Figure 2, alongside the global commodity factor and the most traded commodity for each group. We multiply the global and group factors with their median factor loadings in the most traded commodity's measurement (or output) equation to make the scales comparable.[22] We focus on group factors that account for at least 10 percent of the variation in each commodity within the group. Since the group-specific factors are orthogonal to the global factor, they represent joint variation in commodity prices in each group that is unaccounted for by overall common movements in commodity markets. A closer look at Figure 2 suggests that, relative to the global factor, the group factors generally account for more volatile movements in individual commodity prices (whereas, the global factor accounts for longer swings). For example, the energy group factor registers a sharp increase in 1974, which accounts for the oil price increase following the 1973 Organization of Petroleum Exporting Countries (OPEC) oil embargo. Moreover,

[21] For example, the factor loadings for copper, gold, soybeans, and rubber are 0.45, 0.33, 0.36, and 0.48, respectively. The average factor loading is 0.24 and other than tobacco (for which we estimate a small negative loading), all factor loadings are positive.

[22] For example, panel A in Figure 2 plots the growth rate of crude oil prices, alongside the global and the energy group factors that are multiplied by their respective factor loadings in the crude oil measurement equation.

TABLE 1: Variance Decompositions For Commodity Prices

	1970 - 2019		*1970 - 1999*		*2000 - 2019*	
	Global	**Group**	**Global**	**Group**	**Global**	**Group**
Energy	8.3		5.1	38.8	19.9	
Metals	20.0	24.5	8.9	24.8	44.5	
Precious Metals	20.1	48.1	15.3	55.1	31.7	44.2
Fertilizers	3.4		7.5		0.8	
Grains	11.7	33.0	8.0	40.1	13.9	30.7
FoodOils	16.7		15.1		19.4	
OtherFoods	3.0		3.1		4.3	
Beverages	6.1		7.0		11.6	
Raw Material	11.5		8.1		15.4	
Average	11.2		8.7		17.9	

Note: Percentage of variance accounted by the global and group-specific factors. Averages reported for each group. Results for group factors are reported only if group-specific factor accounts for broad-based within group comovement. The results are based on the methodology discussed in Section 3.2.

the increase in the energy factor occurs during a period when the global factor is declining, indicating the end of the 1972 - 1974 commodity price boom (see Figure 2, panel A). Similarly, the energy factor accounts for the sharp increase in oil price in 1979 (associated with the Iranian Revolution) when overall commodity markets experienced a milder upswing. The precious metals and grains factors also exhibit sharply defined increases and decreases relative to the global factor. An exception is the metals factor, which appears to be less volatile than the global factor.

Results from the variance decomposition exercise, described in section 3.2, provide the average relative contributions of the global and group factors in accounting for the common fluctuations in commodity prices. Table 1 presents the amount of variation in commodity prices captured by the global and group factors for the full sample, 1970 - 2019, and the two subsamples, 1970 - 1999 and 2000 - 2019. For the full sample period, it can be observed that the global factor accounts for, on average, 11.2 percent of the variation in commodity price data. However, the contribution of the global factor varies significantly across different commodity groups. For instance, the global factor plays a much more important role in accounting for movements in metals and precious metals prices (20 percent) versus movements in fertilizer prices (3.4 percent), and other foods and beverages (3 and 6.1 percent, respectively). The varying importance of the global factor across commodity groups is expected—sectors such as metals that have stronger demand- and supply-side linkages with the global economy are expected to have higher correlations with the underlying global factor versus other commodity groups.[23] Moreover, if we compare the two subperiods in Table 1, it can be seen that the comovement in commodity prices has increased since 2000. The global factor accounts for 17.9 percent of the variability in commodity prices on average for the period 2000 - 2019. This is an increase from 8.7 percent of commodity price fluctuations captured by the global factor, on average, during the period 1970 - 1999. Moreover, the increase in the importance of the global factor is broad-based i.e., the number of commodities for which the global factor dominates group-specific factors has increased while the relative contribution of idiosyncratic factors has also decreased over the two periods.[24]

The group factors are important only for certain commodity groups. For the full sample period, 1971 - 2019, we find broad-based synchronization in three sectors, namely, metals, precious metals and grains (24.5, 48.1, and 33 percent, respectively).[25] However, comovement over both subsample periods, 1970 - 1999 and 2000 - 2019, is observed for only precious metals and grains. In particular, the results for grains are consistent given their high substitutability both in terms of production and consumption. Moreover, we do not observe widespread comovement amongst metal prices for the period 2000 - 2019, indicating the increased alignment of metal price movements with the global business cycle (especially, also given the greater importance of the global factor in driving metal prices during this period). The energy factor accounts for 38.8 percent of the variation in oil, gas and coal prices, on average, during the period 1970 - 1999 while it does not account for broad-based within group synchronization for the period 2000 - 2019. A possible explanation is the decoupling of crude oil and natural gas prices as discussed in recent literature (see, amongst others, Brown & Yucel, 2007; Erdos, 2012). Finally, for other groups such as fertilizers and raw materials, price volatility is primarily driven by idiosyncratic disturbances, as these commodity groups are less closely linked to global economic activity and also consists of a more heterogeneous assortment of commodities.

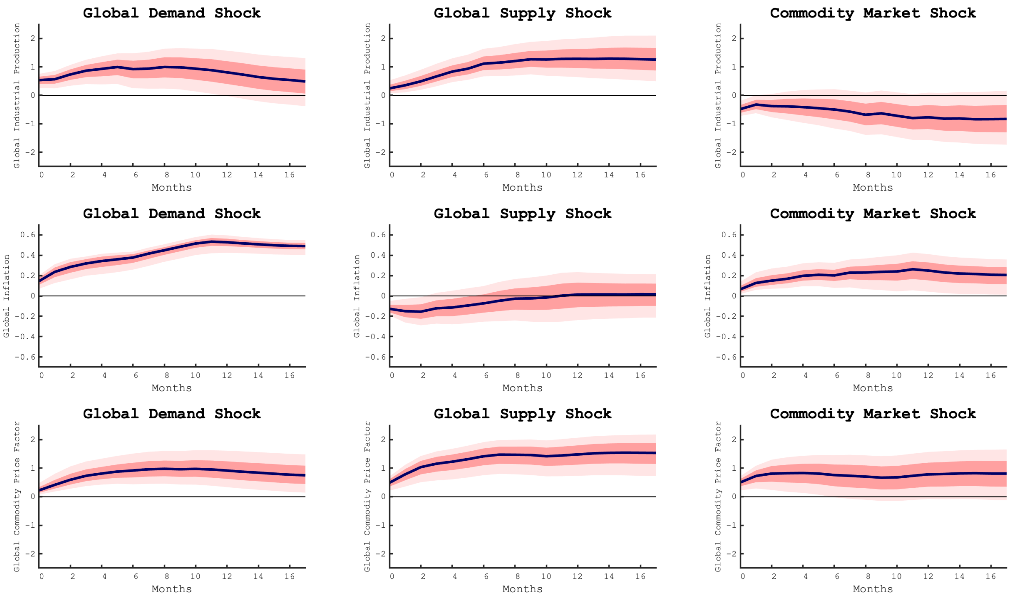
To summarize, the results indicate that the importance of the global commodity factor is increasing over time and it is strongly associated with the global business cycle. However, during particular periods its movements deviate from changes in global economic activity. Also, the group factors appear to account for more volatile movements in commodity prices and they are only important for certain commodity groups. In the next section we attempt to disentangle the different underlying shocks driving the common fluctuations in commodity prices as captured by the global

[23] The detailed results can be seen in Table 2.

[24] Please see Tables 3 and 4 for detailed results from the subsample analysis.

[25] Note that we define broad-based within group synchronization as an estimated underlying group factor accounting for at least 10 percent of the variation in price of each commodity within its respective group. We make an exception for grains, where the grains factor accounts for more than 15 percent variation in each commodity price within its group, except rice.

Figure 3: Responses of Global Commodity Factor to Structural Shocks



Note: Median impulse responses to the three structural shocks, together with $32^{nd} - 68^{th}$ and $16^{th} - 84^{th}$ percentile responses. *Source:* Authors' calculations.

and group factors.

4.2 Drivers of Common Commodity Cycles

4.2.1 Drivers of the Global Commodity Cycle

Impulse Responses. Figure 3 plots the median impulse response functions of the endogenous variables to the three structural shocks, together with the $32^{nd}-68^{th}$ and $16^{th}-84^{th}$ percentile responses. The results are based on the restrictions discussed in section 3.3 with 1.5 million draws of the rotation matrix. We report results for a one-standard-deviation shock in each case and normalize all results to increase the global commodity price factor.

The shape of the impulse responses are broadly consistent with expected results. A positive global demand shock results in a significant increase in all three model variables over time (where positive response at impact is by assumption). The global industrial production index increases for the first 8 months and then gradually declines, with the response turning insignificant after roughly a year. The positive response of global inflation, on the other hand, is persistent over the 16-month horizon. Whereas, the global commodity price factor increases initially, peaks after 10 months and decreases thereafter in response to this shock. A positive global supply shock results in a persistent rise in world industrial production and the global commodity price factor. At the same time, this shock causes a transitory decrease in global inflation, which becomes insignificant after 2 months. Finally, a positive commodity market shock triggers a decrease in global industrial production that is partially significant. It also causes a significant increase in global inflation that begins to decline only after roughly 1 year. A positive commodity market shock also causes a temporary increase in the global commodity factor.

Some of the striking results in Figure 3 include the fact that the response of the global industrial production to commodity market-specific shocks is relatively small. This is consistent with the view that commodity market-specific shocks should have a small impact on global economic activity since these shocks affect real activity only through their impact on commodity prices (see Kilian & Murphy, 2012; Charnavoki & Dolado, 2014).[26] Moreover, global inflation responds more to global demand and commodity market shocks than to global supply shocks.[27] If we compare the response of the global commodity price factor to the three structural shocks, the response of the global factor to global supply shocks is largest and most persistent. As we discuss below, this is consistent with evidence that suggests that sustained increase in commodity prices is typically the result of productivity-enhancing structural change. Finally, the response of the global factor to commodity market shocks is relatively large in the first 2 months—Kilian (2009) obtains similar results for the oil market, where he finds oil price overshooting in response to oil market-specific demand shocks.

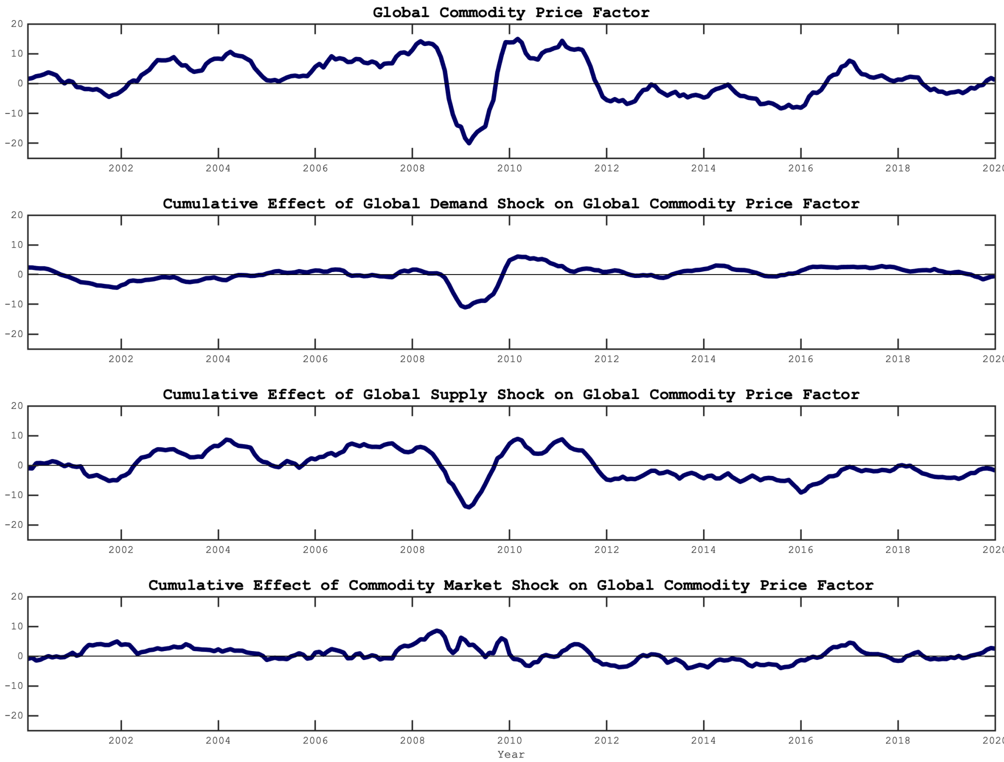
Historical Decomposition. The results in Table 1 indicate that the global commodity price factor captures an increasing fraction of comovement in commodity prices over the past two decades. What drives the synchronized fluctuations in commodity prices during this period? Figure 4 plots the global factor, alongside the cumulative contribution of each structural shock to its evolution based on the historical decomposition for the model.[28] The results indicate that much of the variation in the global factor during this period is attributed to the effects of global supply shocks. Neither global demand shocks nor commodity market shocks are able to explain the overall synchronized surge and

[26] Note that we do not impose an elasticity restriction on the impact response of global industrial production to commodity market shocks as discussed in Section 3.3.

[27] For a discussion regarding the increasingly important role of global demand shocks (versus global supply and oil price shocks) in driving global inflation variability, see Ha, Kose, & Ohnsorge (2018).

[28] Note that the impulse responses presented in Figure 3 describe the average moments in the data by tracing out the response of the global commodity price factor to a one-time structural shock. However, commodity cycles are driven by a sequence of shocks of different signs and magnitudes. It is possible that the impact of a positive global supply shock on the global commodity price factor in one period is suppressed by a negative global supply shock in the later periods. Thus, large and persistent impulse responses reported in Figure 3 are not sufficient evidence for each structural shocks ability to explain commodities cycles. The same argument applies to forecast error variance decompositions (see Kilian & Lütkepohl, 2017). Thus, to understand the cumulative contribution of each shock in the evolution of the global commodity cycle, we use historical decompositions.

FIGURE 4: HISTORICAL DECOMPOSITION: GLOBAL COMMODITY FACTOR
2000 – 2019



Note: Solid line: Global commodity factor and cumulative effect of each structural shock. All results are reported in year-over-year growth rates. *Source:* Authors' calculations.

collapse in commodity prices over this period.[29] This is consistent with the dominant role of China (and to a lesser extent India) in driving commodity markets over the last two decades. In particular, a number of studies have associated the post-2000 commodities boom with increased demand for commodities due to the strong growth in emerging markets, especially China (see, amongst others, Baffes & Haniotis, 2010; World Bank, 2015; Alquist et al., 2020). Moreover, the growth experienced by China during this period has been linked with productivity increases caused by ownership reforms and trade liberalization, which are examples of global supply shocks (Zhu, 2012).[30] Similarly, others

[29]Note that the role of global demand shocks is limited to the global financial crisis period and the subsequent recovery while commodity market shocks account for sharply defined increases or decreases during particularly periods.

[30] An increase in productivity due to, for example, trade liberalization would raise the marginal product of all inputs included in a firm's production function. Since commodities are a key input into production, a boost to the marginal product for commodities would increase the overall demand for commodities and, consequently, result in a joint upswing in commodity prices. Note that most studies that develop dynamic stochastic general equilibrium

ascribe India's economic growth to efficiency and productivity gains due to rapid and comprehensive trade reforms (see, for example, Topalova & Khandelwal, 2011; Kotwal et al., 2011). Finally, the 2000s commodity cycle has been characterized as a "super cycle" i.e., demand-driven surges in commodity prices, which are associated with industrialization of the global economy (Cuddington & Jerrett, 2008; Erten & Ocampo, 2013; Buyuksahin et al., 2016; Baffes & Kabundi, 2020). Long periods of industrialization typically coincide with persistent economic growth that can only come from structural changes or economic reforms that increase total factor productivity (see Zhu, 2012). In particular, Buyuksahin et al. (2016) argue that, "the current commodity price supercycle began in the mid- to late 1990s, the same time as a series of important reforms were occurring in China, including its eventual accession to the World Trade Organization (WTO) in 2001."

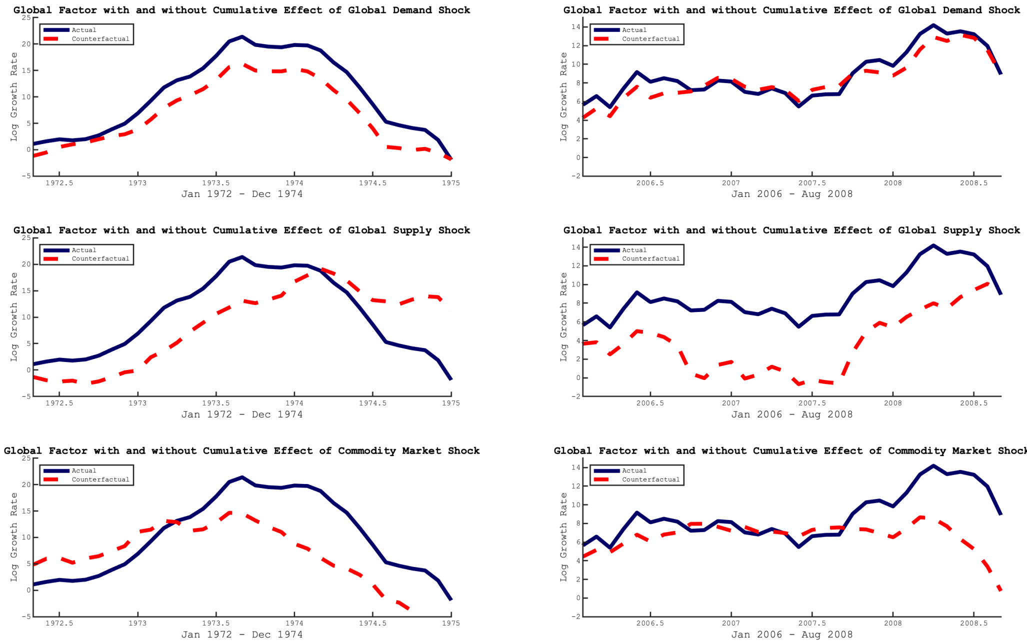
How important have global demand, global supply and commodity market shocks been during major historical boom-bust episodes in commodity markets? Figure 5 plots historical decompositions based on the estimated FAVAR model as counterfactuals. In particular, the left and right panels of Figure 5 show the evolution of the global commodity price factor with and without the three structural shocks during the 1972 - 1974 and 2006 - 2008 commodity price booms, respectively. We focus on these two periods since together with the 1950-51 commodity price boom, they represent the most dramatic booms in commodity markets of the post-WWII period (Radetzki, 2006; Baffes & Haniotis, 2010).[31] For the 1972 - 1974 period, without the realization of global demand shocks, the growth rate of the global commodity price factor would have been considerably lower. In other words, positive global demand shocks helped to maintain a broad-based increase in commodity prices during this period. Similarly, in the absence of global supply shocks, the growth rate of the global factor would have been lower between the period 1972 and early 1974. However, the global factor would have been higher without global supply shocks post early 1974, indicating the presence of a sequence of negative global supply shocks during the 1974-75 recession. In addition, commodity market shocks contribute the most during the post early 1973 period to the joint upsurge in commodity prices. This is consistent with findings that suggest an important role played by speculative demand shocks in increasing commodity prices during the 1972-74 commodity price boom (see Cooper & Lawrence, 1975; C. A. Carter, Rausser, & Smith, 2011).

On the other hand, during the 2006 - 2008 period, global supply shocks played a major role in driving the common increase in prices while the impact of global demand shocks was relatively small. This is consistent with the observation that the 1972-74 boom was different than the 2006-08 boom since the former was associated with high inflation (Baffes & Haniotis, 2010). Moreover,

(DSGE) models in line with Kilian (2009)'s empirical findings, model a shock that impacts all commodity prices as a shock to the representative firm's productivity (see, for example, Bodenstein & Guerrieri, 2011; Plante, 2014).

[31] Results for the full sample period can be seen in Figure 9.

Figure 5: Counterfactuals for the Global Commodity Factor



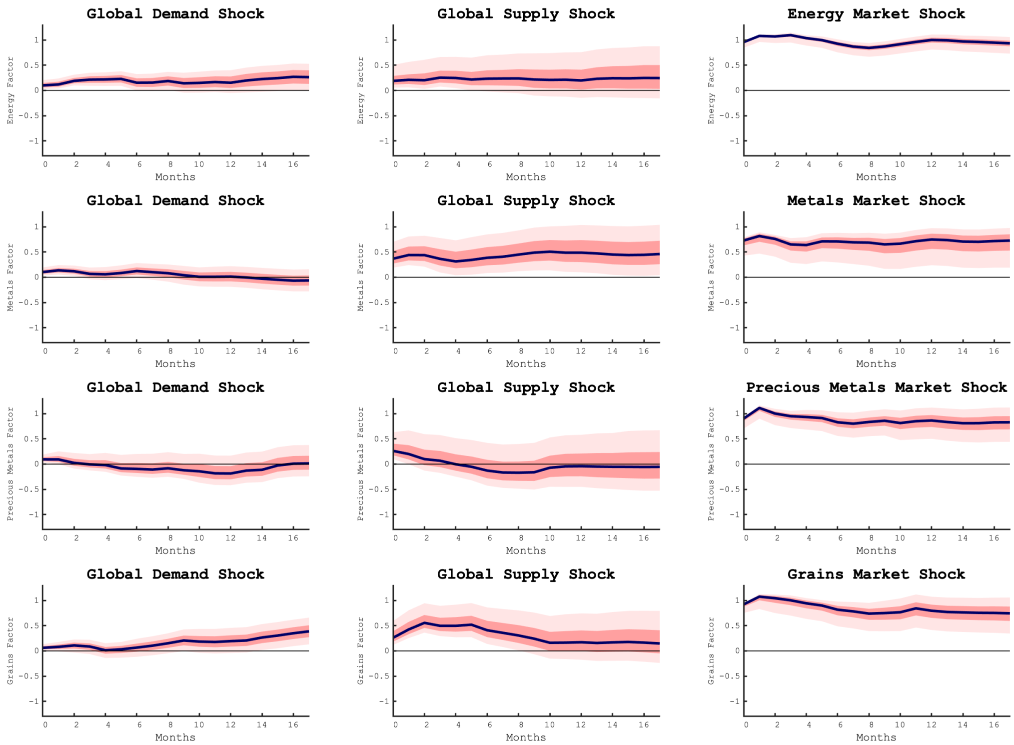
Note: Solid line: Global commodity factor. Dashed line shows the evolution of global factor without each structural shock. All results are reported in year-over-year growth rates. *Source:* Authors' calculations.

commodity market shocks contributed towards the end of this boom-bust episode i.e. post mid-2007. In particular, in the absence of commodity market shocks, the growth of the global factor during the period late 2007 - mid-2008 would have been lower. This result is consistent with the evidence that has suggested the "financialization of commodity markets" as a potential driver of the 2006-08 commodities boom (see, for example, Cheng & Xiong, 2013; Caballero, Farhi, & Gourinchas, 2008). Caballero et al. (2008) have argued that the sharp rise in commodity prices during this period can be attributed to capital inflows into commodity markets following the US mortgage market collapse that created a shortage of saving vehicles in the world financial sector.

4.2.2 Drivers of Group-specific Commodity Cycles

The discussion so far has focused on the underlying drivers of the global commodity cycle. However, as observed in Table 1, there is evidence of broad-based within-group synchronization for certain commodity groups as captured by their respective group factors. To examine what drives group-specific commodity factors, a set of FAVAR models similar to Section 4.2.1 are estimated, but with the global factor replaced by a group-specific factor in each case. Based on the results in Table 1,

Figure 6: Responses of Group-specific Commodity Factors to Structural Shocks

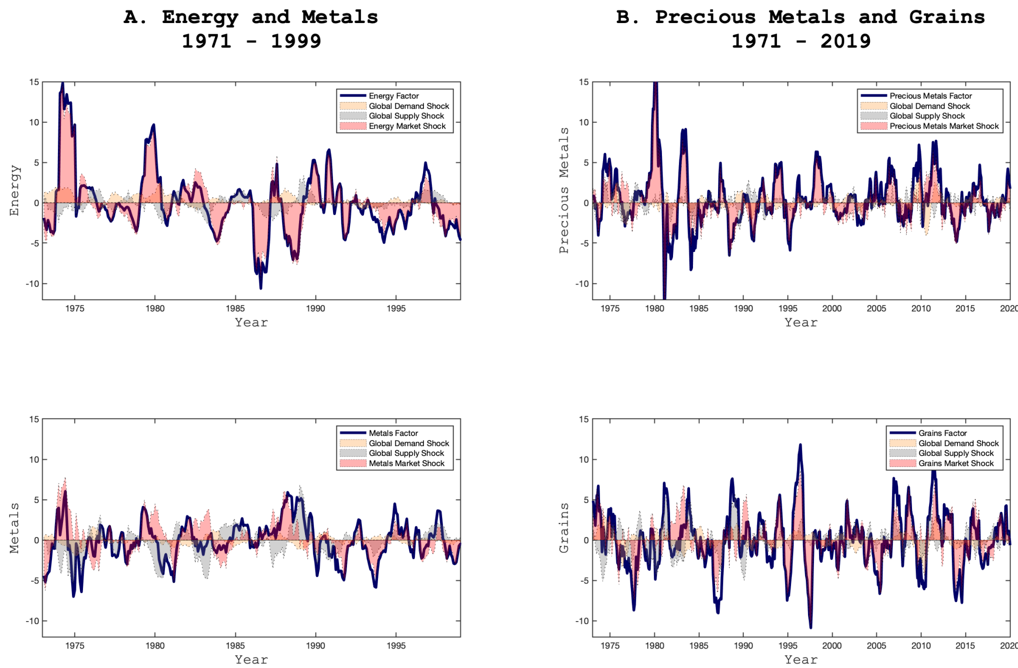


Note: Median impulse responses to the three structural shocks, together with $32^{nd} - 68^{th}$ and $16^{th} - 84^{th}$ percentile responses. *Source:* Authors' calculations.

we focus on precious metals and grains for the full sample period 1971 - 2019 and on metals and energy for the subsample period 1971 - 1999.

Impulse Responses. Figure 6 presents the impulse responses of each group-specific commodity factor to the three structural shocks. In general, the response of grains and precious metal factors to positive global demand shocks is not different from zero while the same shock triggers a relatively small and transitory increase in energy and metal factors. A positive global supply shock, on the other hand, results in a significant and temporary increase in metals and grains, although its impact on precious metals and energy is insignificant. Respective market-specific positive shocks generate a positive response in each case, which is persistent over the 16-month horizon. These results should be interpreted keeping in mind that the group factors represent all common variation for commodity prices within each group that has not already been accounted for by the global factor. Thus, the

Figure 7: Historical Decomposition: Group Commodity Factors



Note: Solid line: Group-specific commodity factors. Shaded areas are the contribution of each structural shock. *Source:* Authors' calculations.

relatively small response of group factors to unanticipated changes in global economic activity is expected. In other words, these results indicate that shocks that are specific to commodity markets are the main drivers of common variation within commodity groups. These results are consistent with the view that group factors are driven primarily by market-specific shocks since unexpected changes in global economic activity should typically impact all commodity markets (Chiaie et al., 2017; Bilgin & Ellwanger, 2017).

Historical Decomposition. To examine the historical contribution of each structural shock to group-specific commodity cycles, we plot the historical decompositions of group factors in Figure 7. The results indicate that the contribution of global demand and global supply shocks to developments in different group-specific commodity factors have been small. In particular, almost all volatility specific to precious metals and energy markets is attributed to precious metals and energy market shocks, respectively. We interpret these as precautionary demand shocks that are specific to precious metals and energy markets. For example, there is a sharp increase in the energy factor in 1979—a period that witnessed a large increase in precautionary demand for oil due to the Iranian Revolution and the Iranian hostage crisis, which raised concerns about the availability of future oil supplies (Kilian, 2009). Similarly, for example, the dramatic spike observed for precious metals around 1980 is associated with high uncertainty during this period and the perception of precious metals as safe-haven assets (see Piffer & Podstawski, 2018). For metals and grains, in addition to market-specific shocks, global supply shocks also contribute to the evolution of their respective group factors.

4.3 Robustness

This section presents results from additional robustness checks of our main findings.

Alternate Subsamples. The results in Section 4.1 suggest that commodity price comovement has increased over time. In particular, the global factor accounts for twice the variation across commodity prices, on average, over the period 2000 – 2019 (versus 1970 – 1990). However, since 2000 – 2019 is a shorter subsample period that includes the global financial crisis, a time that exhibited large co-movement in commodity prices, results may be dominated by a few observations. Thus, we compare the results by estimating the dynamic factor model and computing the variance decompositions for two equally sized subsample periods: 1970 – 1994 and 1995 – 2019.[32]

The results reported in Tables 5 and 6 indicate that our findings remain qualitatively similar—commodity price comovement has increased in recent years. The global factor accounts for 15.7 percent of the variation in commodity prices on average for the period 1995 – 2019. Whereas, its contribution to commodity price variability during the period 1970 – 1999 is 9.7. This translates to a 1.6 times increase in the importance of the global factor. Moreover, the number of commodities for which the global factor is more important than group-specific factors has increased as well, while the relative contribution of idiosyncratic factors has declined over time. Thus, increase in commodity price synchronization is broad-based as suggested by the main results.

Kilian Index. We next check the robustness of the FAVAR results provided in Section 4.2. These results are based on the model that employs the world industrial production index as a measure of global economic activity. As an alternative, we estimate a model that uses Kilian's index of global real economic activity, which is derived from the cost of international shipping in commodity markets (see Kilian, 2009; Kilian & Zhou, 2018). The Kilian's index is a popular measure of worldwide economic activity and it is used in many studies (see, for example, Baumeister & Kilian, 2012; Kilian & Murphy, 2014; Lütkepohl & Netšunajev, 2014; Anzuini, Pagano, & Pisani, 2015; Antolín-Díaz & Rubio-Ramírez, 2018).

[32] Note that this increases the length of the second subsample period. Whereas, this cut-off also corresponds to the start of the commodities supercycle in the mid-1990s.

Figure 10 presents the historical decompositions obtained from the alternative model. The historical decompositions indicate that, in general, our results remain similar to those found using the world industrial production as a measure of global economic activity. The findings suggest that global supply shocks have been the main driver of synchronized fluctuations in commodity prices since 2000. Moreover, the relative importance of the three structural shocks remains similar over the whole sample. However, in comparison to the results based on the model with the world industrial production index, the contribution of commodity market-specific shocks to the 2006 – 2008 commodity price boom is smaller. This is mainly because the world industrial production index is expressed as month-by-month growth rates and it is, thus, able to account for sharper movements in commodity prices that are typically due to commodity-market specific shocks.[33]

Elasticity Restrictions. We also check the sensitivity of our group FAVAR results provided in Section 4.2 by relaxing the lower bound imposed on element $\mathbf{B_{0,(1,3)}}$ of the structural impact multiplier matrix. Recall that we restricted the within month response of the world industrial production index to commodity group-specific shocks to be less than 10 percent. As discussed in Section 3.3, this follows from the assumption that short-run elasticity of global economic activity to a commodity group-specific shock should be small. We relax the lower bound on element $\mathbf{B_{0,(1,3)}}$ to -0.2. This corresponds to a lower bound which is twice the size, in absolute terms, of the restriction in our original identification strategy.

Figure 11 presents the historical decompositions of group commodity factors to each structural shock based on the relaxed lower bound on $\mathbf{B_{0,(1,3)}}$. The results indicate a slightly bigger role of global supply shocks during specific periods for metals, grains, and energy group cycles. However, overall, the results are consistent with our main findings—commodity group-specific shocks, which we interpret as precautionary demand shocks, are most important in driving group cycles.

5 Conclusion

The 2000s synchronized commodities boom-bust cycle has been a reminder of the central role of commodities in the global economy and their close linkages with world trade and financial activity. Although, a large literature has examined common fluctuations in commodity prices and their determinants (both fundamental or "excess"), a unified structural framework has been lacking. Our paper has attempted to fill this gap by identifying both global and group cycles in a broad set of

[33]Note that the Kilian's index is reported in deviations from a linear time trend and, therefore, may capture longer cycles in commodity prices. This would result in under emphasizing the role of commodity market-specific shocks. For more details on different measures of global economic activity, see Kilian & Zhou (2018), Hamilton (2019), Kilian & Zhou (2020), and Baumeister, Korobilis, & Lee (2020).

commodity prices and evaluating their underlying drivers. In particular, we disentangle the role of global demand, global supply and commodity market-specific shocks in driving common commodity cycles.

We start by extracting common factors in commodity price data using a multi-level dynamic factor model. These common factors are identified as global and group cycles in commodity prices. Our results provide evidence of a global cycle in commodities that has become more important over time—the global commodity factor accounts for an increasing fraction of commodity price volatility on average over the past two decades. Moreover, the role of the global factor in capturing price movements is largest and has increased the most for energy, metals and precious metals, consistent with their close relationship with the global economy and industrial activity. In contrast, it explains a smaller fraction of fluctuations in agricultural crops and fertilizers, as these commodities are less closely linked to global economic activity. The volatility in these groups is also typically not captured by group factors, with price changes chiefly driven by idiosyncratic disturbances, with the exception of grains. Grains are among the most substitutable agricultural crop both in terms of consumption and production, and are therefore more likely to have synchronized moves in prices.

We then assess the response of the estimated common factors to global demand, global supply and commodity market shocks using a set of factor-augmented VAR models. Of particular note, the 2000s global cycle in commodity prices is found to be mostly driven by global supply shocks, rather than global demand shocks or commodity market-specific shocks. This is consistent with the dominant role of China in driving commodity markets over the last two decades. In particular, our results suggest that the rapid growth in China caused by trade liberalization and other structural reforms led to productivity gains that increased overall demand for commodities and, consequently, in a joint surge in commodity prices.

We also evaluate the role of each structural shock in driving the 1972-74 and 2006-08 boom-bust episodes in commodity markets. We find evidence that shocks orthogonal to global demand and global supply shocks contributed to the upswing in prices. These shocks are designed to capture speculative or precautionary demand for commodities. Their role was particularly evident in the latter half of the 1972–74 and the 2006–08 price boom and bust, where speculative demand likely exacerbated the peak and trough in prices, and delayed the price crash. The nature of speculative demand, however, has likely changed over time given the financialization of commodities in the recent period while presence of inflation-hedging concerns in the former episode.

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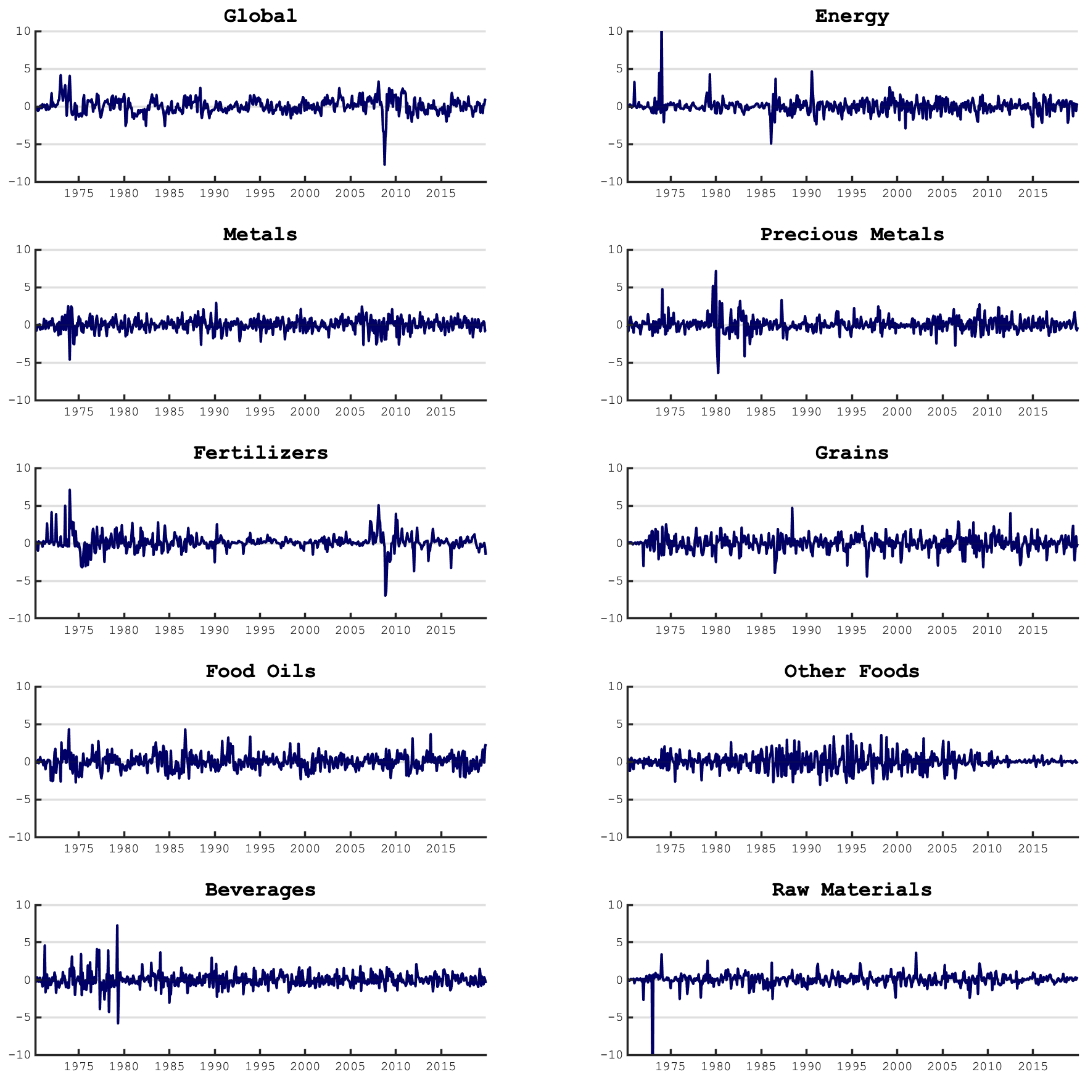
Figure 8: Common Commodity Price Factors: 1971 - 2019



Note: All common factors estimated using DFM (1) - (3). Factors reported in month-over-month growth rates. *Source:* Authors' calculations.

TABLE 2: Variance Decomposition: 1971 - 2019

		Global Factor	**Group Factor**	**Idiosyncratic**
Energy	*Crudeoilaverage*	13.1	84.4	2.5
	CoalAustralian	9.4	4.1	86.5
	Naturalgasindex	2.2	7.2	90.6
Metals	*Aluminum*	19.9	22.4	57.7
	Copper	28.7	30.7	40.7
	Lead	16.3	28.9	54.8
	Tin	20.0	10.6	69.4
	Nickel	18.2	13.4	68.4
	Zinc	16.8	40.8	42.5
Precious Metals	*Gold*	15.2	39.8	44.9
	Platinum	26.4	25.5	48.1
	Silver	18.7	78.9	2.4
Fertilizers	*DAP*	3.8	41.5	54.7
	TSP	5.4	92.0	2.6
	Urea	4.1	8.3	87.7
	Potassiumchloride	0.4	0.5	99.1
Grains	*Barley*	14.2	16.4	69.3
	Maize	14.2	84.0	1.8
	Sorghum	15.1	48.6	36.2
	RiceThai5	2.6	0.5	96.9
	WheatUSHRW	12.4	15.3	72.3
	Soybeans	20.4	18.5	61.1
Food Oils	*Coconutoil*	17.0	81.5	1.5
	Groundnutoil	6.0	0.7	93.3
	Palmoil	23.5	20.8	55.7
Other Foods	*BananaUS*	1.0	90.3	8.7
	Orange	0.3	0.3	99.4
	Beef	4.9	0.3	94.9
	Meatchicken	0.6	0.4	99.1
	ShrimpsMexican	0.5	0.4	99.1
	Sugarworld	10.7	0.3	89.0
Beverages	*Cocoa*	8.6	0.4	91.0
	CoffeeArabica	6.9	0.2	92.9
	Teaavg3auctions	2.7	92.1	5.2
Raw Materials	*CottonAIndex*	12.8	0.3	86.9
	LogsCameroon	6.8	89.8	3.3
	LogsMalaysian	1.1	0.5	98.4
	RubberSGPMYS	35.4	0.2	64.5
	TobaccoUSimportuv	1.5	0.3	98.2
Average		11.2	28.0	60.8

Note: Percentage of variance accounted by the global and group-specific factors. Averages reported for each group. The results are based on the methodology discussed in Section 3.2.

TABLE 3: Variance Decomposition: 1971 - 1999

		Global Factor	**Group Factor**	**Idiosyncratic**
Energy	*Crudeoilaverage*	8.7	14.2	77.1
	CoalAustralian	1.4	14.1	84.5
	Naturalgasindex	5.1	88.0	6.9
Metals	*Aluminum*	5.3	24.5	70.2
	Copper	16.0	34.4	49.7
	Lead	14.4	26.9	58.7
	Tin	6.0	10.7	83.3
	Nickel	4.0	12.4	83.7
	Zinc	7.6	40.2	52.3
Precious Metals	*Gold*	18.7	49.0	32.3
	Platinum	9.9	56.3	33.8
	Silver	17.4	60.0	22.6
Fertilizers	*DAP*	7.9	45.3	46.8
	TSP	8.6	89.5	1.8
	Urea	10.9	7.7	81.5
	Potassiumchloride	2.7	1.8	95.5
Grains	*Barley*	10.0	24.6	65.4
	Maize	11.4	61.5	27.1
	Sorghum	9.1	82.4	8.5
	RiceThai5	2.5	0.6	96.9
	WheatUSHRW	7.3	31.2	61.5
	Soybeans	15.5	21.0	63.5
Food Oils	*Coconutoil*	16.3	25.9	57.8
	Groundnutoil	11.7	4.4	84.0
	Palmoil	17.1	79.8	3.1
Other Foods	*BananaUS*	0.7	80.9	18.4
	Orange	0.6	0.9	98.5
	Beef	4.1	0.9	95.0
	Meatchicken	1.5	1.5	97.0
	ShrimpsMexican	0.8	1.1	98.1
	Sugarworld	11.2	0.4	88.4
Beverages	*Cocoa*	14.0	0.6	85.5
	CoffeeArabica	4.1	0.3	95.6
	Teaavg3auctions	3.1	91.7	5.3
Raw Materials	*CottonAIndex*	7.9	0.2	91.9
	LogsCameroon	7.4	0.6	92.0
	LogsMalaysian	2.5	0.8	96.6
	RubberSGPMYS	22.2	71.3	6.5
	TobaccoUSimportuv	0.6	0.6	98.8
Average		8.7	29.7	62.0

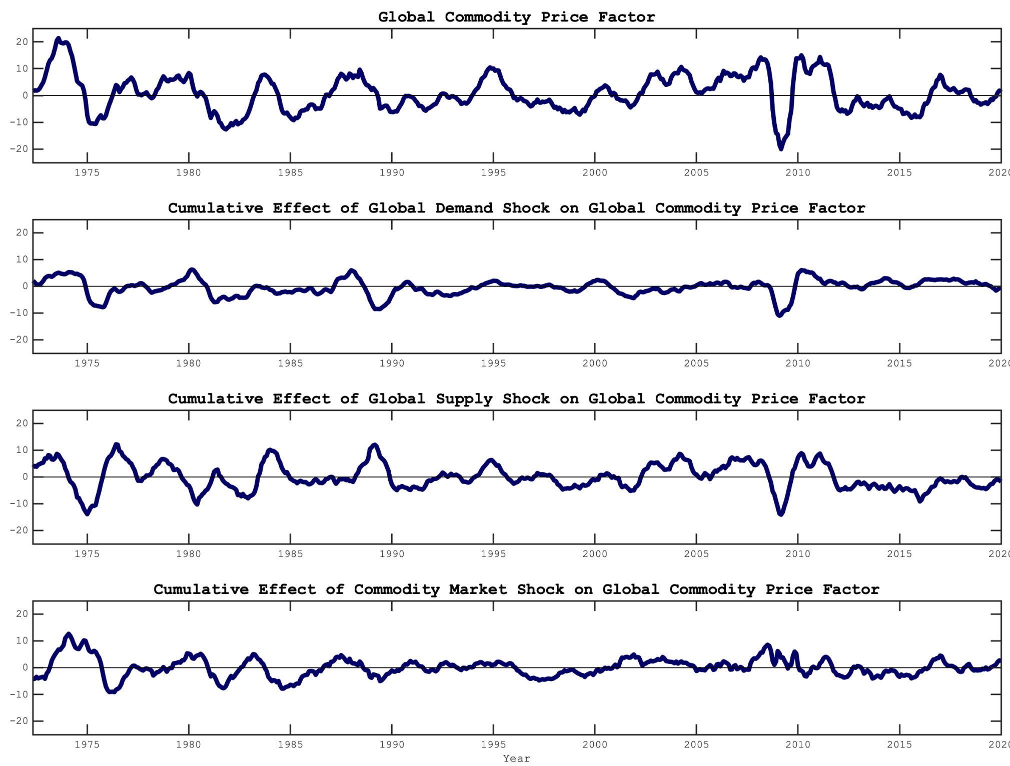
Note: Percentage of variance accounted by the global and group-specific factors. Averages reported for each group. The results are based on the methodology discussed in Section 3.2.

Table 4: Variance Decomposition: 2000 - 2019

		Global Factor	**Group Factor**	**Idiosyncratic**
Energy	*Crudeoilaverage*	34.3	0.5	65.2
	CoalAustralian	23.3	73.9	2.8
	Naturalgasindex	2.1	1.3	96.6
Metals	*Aluminum*	49.2	17.7	33.1
	Copper	53.4	23.0	23.7
	Lead	30.1	25.6	44.3
	Tin	51.9	2.7	45.4
	Nickel	40.7	9.7	49.6
	Zinc	41.3	34.6	24.0
Precious Metals	*Gold*	12.1	79.9	8.0
	Platinum	51.3	11.0	37.8
	Silver	31.6	41.7	26.7
Fertilizers	*DAP*	1.1	60.6	38.3
	TSP	1.1	69.3	29.6
	Urea	0.6	16.7	82.7
	Potassiumchloride	0.6	0.7	98.7
Grains	*Barley*	16.7	14.6	68.7
	Maize	18.5	78.7	2.9
	Sorghum	17.0	44.0	39.0
	RiceThai5	3.7	0.7	95.6
	WheatUSHRW	13.7	15.6	70.8
	Soybeans	30.0	15.0	55.0
Food Oils	*Coconutoil*	21.2	28.1	50.8
	Groundnutoil	0.7	0.4	99.0
	Palmoil	25.7	67.1	7.2
Other Foods	*BananaUS*	1.3	1.2	97.5
	Orange	4.1	92.0	3.9
	Beef	5.3	0.9	93.8
	Meatchicken	0.6	0.4	99.0
	ShrimpsMexican	0.6	2.2	97.2
	Sugarworld	13.7	0.5	85.8
Beverages	*Cocoa*	8.5	0.3	91.2
	CoffeeArabica	14.6	0.9	84.5
	Teaavg3auctions	11.8	76.8	11.3
Raw Materials	*CottonAIndex*	14.3	0.7	85.0
	LogsCameroon	15.8	80.0	4.2
	LogsMalaysian	0.8	6.9	92.4
	RubberSGPMYS	42.1	1.2	56.6
	TobaccoUSimportuv	3.9	0.5	95.6
Average		17.9	25.6	56.2

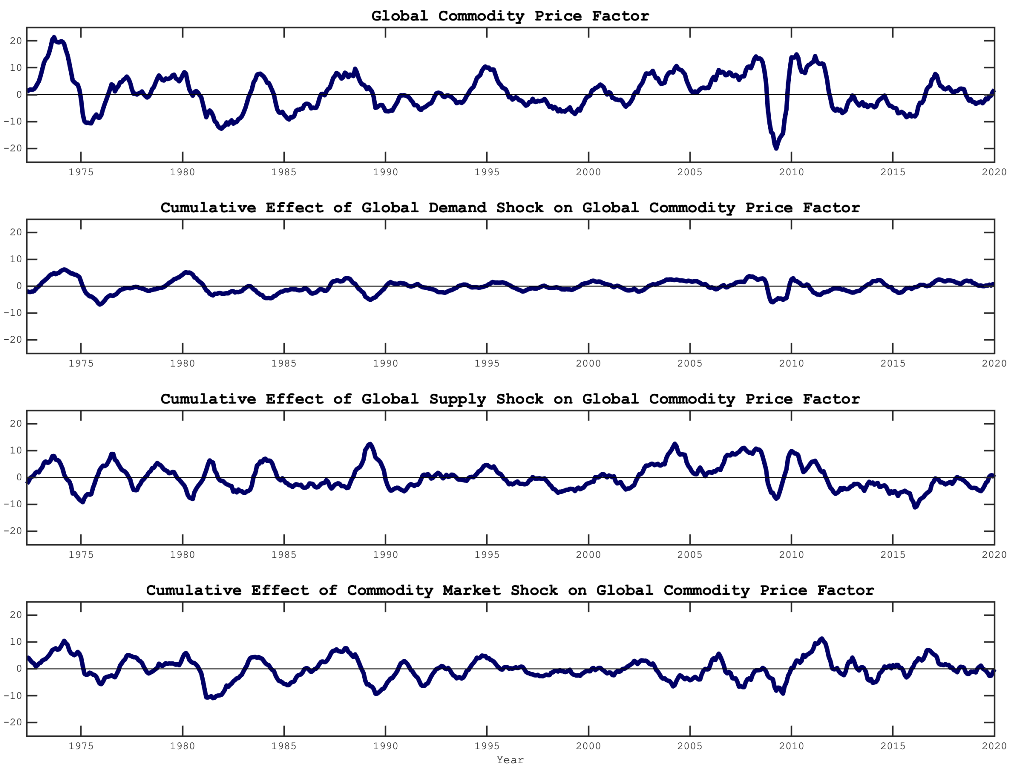
Note: Percentage of variance accounted by the global and group-specific factors. Averages reported for each group. The results are based on the methodology discussed in Section 3.2.

Figure 9: Historical Decomposition: Global Commodity Factor
1971 – 2019



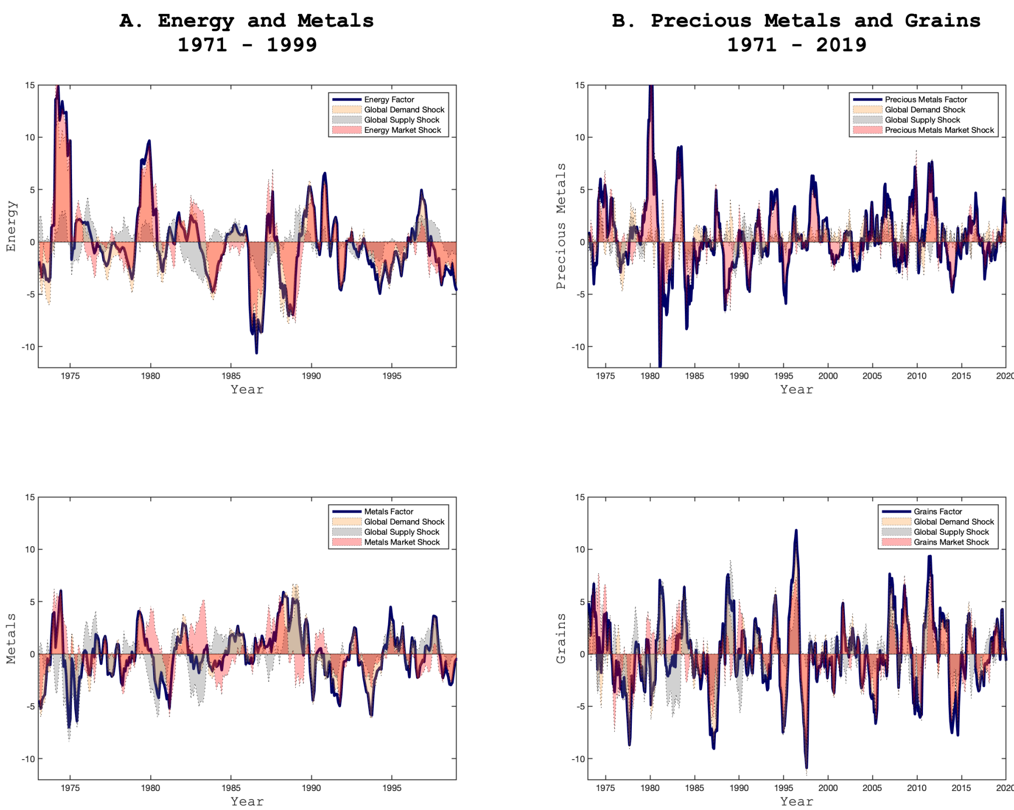
Note: Solid line: Global commodity factor and cumulative effect of each structural shock. All results are reported in year-over-year growth rates. *Source:* Authors' calculations.

Figure 10: Historical Decomposition: Global Commodity Factor with Kilian Index, 1971 – 2019



Note: Solid line: Global commodity factor and cumulative effect of each structural shock. All results are reported in year-over-year growth rates. *Source:* Authors' calculations.

Figure 11: Historical Decomposition: Group Commodity Factors



Note: Solid line: Group-specific commodity factors. Shaded areas are the contribution of each structural shock. Results are based on alternative elasticity restrictions by relaxing the lower bound on element $\mathbf{B_{0,(1,3)}}$ of the structural impact multiplier matrix to -0.2. *Source:* Authors' calculations.

Table 5: Variance Decomposition: 1970 - 1994

		Global Factor	**Group Factor**	**Idiosyncratic**
Energy	*Crudeoilaverage*	8.7	21.9	69.4
	CoalAustralian	1.0	21.9	77.2
	Naturalgasindex	6.1	86.3	7.5
Metals	*Aluminum*	8.7	15.6	75.7
	Copper	22.9	28.5	48.6
	Lead	19.7	18.7	61.6
	Tin	9.5	6.1	84.4
	Nickel	4.9	6.9	88.2
	Zinc	11.0	54.0	35.0
Precious Metals	*Gold*	20.6	44.4	35.0
	Platinum	13.2	49.4	37.4
	Silver	21.6	68.0	10.4
Fertilizers	*DAP*	6.3	48.0	45.7
	TSP	6.9	91.0	2.1
	Urea	8.5	10.0	81.6
	Potassiumchloride	2.2	2.2	95.6
Grains	*Barley*	11.1	24.1	64.7
	Maize	13.7	60.8	25.4
	Sorghum	10.4	79.5	10.2
	RiceThai5	3.6	0.9	95.6
	WheatUSHRW	8.0	28.5	63.5
	Soybeans	16.4	24.4	59.2
Food Oils	*Coconutoil*	20.7	24.4	54.8
	Groundnutoil	11.1	6.7	82.2
	Palmoil	19.8	76.9	3.3
Other Foods	*BananaUS*	0.8	90.1	9.1
	Orange	0.7	1.9	97.4
	Beef	5.2	0.3	94.5
	Meatchicken	2.4	0.9	96.7
	ShrimpsMexican	0.8	1.1	98.1
	Sugarworld	11.1	0.4	88.5
Beverages	*Cocoa*	14.8	82.2	3.0
	CoffeeArabica	4.4	0.5	95.2
	Teaavg3auctions	3.2	0.7	96.1
Raw Materials	*CottonAIndex*	11.5	0.4	88.1
	LogsCameroon	7.4	0.6	92.0
	LogsMalaysian	3.2	0.5	96.3
	RubberSGPMYS	26.8	0.4	72.8
	TobaccoUSimportuv	0.5	88.5	11.0
Average		9.7	29.9	60.3

Note: Percentage of variance accounted by the global and group-specific factors. Averages reported for each group. The results are based on the methodology discussed in Section 3.2.

Table 6: Variance Decomposition: 1995 - 2019

		Global Factor	**Group Factor**	**Idiosyncratic**
Energy	*Crudeoilaverage*	28.68	1.15	70.17
	CoalAustralian	23.78	0.67	75.54
	Naturalgasindex	1.82	91.44	6.73
Metals	*Aluminum*	40.48	24.56	34.96
	Copper	43.66	28	28.34
	Lead	23.89	28.88	47.23
	Tin	44.02	5.49	50.49
	Nickel	37.48	11.18	51.34
	Zinc	29.7	37.32	32.98
Precious Metals	*Gold*	10.4	84.12	5.48
	Platinum	45.98	12.27	41.75
	Silver	26.63	31.74	41.62
Fertilizers	*DAP*	0.5	46.43	53.08
	TSP	0.6	86.09	13.31
	Urea	0.82	8.98	90.2
	Potassiumchloride	0.51	0.37	99.12
Grains	*Barley*	16	16.58	67.42
	Maize	15.3	81.2	3.5
	Sorghum	15.64	47.23	37.13
	RiceThai5	3.35	0.73	95.92
	WheatUSHRW	13.01	17.93	69.06
	Soybeans	25.97	13.9	60.13
Food Oils	*Coconutoil*	19.39	77.55	3.06
	Groundnutoil	1.56	0.45	97.99
	Palmoil	26.04	18.01	55.94
Other Foods	*BananaUS*	1.49	0.74	97.76
	Orange	3.25	0.46	96.29
	Beef	4.99	0.58	94.43
	Meatchicken	0.47	81.16	18.38
	ShrimpsMexican	0.45	0.48	99.07
	Sugarworld	12.56	0.44	87
Beverages	*Cocoa*	6.97	88.68	4.35
	CoffeeArabica	11.04	0.39	88.57
	Teaavg3auctions	9.48	0.34	90.18
Raw Materials	*CottonAIndex*	10.78	0.82	88.4
	LogsCameroon	13.27	82.01	4.72
	LogsMalaysian	0.56	4.68	94.76
	RubberSGPMYS	40.4	0.42	59.18
	TobaccoUSimportuv	2.79	0.72	96.49
Average		15.74	26.52	57.75

Note: Percentage of variance accounted by the global and group-specific factors. Averages reported for each group. The results are based on the methodology discussed in Section 3.2.