



Commodity prices redux: A global factor story

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HIGHLIGHTS

- We employ a BDFM and a FAVAR model.
- We investigate cross-commodity price synchronisation and the factors driving it.
- Macroeconomic and financial factors are key determinants of world commodity prices.
- For commodity group prices, uncertainty is at least as important as the other factors.

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ABSTRACT

In this study, we novelly employ a Bayesian Dynamic Factor Model (BDFM) and a Factor-Augmented Vector Autoregressive (FAVAR) model to investigate the relatively under-explored phenomenon of cross-commodity price synchronisation and the factors driving comovement in commodity prices. Our findings indicate that macroeconomic and financial factors are key determinants of world commodity prices, whereas uncertainty plays a comparatively minor role, accounting for less than 10% initially and remaining below 20% at longer horizons. At the level of commodity group prices, however, uncertainty becomes significantly more important, with its contribution exceeding one-third of the variance at longer horizons across all commodity groups. These results highlight a clear distinction between aggregate and disaggregated dynamics: global commodity prices are largely driven by macroeconomic and financial conditions, implying that policymakers retain meaningful scope to influence them, whereas commodity-group prices are more sensitive to shocks and uncertainty.

1. Introduction

A comprehensive analysis of the behaviour of commodity prices is vital for enhancing our understanding of developments in both financial markets and macroeconomic activity. In the context of financial markets, recent evidence regarding the financialisation of commodity markets highlights the importance of commodity price fluctuations (Tang and Xiong, 2012; Büyükkşahin and Robe, 2014; Le Pen and Sévi, 2018; Boyd et al., 2018; Kang et al., 2023; Hu and Lee, 2024). The consensus from these studies suggests that market participants treat commodities as financial assets. This implies that commodity prices are influenced not only by supply and demand imbalances but also by growing levels of commodity trading activity. Such insights are important for regulators, as the creation of commodity price bubbles may lead to systemic crises (Chatziantoniou et al., 2021). Furthermore, investors can use this information to make decisions about portfolio optimisation, financial risk management, and commodities trading (Degiannakis and Filis, 2022).

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Turning to macroeconomic activity, fluctuations in commodity prices can serve as a driver of economic growth. An early contribution to this line of thought is the study by [Cody and Mills \(1991\)](#), who argue that commodity prices provide valuable insights into future economic changes. More specifically, commodity prices can be considered as an economic indicator, thereby offering information that can improve economic performance. For instance, higher commodity prices (i.e., oil prices) can contribute to inflationary pressures. Higher oil prices increase production costs, which are subsequently passed on to consumers, leading to higher retail prices and, consequently, higher expected inflation ([Hamilton, 1996](#)). Such developments could offer valuable information for policymakers. In response to growing inflationary pressures, central banks could tighten monetary policy by raising short-term interest rates ([Basher and Sadorsky, 2006](#)).

While the literature provides evidence of a range of factors that influence price movements in commodity markets, the cross-commodity synchronisation of prices and the extent to which different factors explain the comovement of commodity prices is under-researched. Existing studies have taken several approaches. For example, [de Nicola et al. \(2016\)](#) employ correlation coefficients to analyse the co-movement of commodity price returns as well as using a linear regression analysis to find an association with stock market volatility. On the other hand, [Delle Chiaie et al. \(2022\)](#) extract and decompose factors, finding that commodity price movements are largely explained by the global factor. Similarly, [Alquist et al. \(2020\)](#) highlight the importance of the global factor in influencing commodity price co-movements. In a similar vein, [Xia and Zhou \(2023\)](#) show that the global factor is particularly important for non-export and fuel commodities, whereas the regional factor dominates for non-fuel exported commodities. The contribution of this paper is to provide an in-depth analysis of the comovement of commodity prices such that we simultaneously estimate the dynamic world factor alongside different commodity group factors. This allows us to explore the relative importance of different factors before investigating the categories of global determinants that explain the world and commodity group factors. This second step, where we examine the categories of global determinants, is a novel and important contribution beyond existing studies, as it connects the estimated factors to their underlying global drivers and facilitates policy-relevant interpretation.

We apply a novel two-step method, which is an extension of the approach by [Bernanke et al. \(2005\)](#). In the first step, we apply a Bayesian Dynamic Factor Model (BDFM) to examine the comovement among our entire set of commodity prices over the period 1998–2023. While this is generally a popular approach to examine the comovement of data series ([Kose et al., 2008](#); [Isomirdinov et al., 2024](#)), it is new to this branch of literature. More specifically, we distinguish between the world factor (common to all commodity prices) and four commodity group factors (common to a certain subset of commodity prices): energy, precious metals, industrial metals and agricultural. In the second step, we apply a Factor-Augmented Vector Autoregressive (FAVAR) model to investigate categories of global determinants that explain the world and commodity group factors. Our categories are global financial market activity, global macroeconomic activity, and global uncertainty, and these categories are associated with sixteen explanatory variables. FAVAR is ideally suited to cases where categories are best represented by a collection of variables as opposed to one individual variable. Therefore, this method allows us to examine a more comprehensive range of variables than other studies in this literature.

Our findings show that world prices are influenced more by macroeconomic and financial factors compared to uncertainty factors. In the case of the prices of commodity groups, uncertainty plays a relatively more important role in driving commodity group prices compared to world prices. Overall, our novel methodological approach, which considers a wide collection of determinants, provides a more holistic view of the global drivers of commodity prices. The remainder of this study is organised as follows. In [Section 2](#), we review the related literature on the determinants of commodity prices. In [Section 3](#), we provide a description of the dataset. Moreover, we describe the two-step process. Next, we present and discuss the empirical findings of the study in [Section 4](#). Finally, [Section 5](#) concludes the study and discusses policy implications.

2. Literature review: global determinants of commodity prices

A key objective of this paper is not only to identify common world and commodity-group factors driving price comovement, but also to uncover the underlying global forces that explain these latent factors. To guide this second-stage investigation, we organise the literature into three broad categories of determinants—global financial activity, global macroeconomic conditions, and global uncertainty—which provide the conceptual basis for interpreting the drivers of the estimated factors.

A first strand of the literature highlights the influence of financial market conditions on commodity prices, particularly through stock market volatility and financial stress. Several studies document that stock market volatility is closely linked to global commodity price dynamics ([Cochran et al., 2015](#); [Chiarella et al., 2016](#); [Bakas and Triantafyllou, 2018](#); [Kang et al., 2020, 2024](#)), with [Kang et al. \(2020\)](#) finding that higher global stock market volatility negatively affects commodity prices. Related contributions further report significant spillovers and contagion between stock and commodity markets ([Creti et al., 2013](#); [Mensi et al., 2013](#); [Ahmed and Huo, 2021](#); [Tiwari et al., 2022](#); [Enilov et al., 2023](#); [Zhao et al., 2023](#); [Wang et al., 2023](#)), while the impact of financial stress on commodity price volatility has also been explored ([Nazlioglu et al., 2015](#); [Reboredo and Uddin, 2016](#); [Chen et al., 2023](#)).

A second strand focuses on macroeconomic determinants, emphasising the role of exchange rates, interest rates, and global demand conditions. Exchange rate movements have been found to contain predictive information for commodity prices ([Chen et al., 2010, 2014](#)), and evidence of causality between exchange rates and commodity prices is reported for commodity-exporting as well as developed economies ([Zhang et al., 2016](#); [Ayres et al., 2020](#)). Monetary conditions also appear important: research has found that commodity prices are negatively related to U.S. interest rates ([Byrne et al., 2013](#); [Frankel, 2014](#)), while lower interest rates may contribute to stronger commodity price correlation ([Gruber and Vigfusson, 2018](#)). Beyond macroeconomic variables, global real economic activity is expected to drive commodity prices through demand pressures reflected in shipping and freight indicators ([Kilian, 2009](#); [Gargano and Timmermann, 2014](#); [Tiwari et al., 2024](#)). Overall, unexpected fluctuations in global economic activity play a role in commodity price movements ([Kilian and Zhou, 2018](#); [Alquist et al., 2020](#); [Hamilton, 2021](#)).

More recent contributions emphasise uncertainty as an additional driver of commodity market dynamics. Macroeconomic uncertainty has been shown to influence commodity prices and futures returns (Joëts et al., 2017; Bahloul et al., 2018), while economic policy uncertainty affects commodity price cycles and spillover transmission (Agnello et al., 2020; Mokni et al., 2020; Ren et al., 2022). Rising uncertainty may increase firms' financing costs and reduce investment activity (Gilchrist et al., 2014), with Joëts et al. (2017) finding commodity markets to be highly sensitive to such shocks. Geopolitical risk has also been identified as an important factor shaping commodity price discovery and connectedness, influencing returns and volatility spillovers across markets (Wang et al., 2022; Gong and Xu, 2022; Foglia et al., 2023; Baur and Smales, 2020).

Although this literature provides extensive evidence on individual determinants, fewer studies assess multiple categories of global drivers jointly. Early work by Akram (2009) examines the role of the US dollar and interest rates using an SVAR model, while Jacks and Stuermer (2020) focus on supply and demand dynamics. More recently, Bouri et al. (2021) highlight the importance of economic uncertainty and activity in shaping commodity futures connectedness, and Yang et al. (2022) examine trade policy uncertainty and geopolitical risks using a TVP-VAR model with stochastic volatility.

By reviewing the literature on the global determinants of commodity prices, we find that there is a lack of studies considering a comprehensive range of variables that represent the determinants. In order to explore a large number of potential determinants, we need to subdivide the variables into three categories of global determinants. To conduct this exercise, we depart from the methodological approaches used in the prior literature. Therefore, we employ a novel two-step approach, starting with a BDFM that allows us to estimate world and commodity group factors that drive co-movements in commodity prices. In the second step, a FAVAR model is used to reveal the categories of global determinants that explain these factors. This new approach allows us to take advantage of a large range of variables that potentially explain commodity prices.

3. Data and methodology

3.1. Data collection and description

The quarterly dataset we employ consists of sixteen commodity prices, and sixteen variables that are considered determinants of commodity prices. Our period of study, 1998Q1 to 2023Q4, is dictated by data availability.¹ Our sample incorporates major global economic events such as the growth of the Chinese economy (2004–2007), global financial crisis (2007–2009), tensions in the Strait of Hormuz between the United States, Iran, and the Gulf Arab states (2019–2020), COVID-19 pandemic (2020–2021), and the Russian invasion of Ukraine (2022–). Before using BDFM the time series of commodity prices were logarithmised, first differentiated, and demeaned.

With reference to the commodity prices, we employ the 1-month futures prices, which are grouped into four categories, namely, energy, precious metals, industrial metals, and agricultural. More specifically, energy commodities include four series: WTI crude oil, heating oil, gasoline, and natural gas. Precious metals incorporate gold, palladium, platinum and silver. Industrial metals include another four series: aluminium, copper, nickel, and zinc. Agricultural commodities comprise corn, cotton, soybeans, and wheat. All series are obtained from Bloomberg. The commodity futures prices are converted into real prices, and then we use the natural logarithm.² The motivation for this choice stems from the literature.³

Turning to the global determinants, we proxy factors that affect commodity price fluctuations: global financial market activity, global macroeconomic activity, as well as global uncertainty including macroeconomic and geopolitical. Financial stress, financial market indices, and financial market volatility are all employed to proxy global financial market activity. The measures of the Federal Reserve Bank of Kansas City and the FRED of St. Louis are used to approximate financial stress. The Morgan Stanley Capital International index for developed as well as emerging and developing markets is used to approximate financial (stock) market performance in terms of stock market returns. The VIX index, and the financial uncertainty index are used to capture financial (stock) market performance in terms of stock market volatility.

With reference to global macroeconomic activity, the short-term official/policy rates for advanced countries (excluding the US) and emerging countries are proxies of global interest rate fluctuations. Real (CPI-based) exchange rates for advanced countries (excluding the US) and emerging countries are proxies of global exchange rate movements. Furthermore, the global economic activity index and the Baltic index are both used to approximate shipping rates and, consequently, global economic activity.

Finally, regarding global uncertainty, the global economic policy uncertainty index and the macroeconomic uncertainty index are used to approximate global macroeconomic uncertainty, whereas the international geopolitical index and the historical geopolitical index are used to capture global geopolitical uncertainty. A detailed explanation of the definitions of the variables and the data sources can be found in Appendix A.⁴

¹ More specifically, the start date is attributed to the fact that the industrial metals commodity prices are available from late 1997. Therefore, the unavailability of such data creates constraints for examining a larger sample.

² We deflate the futures prices in order to obtain the real prices by using the US CPI, which is taken from the Federal Reserve Bank of St. Louis.

³ More specifically, Baumeister and Kilian (2014) refer to the construction of real-time forecasts of the real price of oil based on oil futures prices.

⁴ The FAVAR framework used in the second stage of the analysis treats all variables as endogenous, allowing us to explicitly account for potential reverse causality. As a result, strictly exogenous variables had to be excluded from the model.

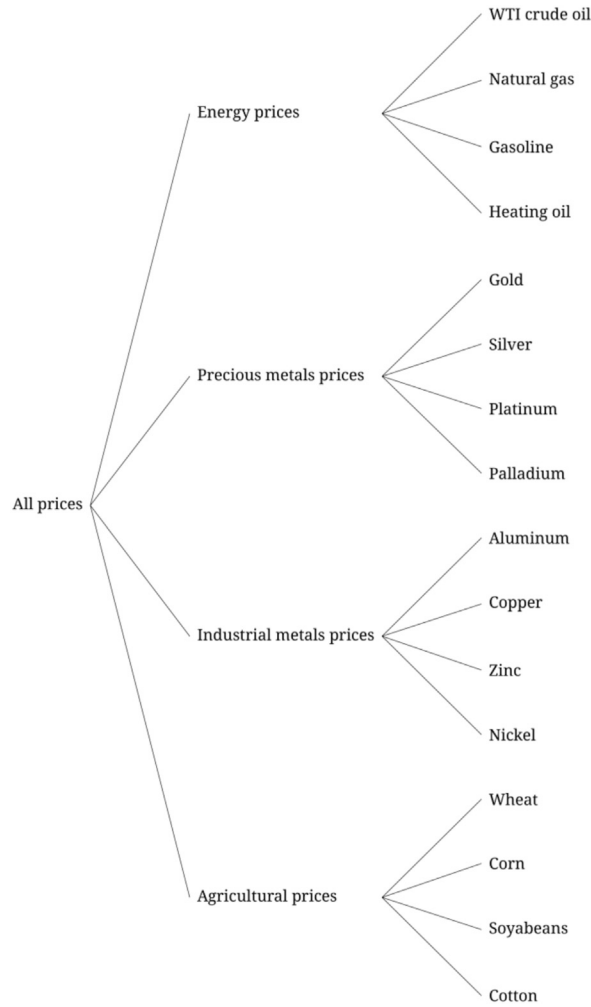


Fig. 1. 2-level Bayesian dynamic factor model structure. Note: The figure presents the relationship between the data structure and the factors within the 2-level BDFM.

3.2. Setup of the model

Before setting up the model, the time series of commodity prices was log-transformed, first-differenced, and demeaned. We utilise a dynamic factor model, first proposed by Geweke (1977), to extract a common component of commodity variables in order to assess the degree of their co-movement at the world and group levels. The present study utilises a 2-level dynamic factor model estimated using the Bayesian approach (BDFM) (Otrok and Whiteman, 1998; Kose et al., 2003, 2008, 2012; Jackson et al., 2016). The structure of the model is shown in Fig. 1.⁵

Let $N(= 16)$ denote the total number of commodity variables used in the analysis and $T(= 105)$ the length of the variables. In our analysis, we consider the quarterly growth rates of commodity prices. An observable variable is denoted by y_{it} , where $i = 1, \dots, N$ and $t = 1, \dots, T$. Within the model, there are two types of factors: the world (W) factor (common to all variables under scrutiny) and the commodity group (C) factor (common to all variables within a given commodity group—each group consists of four time series of commodity prices). Accordingly, the equation for the observable variable can be written as follows:

$$y_{it} = \alpha_i + \beta_i^W F_t^W + \beta_i^{C_m} F_{mt}^{C_m} + \varepsilon_{it}, \quad (1)$$

where m denotes the commodity group with $m \in [1, 4]$, while F_t^W and $F_{mt}^{C_m}$ denote the world and the commodity group factors, respectively. In addition, the component β_i^z , where $z = W$ or C_m , represents the factor loadings and shows the degree to which the variation in y_{it} can be attributed to each factor. The unexplained part of y_{it} is given by the idiosyncratic term ε_{it} , which shows the variation explained by developments specific to a given variable and measurement error. Idiosyncratic terms can be serially correlated but are assumed to be normally distributed and cross-sectionally uncorrelated at all leads and lags, $E(\varepsilon_{it}, \varepsilon_{jt-s}) = 0$ for $i \neq j$

⁵ For more on multi-level dynamic factor models, see Breitung and Eickmeier (2016), while for hierarchical dynamic factor models, see Moench et al. (2013).

(Kose et al., 2008; Jackson et al., 2016; Ha et al., 2023, 2024). The idiosyncratic term follows autoregression of order p :

$$\varepsilon_{it} = \phi_{i1}\varepsilon_{it-1} + \phi_{i2}\varepsilon_{it-2} + \dots + \phi_{ip}\varepsilon_{it-p} + u_{it}, \quad (2)$$

where $u_{it} \sim N(0, \sigma_i^2)$. Similar to the idiosyncratic term, the evolution of factors is governed by the autoregression of order q . Accordingly, factor k follows an $AR(q)$ process:

$$F_{it}^k = \Psi_{k1}F_{it-1}^k + \Psi_{k2}F_{it-2}^k + \dots + \Psi_{kq}F_{it-q}^k + v_{kt}, \quad (3)$$

where $v_{kt} \sim N(0, \sigma_k^2)$. Moreover, v_{kt} for all $k = 1, \dots, 5$ and ε_{it} are all mutually orthogonal. This assumption is required to allow for variance decomposition (Jackson et al., 2016). In the main results presented in this study, both q and p were set at 3 (quarters). We experimented with different lag structures (with p and q , set to 1, 2, 4, 5, 6, 7, and 8), and our results remained qualitatively similar.⁶ This should come as no surprise, as the variance around zero of a prior on polynomial terms declines exponentially with the lag. The details of the prior structure are left for Section 3.3.

The model described by Eqs. (1)–(3) suffers from rotational indeterminacy, and, consequently, it is impossible to identify the signs and scales of factors and factor loadings separately. To overcome this issue, the signs are identified by the requirement that one factor loading is positive for each factor. Specifically, following Kose et al. (2003), the world factor is positive for the price of oil. The commodity group factors are identified by setting the requirement of positive factor loading for the first factor in a given group (see Fig. 1). Scale identification follows Sargent et al. (1977); Stock and Watson (1989, 1992, 1993) by assuming that each σ_k^2 is constant. This is a common identification strategy in the literature, recently adopted by Beck and Jackson (2024) and Beck and Okhrimenko (2025). We experimented with the identification scheme by varying both the time series that load positively on a given factor and the prior assumptions on the innovation variances. The results remained qualitatively similar across all specifications. For brevity, we do not report these results in the paper, but they are available upon request.

3.3. Model estimation, priors, and the share of variance attributable to a factor

The model set out in Eqs. (1)–(3) is estimated using the approach proposed by Otrok and Whiteman (1998). It applies a Gibbs sampling method (Chib and Greenberg, 1996) to approximate the marginal and joint distributions by sampling from the conditional ones. As all the conditional distributions are known (parameters given data and factors, and factors given data and parameters), a Markov Chain Monte Carlo (MCMC) can be applied to generate random samples from the joint posterior distribution of the unknown parameters and the unobserved factors.⁷ The Gibbs algorithm can be summarised by the following three steps:

1. Simulation of AR coefficients and the variance of innovation shocks to equations (2-3) conditional on a draw of factors.
2. Draw of factor loadings conditional on the draw of factors.
3. Simulation of factors conditional on all the above parameters.

These steps are repeated 200,000 times to ensure the convergence of the chains, with the first 100,000 draws being discarded.⁸

We conform to the standard practice of utilising uninformative priors (Kose et al., 2008; Crucini et al., 2011; Jackson et al., 2016; Chen, 2018; Beck, 2021; Beck and Jackson, 2024). The prior on all factor loadings is $N(0, 1)$, while for the autoregressive parameters the prior is $N(0, \Sigma)$, where:

$$\Sigma = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 0 & 0.5 & 0 & \dots & 0 \\ 0 & 0 & 0.25 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 0.5^{q-1} \end{bmatrix}. \quad (4)$$

The prior on the innovation variances in the observable equation is given by Inverted Gamma:

$$\sigma_i^2 \sim IG(6, 0.001), \quad (5)$$

which can be classified as diffuse. Various changes in the prior structure had a very limited impact on the results.

The main questions addressed in the present paper concern the relative importance of the world factor and the commodity group factors in driving commodity prices. Therefore, the share of variance attributable to the world factor, the commodity group factors and, consequently, the idiosyncratic factor were estimated. With orthogonal factors, the variance of the variable that is observable,

⁶ The results are not reported for brevity but are available upon request.

⁷ The more detailed description of the estimation process is beyond the scope of this paper. The interested reader is referred to Otrok and Whiteman (1998) and Jackson et al. (2016).

⁸ We conducted a robustness test with a lower number of repetitions. We got virtually the same results using 2000 repetitions, out of which the first 1000 were dropped.

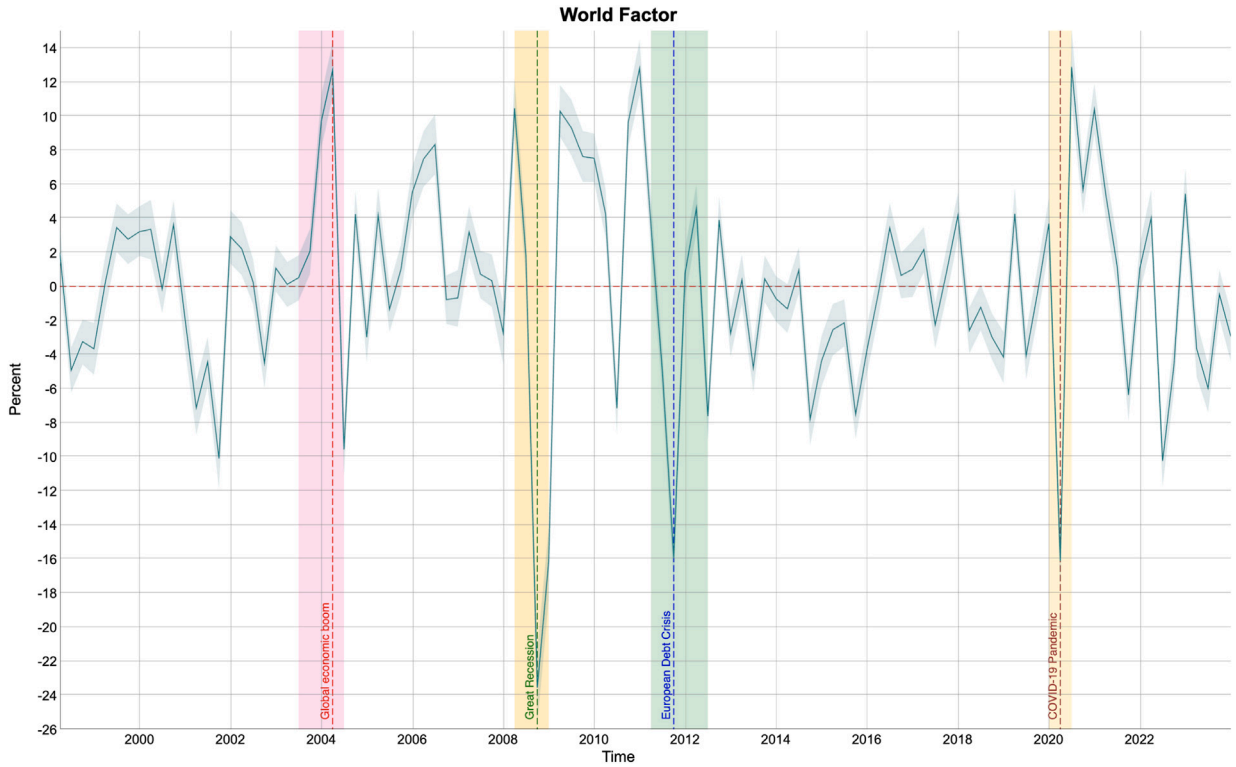


Fig. 2. The World Factor. Notes: 1/The Shaded area around the factor represents the interval between the 33rd and 66th percentiles of the posterior distribution. 2/The dashed line represents the main event of the period; the Shaded area represents the approximate length of the event. 3/The vertical axis is the percentage change from the previous period in the factor that drives the prices.

y_{it} , can be written as follows⁹:

$$\text{var}(y_{it}) = (\beta_i^W)^2 \text{var}(F_t^W) + (\beta_i^{C_m})^2 \text{var}(F_{mt}^{C_m}) + \text{var}(\varepsilon_{it}). \quad (6)$$

Consequently, the share of variance attributable to factor k is given by:

$$VS_{it}^k = \frac{(\beta_i^k)^2 \text{var}(F_t^k)}{\text{var}(y_{it})}. \quad (7)$$

Within this setting, the variance share attributable to a given factor depends on two elements. Firstly, the magnitude of the variance of factor k . Secondly, it depends on the responsiveness of a given time series to a given factor, measured by the (square of the) factor loading.

3.4. Factor plots

We will now examine the potential economic interpretations for five different unobserved dynamic factors that explain the co-movements of the commodity prices under consideration. The highs and lows of the world factor, shown in Fig. 2, are induced by changes such as the global economic boom around 2004, which was primarily driven by Chinese economic growth. Two sharp reductions in the world factor can be identified around the periods of the Great Recession (2007–2009) and the European debt crisis (2010–2012), which was also linked to weak global demand. On the other hand, COVID-19 led to a sharp contraction of production. Among these three major events, the largest drop in the size of the factor (in percent) is during the Great Recession. In addition to highlighting the importance of this episode, this more generally indicates the negative impact that very high levels of risk and greater exposure to losses have on commodity markets.

The commodity group factor plots are presented in Fig. 3. Turning first to the energy factor, noticeable peaks occur in 1999 and 2021, both originating from OPEC's intervention in the oil market to cut oil production. In 1999, this can be attributed to the previous year's oil price collapse following the Asian financial crisis and oversupply in the market. On the other hand, in 2021, there was rising energy demand. Ozili and Ozen (2023) argue that energy commodities and specifically gasoline prices increased globally,

⁹ To ensure that the variance shares sum up to one we follow Kose et al. (2003) and orthogonalised the sampled factors. An interested reader is referred to Section 3.4 of Jackson et al. (2016).

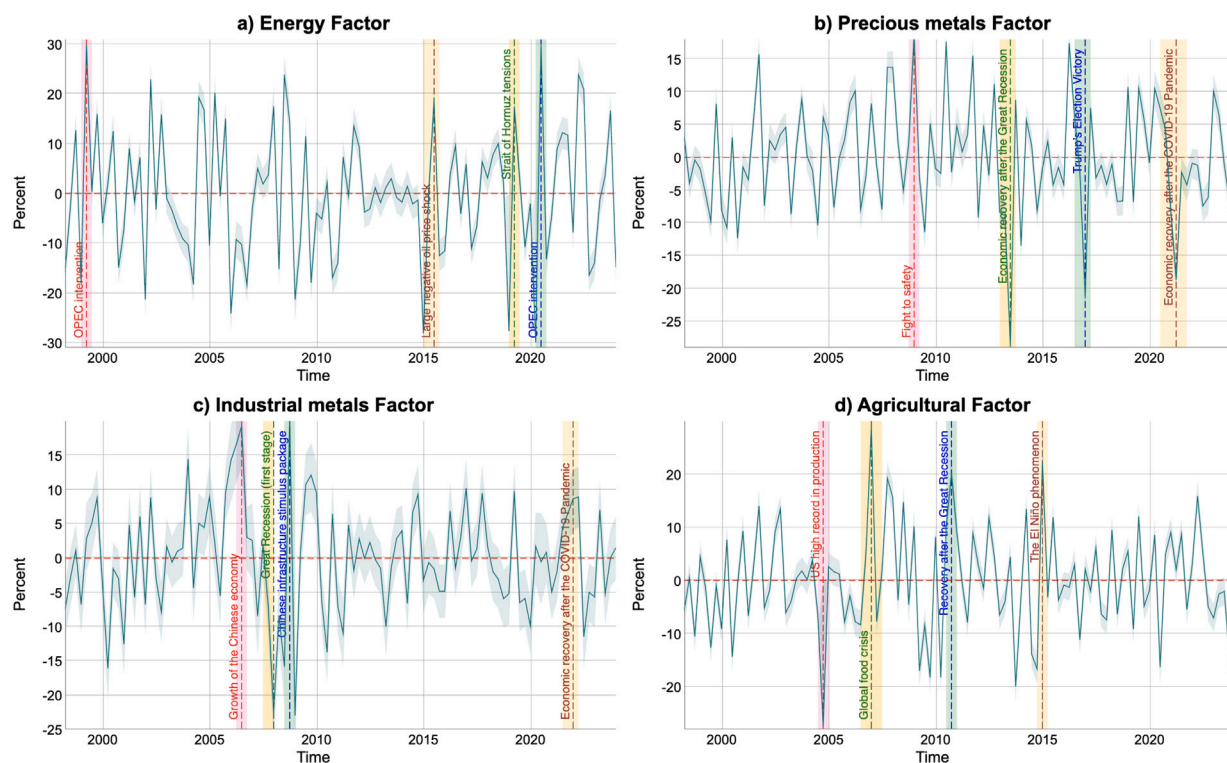


Fig. 3. The commodity group factors. *Notes:* 1/ Shaded area around the factor represents interval between 33rd and 66th percentiles of the posterior distribution. 2/ Dashed line represents main event of the period; Shaded area represents the approximate length of the event. 3/ the vertical axis is the percentage change from the previous period in the factor that drives the prices.

and this increase in gasoline prices occurred during the period when the COVID-19 pandemic restrictions were lifted in 2021. In contrast, there was a large drop in the energy factor around 2014/2015 due to the significant oil price decline, which was reflected in large negative oil price shocks, originated mainly from a slowdown in the global demand for oil and partly from increased shale oil production (Baumeister and Kilian, 2016a; Kilian, 2016). According to Baumeister and Kilian (2016b), this oil price decline was followed by a decline in the price of gasoline. On the other hand, the tensions in the Strait of Hormuz between the United States, Iran, and the Gulf Arab states (2019-2020) led to increasing energy commodity prices. The Strait of Hormuz is used to transport a fifth of the world's petroleum and a quarter of the world's liquefied natural gas.

With reference to the precious metals factor, we observe one increasing pattern in 2008. More specifically, during the wake of the Great Recession in 2008 and the unprecedented high levels of uncertainty in the global economy, the demand for precious metals and, consequently, their prices continued to rise. For instance, gold reached over \$1000 per ounce by the end of 2008. This situation indicated a flight to safety where investors attempted to protect their assets from financial turmoil, and thus, precious metals acted as safe haven assets. In this regard, Uddin et al. (2018) argue that gold, silver and palladium exhibit increasing behaviour during the Great Recession. Furthermore, we observe three abrupt falls around 2013, 2016/2017 and 2021. In April 2013, gold experienced its largest drop as gold prices fell 23%, the largest annual decline since 1981. This can be linked to a favourable economic climate, highlighting the end of the period for safe-haven assets. In addition, the election of Trump as the President of the US was associated with reductions in precious metals prices during 2016 and 2017. Factors that contributed to the declining pattern following this election included the appreciation of the US dollar and higher interest rates. Since gold is priced in dollars, a stronger dollar is historically linked to weaker gold prices as it makes gold an expensive asset for investors. Similarly, high interest rates offer greater returns and opportunities for investors to save and hence gold or silver become less attractive investments. Finally, the notable fall in 2021 was attributed to the end of COVID-19 pandemic uncertainty and thus a transition to economic recovery that shifted the perception of investors from safe haven assets to riskier assets.

As regards the industrial metals factor, we observe a rise in the late 1990s followed by a decline in early 2000s. These patterns can be attributed to strong global demand and the dot-com bubble economic decline, respectively, which both significantly affected industrial activities (Humphreys, 2010). Furthermore, it is evident that there is a persistent increasing pattern from 2005 until the beginning of the Great Recession. To this end, we mention the growth of the Chinese economy (2004–2007) and, consequently, the increasing demand for industrial commodities due to China's massive investments in real estate and infrastructure. Then, during the Great Recession in 2008, there was a major reduction and one sharp increase in 2009, which are both of similar magnitude. Indeed, during the first stage of the Great Recession, industrial metals prices collapsed due to the considerable drop primarily in Chinese demand and other emerging countries (i.e., India) for industrial commodities. However, this situation changed in the following year,

2009, when the Chinese government announced an economic stimulus package aimed mainly at funding infrastructure, which in turn positively affected the demand for industrial metals. Lin et al. (2017) refer to the Chinese industrial growth prior to and after the Great Recession, which was interrupted during the crisis period. Finally, the economic recovery following the COVID-19 pandemic led to higher prices for industrial metals. It is evident that this recovery was faster compared with the Great Recession, and this is attributed to factors such as weaker pre-pandemic industrial metals prices against stronger pre-Great Recession industrial metals prices, which led to quick price recovery. In addition, disruptions to metals supply and demand, as well as government stimulus measures, impacted the recovery of industrial metals prices.

With regard to the agricultural factor, one noticeable decreasing pattern appears in 2005. More specifically, U.S. farmers produced their largest-ever cotton crop and second-largest corn and soybean crops in 2005, which caused a significant reduction in their prices. Moreover, agricultural prices rose sharply in 2006/2007, 2010/2011 and 2015. In particular, the 2006/2007 price hike was attributed to the U.S. policy of using biofuels. This policy caused large volumes of corn to be diverted away from food and livestock production and into the production of ethanol for use as a transport fuel. Thus, increased biofuel production resulted in higher agricultural prices and consequently contributed to a global food crisis. In addition, during 2010/2011, the recovery of the global economy after the Great Recession created growth expectations for advanced and emerging economies and, hence, a positive economic environment. Finally, agricultural prices rose sharply upwards in 2015, potentially due to the El Niño periodic weather phenomenon. To this end, 2015 was the peak year for El Niño and this contributed to extreme events such as droughts and heavy rainfall worldwide. Therefore, such extreme events caused severe reductions in the global availability of agricultural commodities and hence increased their prices. The impact of El Niño on agricultural commodities during this period has been discussed by Bonato et al. (2023).

On a final note, considering the evolution of the factor plots over time that is illustrated in Figs. 2 and 3, we discern some additional notable patterns. More specifically, the plots suggest that the evolution of factors is indeed highly event-dependent and exhibits magnitudes that fluctuate between positive and negative areas. More specifically, we observe the percentage change in commodity prices from the previous period to the next, capturing the rate of change in the factor that drives the prices. Such percentage changes approach the extreme rate of 30% (either positive or negative). Therefore, events appear to play a significant role in triggering a significant increase or decrease in factor values between two periods.

3.5. Factor augmented vector autoregression

In the second stage of the analysis, we extend the approach from the previous section to consider three potential categories of global determinants behind the changes in commodity prices. In order to obtain these categories/factors, we employ a one-factor model to extract the common component from the data in the three categories. Consequently, we obtain the macroeconomic factor, financial factor, and uncertainty factor. This allows us to assess the impact of the three categories of global determinants on the world and commodity group factors driving the evolution of commodity prices.

We estimate five VAR models with the three categories of determinants and one of each of the factors estimated in the previous stage (one world factor and four commodity group factors). We use the model setup adopted by (Baumeister and Hamilton, 2018), where the structural form of the model is given by:

$$AF_t = BF_{t-1} + u_t \quad (8)$$

where F_t is an $(n \times 1)$ vector of observed variables at time t , A is an $(n \times n)$ matrix of contemporaneous structural relations, F_{t-1} an $(np + 1 \times 1)$ vector with a constant and lag of F_t , and u_t is a vector of noise innovations. The reduced form of this model is given by:

$$F_t = \Phi F_{t-1} + \varepsilon_t \quad (9)$$

$$\Phi = A^{-1}B \quad (10)$$

$$\varepsilon_t = A^{-1}u_t \quad (11)$$

The parameters of the VAR given in Eqs. (9)–(11), Φ and $E(\varepsilon_t, \varepsilon_t')$ are estimated with OLS. To identify the model, we impose a recursive structure on A , commonly referred to as a Cholesky decomposition. The matrix A is lower triangular, with the following form:

$$A = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \quad (12)$$

In order to examine the impact of macroeconomic, financial, and uncertainty factors on one of the commodity price factors, we performed variance decomposition within the five VAR models we estimated. The ordering of the variables in the results reported in the main text is: macroeconomic, financial, and uncertainty factors with one of the commodity price factors at the end. However, the ordering of the variables has no bearing on the results after three periods. The results with different orderings are not reported for brevity but are available upon request.

Table 1
Share of variance explained by the World, Commodity, and Idiosyncratic factors (1998–2023).

Group	Commodity	Factor	Percentile		
			33	50	66
Energy	WTI	World	26%	29%	33%
		Commodity	59%	63%	67%
		Idiosyncratic	6%	7%	8%
	Natural gas	World	2%	3%	4%
		Commodity	6%	7%	9%
		Idiosyncratic	88%	89%	90%
	Gasoline	World	22%	26%	30%
		Commodity	52%	56%	60%
		Idiosyncratic	17%	18%	19%
	Heat oil	World	21%	24%	27%
		Commodity	46%	49%	52%
		Idiosyncratic	26%	27%	28%
Precious metals	Gold	World	4%	6%	7%
		Commodity	67%	71%	75%
		Idiosyncratic	19%	23%	27%
	Silver	World	35%	38%	41%
		Commodity	37%	40%	44%
		Idiosyncratic	19%	21%	24%
	Platinum	World	46%	50%	54%
		Commodity	9%	11%	13%
		Idiosyncratic	36%	39%	42%
	Palladium	World	21%	24%	27%
		Commodity	1%	2%	3%
		Idiosyncratic	71%	74%	77%
Industrial metals	Aluminium	World	1%	3%	5%
		Commodity	1%	2%	6%
		Idiosyncratic	91%	94%	95%
	Copper	World	54%	58%	62%
		Commodity	17%	21%	25%
		Idiosyncratic	17%	20%	24%
	Zinc	World	27%	30%	33%
		Commodity	28%	34%	40%
		Idiosyncratic	32%	37%	42%
Agricultural	Wheat	World	1%	2%	3%
		Commodity	34%	37%	40%
		Idiosyncratic	58%	61%	64%
	Corn	World	11%	13%	15%
		Commodity	55%	59%	62%
		Idiosyncratic	26%	28%	31%
	Soybeans	World	11%	13%	15%
		Commodity	43%	46%	49%
		Idiosyncratic	38%	41%	44%
	Cotton	World	23%	25%	27%
		Commodity	4%	5%	6%
		Idiosyncratic	68%	69%	71%

Note: Shaded rows indicate the factor that explains the largest share of variance at the median (50th percentile) for each commodity.

4. Empirical results

4.1. Latent factor estimation results

In the first step of our analysis, we generate a variance decomposition as shown in Table 1,¹⁰ which allows us to identify the percentage share of the variance attributable to each factor, where the calculation is based on Eq. (7).¹¹ We also experimented with

¹⁰ Qualitatively similar results to those presented in the main text are obtained when using data deflated by the world price level, weekly forward prices, and 3-month forward prices. Correlations between the components of the baseline model and those obtained under the three alternative specifications are reported in Appendix C.

¹¹ All factor loadings are positive. The moments of the posterior distribution of the factor loadings are presented in Appendix B.

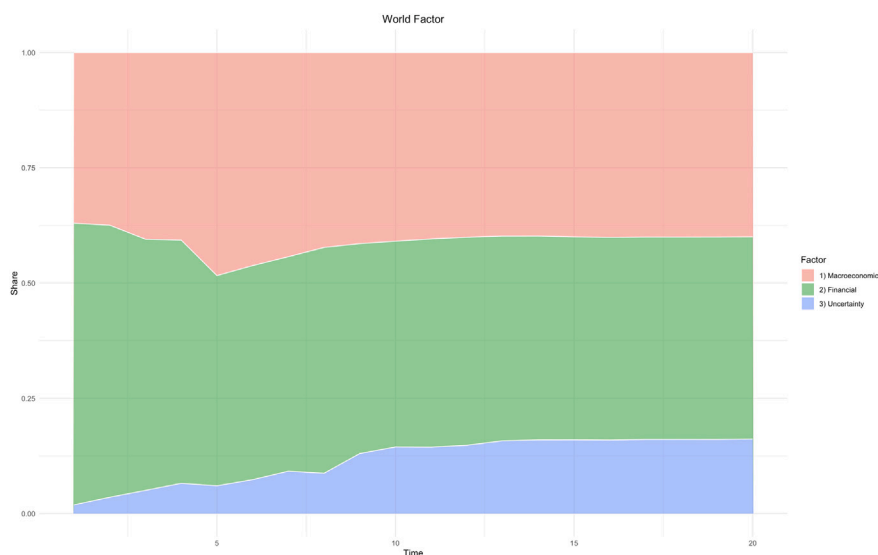


Fig. 4. FAVAR Results: World Factor. Notes: Time is expressed in quarters; graph depicts shares of variance explained by Macroeconomic, Financial, and Uncertainty factors.

the BRENT oil price instead of WTI, and this generated very similar results, which are available upon request. In the case of factor loadings, they are all positive, and therefore, all the commodity prices are positively correlated with the factors. Appendix B shows the results and their interpretations.

In the case of variance decomposition, we can see which factors are the most important for each commodity. We interpret the results based on estimates from the 50th percentile (median), while the 33rd and 66th percentiles can be treated as confidence bands. Firstly, for all types of energy commodities apart from natural gas, the commodity factor dominates. This result suggests that there are variables specific to the group of energy commodities that tend to drive the movement of crude oil, heating oil and gasoline prices. We can also identify a similar pattern in the case of the agricultural commodities where the commodity factor dominates in the cases of corn, soybeans and wheat, while cotton is an exception. Therefore, once again, we have evidence of a common agricultural group driver/s for the movement of corn, soybeans and wheat. Examples of potential drivers specific to the group of energy commodities and the group of agricultural commodities are highlighted in Fig. 3.

Turning to precious metals, we identify one of the only two cases where the world factor explains the majority of the share of the variance: platinum. However, for silver, the world factor still explains a large share of the variance. This suggests that drivers common to all commodity groups determine the prices of platinum and silver. Potential examples of events common to all commodity groups are shown in Fig. 2. In the case of gold, 71% of the variance is explained by the commodity group factor. While for palladium, the idiosyncratic factor explains 74% of the variance. This result suggests that the movement of palladium prices is driven by factors specific to this particular commodity. Finally, the idiosyncratic factor explains 94% of the share of the variance for aluminium and 66% for nickel. Once again, this suggests that factors specific to the individual commodities drive their prices. The second case of the dominance of the world factor is for copper, where it explains 58% of the variance. All three factors explain similar shares of the variance for zinc. Given the importance of the commodity group and world factors, the next section examines three categories of determinants that may be important drivers of world prices and commodity group prices.

4.2. FAVAR results

4.2.1. Analysis of the world factor

We now turn to the second step of our analysis, which involves three categories of determinants that include the variables described in Appendix A. We firstly extract the three common factors for the determinant categories and obtain: macroeconomic factor, financial factor and uncertainty factor, henceforth driving factors. Secondly, we estimate 5 VAR models.¹² The explained part of the impact of the driving factors on the world price factor is depicted in Fig. 4, where the variance decomposition is based on 20 quarters. If we reduce the number of quarters to 10, the results remain qualitatively similar.

The macroeconomic factor relates to a range of determinants, which include interest rates, exchange rates and measures of global economic activity. The macroeconomic factor could work through the demand channel. For instance, higher economic activity causes increases in the demand for all commodities and, consequently, their prices. Moreover, interest rate changes and exchange rate fluctuations tend to affect commodity prices. For example, a reduction in demand for commodities is anticipated in case of higher

¹² In the figures, we assumed that the shock originates from the macroeconomic factor. However, the results remain qualitatively similar regardless of which factor the shock has originated. For details, see Section 3.5.

interest rates or an appreciation of the US dollar. The study by Akram (2009) indicates the significant effect of declining interest rates on commodity prices. Agnello et al. (2020) document that higher global interest rates correspond to shorter booms and longer busts in commodity prices. In this respect, we can make a reference to the European debt crisis, which caused a significant reduction in economic activity and consequently reduced the demand for all commodities.

Similarly, the financial factor may exert an impact on the world factor. In this regard, a well-performing stock market influences investors' sentiment to invest in assets, including commodities, which drives commodity prices to persistently rise. Tiwari et al. (2022) show that the relationship between commodity prices and stock returns is time-varying and depends on the prevailing economic regime. Furthermore, financial instability is expected to affect investor behaviour and cause commodity prices to fluctuate widely. Chen et al. (2023) document a highly significant and persistent effect of financial instability (stress) on commodity price volatility. To this end, the Great Recession, which could be considered as a financial market-specific event, has contributed to a sharp reduction in commodity prices.

Turning our attention to the uncertainty factor, geopolitical tensions could cause increasing fears about the future availability of commodities, specifically in the producing regions and, thus, the supply side. Intense global geopolitical unrest creates a belief among the economic agents that a shortage in supply is expected to happen in the future. In the same vein, macroeconomic uncertainty may significantly affect commodity prices in the form of expectations about economic stability. On the one hand, Antonakakis et al. (2017) discuss the impact of geopolitical and economic unrest on the commodity markets with a particular focus on oil prices. On the other hand, Agnello et al. (2020), who employ geopolitical risk and economic policy uncertainty, do not report a significant impact on commodity prices. In this regard, we could document the tensions in the Strait of Hormuz, the world's most important global energy security transit chokepoint. This could be regarded as a geopolitical event that causes supply disruptions and increases the costs of commodity shipping.

The explained part of the impact of the macroeconomic and financial factors on the world factor declines over time. This can be attributed to the fact that changes in macroeconomic indicators, such as a change in interest rates by the central bank, or a change in a financial indicator, such as higher stock market returns or reduced stock market volatility, tend to directly influence the valuation of commodities. In particular, the financialisation of commodity markets and, consequently, the fact that commodities are regarded as financial assets implies that their sensitivities appear to have risen to macroeconomic and financial development news (Roache and Rossi, 2010). Furthermore, Elder et al. (2012) report that macroeconomic and financial shocks exert a strong and instantaneous impact on commodity prices. In fact, investors respond rapidly to such shocks as commodities can be used as a hedge against inflation and increasing stock market volatility or increasing financial stress (Baur and Lucey, 2010).

In contrast, the initial explained part of the response of the world factor to the uncertainty factor is much smaller than the other driving factors. Indeed, a time delay exists in the effect of the uncertainty on the commodities and this could be associated with delays in investment decisions by firms unpredictable production delays and increased transportation costs. Such delays influence the return and volatility of commodity prices, creating a lag in price performance, and thus, a weaker performance is expected in the commodity markets (Kang and Ratti, 2013; Aloui et al., 2016; Mokni et al., 2020; Shahbaz et al., 2024).

4.2.2. Analysis of the group factors

In this subsection, we present and discuss results that focus on the responses of the commodity factors to each of the driving factors. This allows for a detailed investigation of the underlying relations. We begin our group factor analysis by considering the macroeconomic factor. The results are reported in Fig. 5.¹³ More specifically, at the end of the period, the share of variance attributed to the macroeconomic factor is largest in the case of the energy factor, followed by the agricultural factor, then the precious metals factor and lastly, the industrial metals factor.

In this regard, the macroeconomic factor also appears to exert a greater instantaneous impact which is also higher in magnitude and thus more prevalent on the energy factor in comparison with the other three factors. Macroeconomic fundamentals such as interest rates, exchange rates, and real economic activity can strongly affect aggregate supply and demand for energy commodities. More specifically, an increase in real economic activity originating from decreasing shipping rates or a business cycle expansion is expected to positively impact the consumption and prices of energy commodities. For instance, Bunn et al. (2017) discuss the ability of macroeconomic fundamentals to drive the prices of energy commodities. Kilian and Vega (2011) indicate that energy commodities such as oil and gasoline may act as asset prices and jump in response to macroeconomic fundamentals or news. The precious metals factor, the industrial metals factor, and the agricultural factor show a negligible direct impact and lower magnitude in their responses to the macroeconomic factor. For example, by emphasising the precious metals factor, changes in macroeconomic fundamentals (i.e., a rise in interest rates) may tend to reduce the attractiveness of precious metals. Our results are in line with Batten et al. (2010) who document that there is limited evidence that macroeconomic factors significantly affect the prices of precious metals.

The additional information we get from Fig. 5 includes the explained part of the share of variance that is associated with the financial factor. In this regard, at the end of the period, the financial factor affects the agricultural factor the most, followed by energy and industrial metals factors, and then, closely behind, precious metals. The most prominent initial impact of the financial factor is on the agricultural factor and the industrial metals factor. Financial indicators such as stock market returns, stock market volatility and financial stress have an increased influence on all commodity price fluctuations. In this respect, Adams et al. (2020) report that financial indicators are the main factors that explain the variability in all commodity prices through the financialisation of commodity markets and the fact that commodities have been transformed into financial assets. Furthermore, Crespo Cuaresma et al.

¹³ As a robustness check, we also estimated a SVAR and obtained similar results. The model and the results are described in Appendix D.

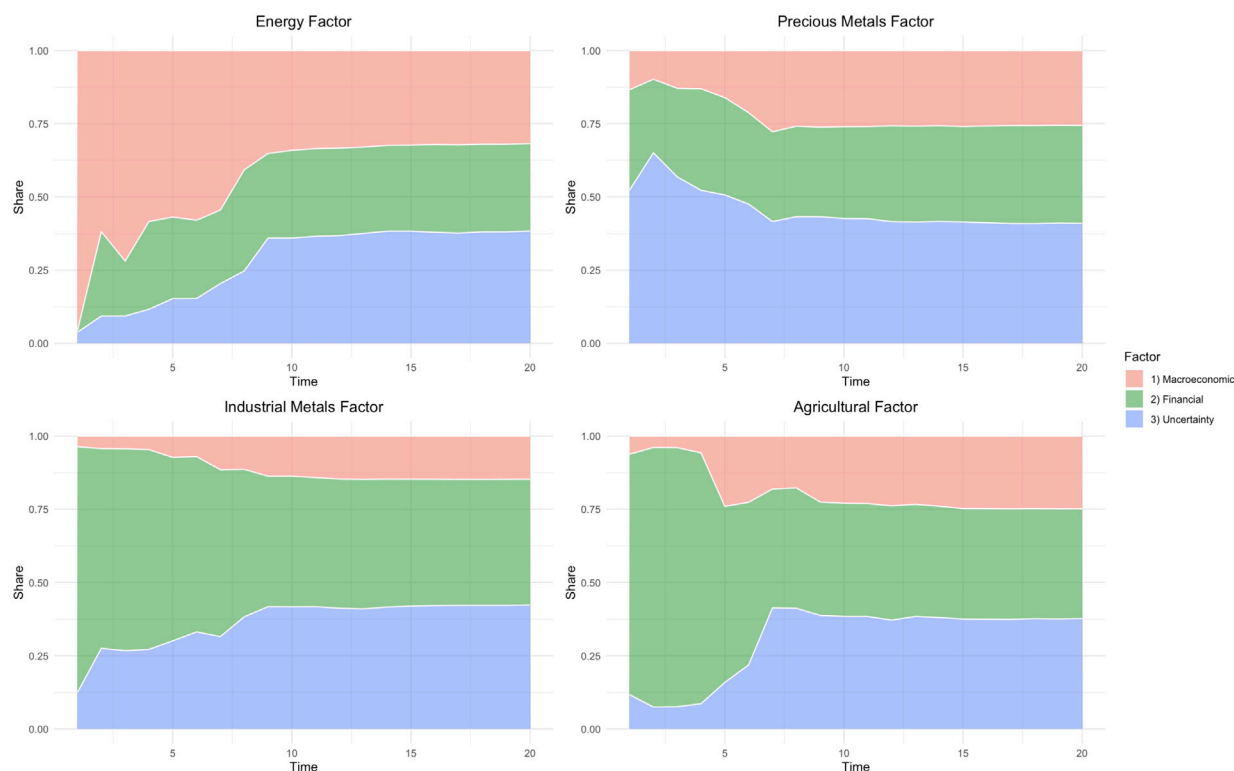


Fig. 5. FAVAR Results: Commodity Groups. Notes: Time is expressed in quarters; graph depicts shares of variance explained by Macroeconomic, Financial, and Uncertainty factors.

(2021) indicate the ability of financial variables to exercise a significant impact on agricultural commodities, whereas [Chen et al. \(2019\)](#) document the significant effects of financial factors to influence industrial metals commodities.

Finally, we turn to the uncertainty factor, which, by the end of the period, is most important in the case of the energy and agricultural factors, followed by the precious metals factor, and then the industrial factor. [Bakas and Triantafyllou \(2019\)](#) show that macroeconomic uncertainty is higher for energy commodities compared to the precious metals, industrial metals, and agricultural commodities. Nevertheless, our results indicate that the most direct impact is related only to the precious metals factor. Indeed, [Joëts et al. \(2017\)](#) find that macroeconomic uncertainty generates a high sensitivity to agricultural and industrial metals variability, while the effect on precious metals is more parsimonious, and this confirms the safe-haven role of precious metals. Moreover, [Baur and Smales \(2020\)](#) report that the response of other commodities differs from the response of precious metals in the existence of geopolitical uncertainty. The fact that precious metals respond instantaneously to the uncertainty factor is justified by the activities of investors to store wealth directly during periods of high uncertainty by using precious metals as hedging instruments (see, for instance, [Li and Lucey, 2017](#); [Bilgin et al., 2018](#); [Huynh, 2020](#)). Overall, world prices are influenced by macroeconomic, financial and, to a lesser extent, uncertainty factors. Uncertainty plays a relatively more important role in driving commodity group prices compared to world prices.

5. Conclusions

In this paper, we provide a holistic picture of what global factors drive commodity prices by novelly using a BDFM and FAVAR model. In the first step, using the BDFM, we have examined the comovement among our entire set of commodity prices over the period 1998–2023. We distinguish between the world factor and four commodity group factors. Secondly, we have considered three categories of determinants (driving factors), namely, macroeconomic, financial, and uncertainty factors, which are based on sixteen variables, where we have explored which categories of determinants (driving factors) explain the world and four commodity group factors. Our main findings can be summarised as follows. First, macroeconomic and financial factors are the primary drivers of global commodity prices, while uncertainty accounts for a much smaller share, remaining below 10% initially and below 20% even at longer horizons. Second, uncertainty plays a much stronger role at the commodity-group level, accounting for more than one-third of the variance at longer horizons across all commodity groups.

Policy interest in the impact of uncertainty has significantly increased in recent years as we have experienced several unexpected shocks, including COVID-19, Brexit and the outcome of the US elections. However, our results suggest that uncertainty is not as important as macroeconomic and financial factors in explaining world commodity prices. Therefore, this implies that policymakers can influence world commodity prices through the formulation of macroeconomic policies, which impact interest rates and exchange

rates. In addition, we find support for the financialisation of commodity markets, whereby trading activity has an important role in determining world commodity prices. There is a relatively larger importance of shocks or uncertainty in the case of commodity group prices. For example, Trump's first election victory is more likely to have a relatively stronger impact on the prices of precious metals than world commodity prices. Similarly, OPEC's intervention in the oil market is an unexpected event that is more likely to have a relatively larger impact on energy prices than world commodity prices. These patterns can also be traced back to the factor plots. Overall, the key takeaway is that policymakers have greater scope to influence global commodity prices through macroeconomic and financial channels, whereas disaggregated commodity prices are more sensitive to shocks and uncertainty.

Potential avenues for future research in this field of study could include the thorough investigation of other factors that affect commodity prices, such as speculation or inventories and, in general, data that are not publicly available. Moreover, future research may expand the analysis by incorporating additional channels, such as the consumption channel (changes in consumer confidence) or the investment channel (technological advances).

CRedit authorship contribution statement

Krzysztof Beck: Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Michail Filippidis:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Karen Jackson:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Georgios Magkonis:** Writing – review & editing, Software, Methodology, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Data sources

See [Table A](#).

Table A
Variables used to construct the FAVAR categories.

Brief description of variable	Proxy for	Data source
Financial category — Global financial market activity		
Kansas City Financial Stress Index	Financial market instability	Federal Reserve Bank of Kansas City
Financial Stress Index	Financial market instability	Federal Reserve Bank of St. Louis
VIX index	Stock market volatility	Bloomberg
Financial Uncertainty Index	Stock market volatility	www.sydneyludvigson.com
MSCI World Index (developed economies)	Stock market returns	Bloomberg
MSCI Index (emerging and developing economies)	Stock market returns	Bloomberg
Macroeconomic category — Global macroeconomic activity		
Interest rate (developed economies, excl. US)	Interest rate	Federal Reserve Bank of Dallas
Interest rate (emerging economies)	Interest rate	Federal Reserve Bank of Dallas
Exchange rate (developed economies, excl. US)	Exchange rate	Federal Reserve Bank of Dallas
Exchange rate (emerging economies)	Exchange rate	Federal Reserve Bank of Dallas
GEA	Global economic activity	Federal Reserve Bank of Dallas
Baltic Index	Global economic activity	Bloomberg
Uncertainty category — Global uncertainty (macroeconomic and geopolitical)		
EPU	Macroeconomic uncertainty	www.policyuncertainty.com
MUI	Macroeconomic uncertainty	www.sydneyludvigson.com
GPR International	Geopolitical uncertainty	www.matteoiacoviello.com
GPR Historical	Geopolitical uncertainty	www.matteoiacoviello.com

Appendix B. Factor loadings

Table B

The factor loadings on the world and the commodity factors of commodity prices over the 1998–2023 period.

Factor	World			Commodity		
Percentile	33	50	66	33	50	66
WTI	2.00	2.11	2.23	0.42	0.53	0.66
Natural gas	1.02	1.08	1.14	0.18	0.28	0.39
Gasoline	1.01	1.13	1.25	1.54	1.62	1.71
Heat oil	0.57	0.62	0.69	0.46	0.52	0.57
Gold	2.12	2.24	2.36	1.19	1.27	1.36
Silver	1.07	1.14	1.21	0.58	0.66	0.73
Platinum	1.57	1.67	1.76	1.49	1.59	1.69
Palladium	0.80	0.85	0.90	0.47	0.55	0.63
Aluminium	0.47	0.51	0.55	0.78	0.86	0.95
Copper	0.59	0.62	0.66	0.85	0.90	0.95
Zinc	1.48	1.57	1.65	1.16	1.25	1.34
Nickel	0.88	0.93	0.99	0.99	1.05	1.11
Wheat	1.22	1.29	1.37	1.05	1.13	1.20
Corn	0.40	0.44	0.49	0.80	0.85	0.90
Soybeans	1.28	1.38	1.48	1.15	1.23	1.31
Cotton	0.26	0.34	0.42	0.34	0.38	0.43

The results point to substantial heterogeneity in the extent to which commodity prices are driven by global, sectoral, and idiosyncratic forces (Table B).

Energy commodities tend to load more strongly on the commodity-group factor than on the world factor, particularly refined products such as gasoline and heating oil. This pattern reflects the importance of sector-specific mechanisms, including refining capacity constraints, transportation bottlenecks, and regulatory factors, which are not fully captured by global macroeconomic conditions. The variance decompositions corroborate this interpretation, showing that the commodity factor explains the largest share of price variation for most energy commodities. Natural gas constitutes an exception, with a dominant idiosyncratic component, consistent with the fragmented and regionally segmented nature of gas markets.

For precious and industrial metals, the importance of common factors varies across commodities. Gold and silver exhibit relatively strong co-movement with global factors, while palladium and aluminium display weaker loadings and a very large idiosyncratic component in the variance decomposition. At the median horizon, idiosyncratic shocks account for the majority of price fluctuations for these commodities, reflecting supply concentration, market thinness, and exposure to commodity-specific disruptions.

Overall, the joint evidence from factor loadings and variance decompositions highlights the heterogeneous transmission of global and sectoral shocks across commodity markets. While world factors capture broad macroeconomic influences, commodity-group and idiosyncratic factors play a central role for commodities characterised by supply rigidities and market-specific dynamics.

Appendix C

See Table C.

Table C

Correlation of model output from the main results with the output from robustness checks.

	World price level	Weekly forward prices	3-month forward prices
World Factor	0.99	0.97	0.99
Energy Factor	0.99	0.96	0.99
Precious Factor	0.99	0.95	0.99
Industry Factor	0.93	0.87	0.93
Agricultural Factor	0.99	0.96	0.99
Factor Loadings	0.95	0.94	0.96
Variance Decompositions	0.94	0.93	0.94

Notes: The column with the heading:

- 1) World price level - refers to the model obtained with the data deflated using the World price level;
- 2) Weekly forward prices - refers to the model obtained with one week forward prices;
- 3) 3-month forward prices - refers to the model obtained with one 3-month forward prices.

Appendix D

To assess the robustness of the results and to account for the potential effects of contemporaneous spillovers, we consider a structural VAR of the following form:

$$AF_t = B(L)F_{t-1} + u_t, \quad E(u_t u_t') = I, \quad (13)$$

where

$$F_t = \begin{pmatrix} \text{Macro}_t \\ \text{Financial}_t \\ \text{Uncertainty}_t \\ \text{Commodity}_t \end{pmatrix}. \quad (14)$$

In the baseline specification, identification relies on a recursive (Cholesky) structure that restricts contemporaneous interactions. To explicitly incorporate contemporaneous spillovers, we relax the recursive identification by allowing selected off-diagonal elements of the contemporaneous impact matrix A to be freely estimated:

$$A = \begin{pmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & a_{23} & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix}. \quad (15)$$

The unrestricted coefficients a_{23} and a_{43} capture contemporaneous spillovers from the uncertainty factor to financial conditions and commodity prices, respectively. Unlike the recursive specification, this structure allows uncertainty shocks to affect these variables within the same period.

The reduced-form representation is given by

$$F_t = \Phi F_{t-1} + \varepsilon_t, \quad \varepsilon_t = A^{-1}u_t. \quad (16)$$

Variance decompositions are computed from the structural moving-average representation

$$F_t = \sum_{j=0}^{\infty} \Psi_j u_{t-j}, \quad \Psi_j = \Phi^j A^{-1}, \quad (17)$$

where the impact matrix A^{-1} embeds the contemporaneous spillovers implied by the unrestricted elements of A . The forecast error variance decomposition attributes the h -step-ahead forecast error variance of each variable to the individual structural shocks, capturing both contemporaneous and dynamic transmission channels.

The results are depicted in Figs. 6 and 7.

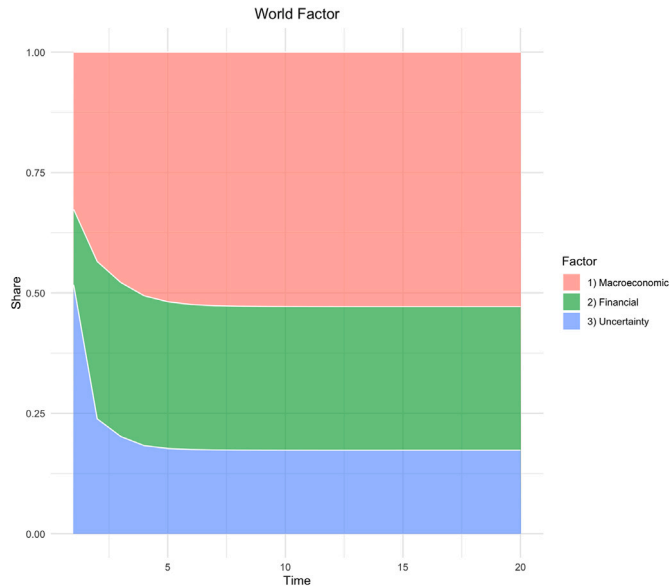


Fig. 6. FAVAR results from Structural VAR: World Factor. *Notes:* Time is expressed in quarters; graph depicts shares of variance explained by Macroeconomic, Financial, and Uncertainty factors.

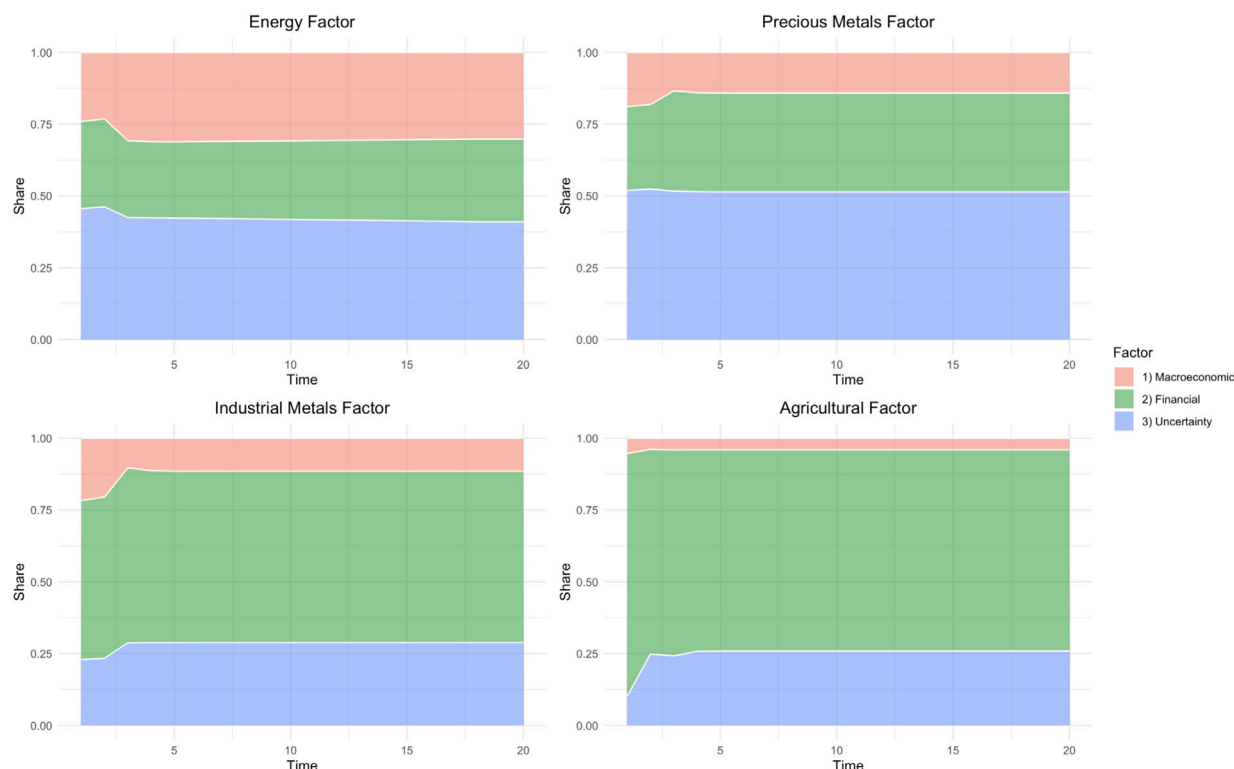


Fig. 7. FAVAR results from Structural VAR: Commodity Groups. Notes: Time is expressed in quarters; graph depicts shares of variance explained by Macroeconomic, Financial, and Uncertainty factors.

Data availability

Data will be made available on request.

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