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The three co's to jointly model commodity markets: co-production, co-consumption and co-trading

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Abstract
In this study, we develop a framework, based on a global vector autoregression (GVAR) model, to unite two perspectives on commodity markets, the commodity-specific, single-market-centered approach, investigating the micro- and macroeconomic drivers of commodity prices, and the market perspective, which observes joint movements of commodity prices on exchanges. Thereby, the GVAR model disentangles single market from inter-market effects, while simultaneously accounting for the impact of macroeconomic factors. We apply the framework to the six industrial metals markets, reflecting their interdependencies via their co-production, co-consumption, or co-trading relation. In particular, the numerous significant spillover effects in the cross-commodity dimension underline the importance of jointly modeling commodity markets. While the strong co-movement between industrial metal prices is represented exceptionally well by our framework, the microeconomic supply and demand attributes of the commodities have significant impact, within and across markets, even on price variables, highlighting their relevance in modern commodity market models. Moreover, we detect global shocks, e.g., an increase in global demand, affect each commodity market to a similar extent.

Keywords Commodities · Metal markets · Co-movement · Microeconomic factors · Global vector autoregressive model

JEL Classification Q02 · Q31 · C32 · C51

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1 Introduction

In our study, we propose and empirically apply a framework to unite two perspectives on commodity markets. The first one originates from the classical fundamental theory, which states a good's price is the result of its supply and demand equilibrium, see Hotelling (1931) and Deaton and Laroque (2003), and therefore models commodity markets via microeconomic and macroeconomic determinants. The second perspective originates from the empirical observation of common patterns in commodity prices. While commodities, in particular metals, are joint inputs in many construction and manufacturing applications, as well as joint outputs from individual mining operations, see Cuddington and Jerrett (2008), empirical studies detect the joint movement of commodity prices exceeds the co-movement allocable to the joint production and joint consumption of related commodities, see Pindyck and Rotemberg (1990). According to Vansteenkiste (2009), this co-movement behavior is partly driven by a common factor, which in turn is mainly driven by macroeconomic fundamentals. However, Tang and Xiong (2012) state the financialization of commodities increased the co-movement significantly, revealing the importance of financial markets and their effects for the determination of commodity prices.

To aggregate both perspectives, we apply a global vector autoregression (GVAR) model, which was initially designed by Pesaran et al. (2004) to analyze the world economy from an individual country level, under the limitation of small sample data sets. In a first step, we model each commodity market separately using vector autoregression (VAR) models with the commodity-specific, microeconomic supply, demand and price variables, as well as exogenous, macroeconomic attributes to account for the impact of economic activity, exchange rates and monetary policy on commodity prices. Subsequently, we link the individual VAR models to a global VAR (GVAR) model, hereby reflecting interdependencies as well as spillover effects between commodity markets. Therefore, we represent the relation between the commodities via information on co-production, co-consumption and co-trading of the commodities. Further, we investigate the spillover effects within and beyond commodity markets by applying generalized impulse response functions (GIRF) and provide more insights into the markets via a generalized forecast error variance decomposition (GFEVD) and correlation analysis.

In the empirical part of our study, we apply the framework to the industrial metal markets. Hereby, we reflect the interdependencies between the markets via their co-production, co-consumption or co-trading relation. Therefore, we estimate the GVAR model several times, connecting the individual, commodity-specific VAR models of the industrial metals with different weight matrices. First, we calculate a weight matrix representing the co-production relation by the common supply concentration. Second, a weight matrix based on co-consumption is approximated by the demand for industrial metals in the five largest industries, which in summary account for up to 90% of the worldwide industrial metal demand. Finally, the co-trading of financial investors at commodity markets is reflected by a weight matrix based on the correlation of trading volumes on the LME Futures exchange.

Our contribution to the literature on commodity markets is twofold. First, we propose a framework which incorporates the micro- and macroeconomic based theory as well as interdependencies between commodity markets. Second, the empirical validation of the framework provides new insights, as it disentangles single-market effects from inter-market effects in the industrial metal markets, while controlling for macroeconomic factors.

Hereby, our framework is able to represent the strong co-movement in commodity prices, in line with the publication of Tang and Xiong (2012). Moreover, the analysis detects strong interdependencies between the aluminum and copper market, which most likely originate from their joint consumption. In addition, various spillover effects between supply and demand variables within and across the commodity markets underline the importance of jointly modeling commodity markets. Further, we reveal microeconomic variables still influence prices significantly in modern markets. Finally, global shocks affect each commodity market to a similar extent. In particular, an increase in the global demand leads to rising commodity-specific demand as well as rising prices.

The remainder of this paper is structured as follows: Sect. 2 provides an overview over previous empirical work on commodity markets. In Sect. 3, our framework is presented in detail, while the empirical analysis and the results are described in Sect. 4, before Sect. 5 concludes.

2 Overview of commodity markets

In a short literature overview on commodity markets, we introduce two differing, yet valid perspectives. The first perspective relies on the classical fundamental theory which states a good's price is the result of the supply and demand equilibrium, while it additionally considers further price determinants, beyond the commodity-specific supply and demand. Within the second perspective, studies investigate the joint price behavior of (un-)related commodities on exchanges. Hereby, the studies show the joint production, consumption and the simultaneous impact of macroeconomic variables are unable to fully describe the co-movement of prices and attribute this behavior partly to the financialization of commodity markets.

2.1 Determinants of commodity prices

In general, commodities are a cornerstone of many economies, for commodity exporters as well as for commodity importers, see Byrne et al. (2013). In particular, industrial metals play an important role, as they are commonly used across a wide range of applications, ranging from small wires made of copper, to aircraft parts made from aluminum. Therefore, the classical fundamental theory, which states the supply and demand of a good determine its equilibrium price, remains valid for commodities, see Hotelling (1931) and Deaton and Laroque (2003). Moreover, Frankel and Rose (2010) emphasize the relevance of these factors, while they additionally account for global demand increases.

The empirical evidence for the impact of commodity-specific supply on commodity prices is mixed. While Ahumada and Cornejo (2014) detect significant long-run price effects of supply fluctuations, measured by the commodity-specific production value, Stuermer (2018) only finds mixed evidence of supply factors on prices, which he hypothesizes to be caused by the different elasticities of markets. Specifically, supply shocks are of significant importance for tin and copper, whereas the impact on crude oil prices is small to not measurable.

Due to data restrictions, the literature focusing on the impact of commodity-specific demand on prices is limited. Among the few studies considering commodity-specific supply as well as commodity-specific demand variables are Thomas et al. (2010) and Chen et al. (2019), who investigate the attributes' impact on the price of oil and copper, respectively. Hereby, both studies underline the importance of supply and demand for modeling commodity price fluctuations.

In contrast to these commodity-specific analyses, most of the studies approximate commodity demand via different measures of economic activity, such as the gross domestic product (GDP) or industrial production, see, for example, Ahumada and Cornejo (2014), Baffes and Savescu (2014), Borensztein and Reinhart (1994), Byrne et al. (2013), Deaton and Laroque (2003), Issler et al. (2014), Klotz et al. (2014) and Stuermer (2018). Hereby, Baffes and Savescu (2014) state industrial production positively affects prices, while Issler et al. (2014) provide empirical evidence of synchronized cycles in metal prices to those in industrial production. Moreover, the results of Borensztein and Reinhart (1994) indicate the consideration of global demand in commodity price frameworks improve the model fit as well as the forecast ability.

Using the world GDP as proxy for the global demand, Deaton and Laroque (2003) reveal demand fluctuations influence commodity prices in the short-run, whereas Stuermer (2018) detects global demand is the main determinant of prices, especially in the long-run. Further, Byrne et al. (2013) account for the global demand by including the growth rate of the US real GDP, whereas Ahumada and Cornejo (2014) as well as Klotz et al. (2014) focus on China's GDP and find significant effects on prices. Moreover, Helbling et al. (2008), as well as Frankel and Rose (2010) state the 2007–08 commodity price boom was caused by an increase in demand, i.e., through the growth of emerging economies and the biofuels trend. In particular, China was responsible for about 90% of the increase in the world consumption of copper from 2000 to 2006, see Helbling et al. (2008). While economic activity is commonly used as a demand proxy, it can undoubtedly also be interpreted as macroeconomic variable, indicating the significant influence of macroeconomic determinants on commodity prices. Therefore, commodity market models additionally include factors like exchange rates and interest rates, see Vansteenkiste (2009), for example.

While most of the commodities are traded in US dollar, they are rarely mined in the USA, which is why a decline in the dollar price would lead to an increase in the dollar price of the commodities or to a decrease in the foreign currency price. Therefore, exchange rates should, theoretically, be linked to future commodity prices through the terms of trade and income channel, as outlined by Chen et al. (2010), who empirically validate the importance of this factor by its out-of-sample predictive power on prices. Moreover, Lombardi et al. (2012) argue commodity exporters will raise commodity prices to ensure their purchasing power, in case the dollar looses value, and detect a statistically significant, negative effect of exchange rates to metal prices in their study. Further, Akram (2009) and Ahumada and Cornejo (2014) underline the negative relation between the real dollar exchange rate in their empirical analyses.

Monetary policy, commonly represented by (short-term) interest rates, is a central element of commodity price models, see Anzuini et al. (2013). Already in the theoretical model of Hotelling (1931), interest rates play a crucial role, as future commodity prices are hypothesized to rise by the interest rate, which is caused by the cost of capital and the speculation on mean reverting prices. In general, lower interest rates will lead to a portfolio shift of investors, out of bonds into other asset classes, in particular commodities, see Calvo (2008). Further, the lower interest rates will additionally reduce the cost of capital for holding a commodity, ultimately leading to lower storage costs and an elevated demand for commodities, while simultaneously sparking the incentives of commodity producers to decrease the supply, as the allocation of their revenues in bonds becomes less profitable, see Frankel (2014). Overall, lower interest rates will lead to higher commodity prices.

Empirically, Ahumada and Cornejo (2014); Byrne et al. (2013) and Vansteenkiste (2009) generally detect a significant negative impact of interest rate shocks on commodity prices, while Akram (2009) even discovers an overshooting behavior, as the market overreacts to changes in the interest rate. With focus on the Chinese monetary policy, Klotz et al. (2014) confirm this overshooting reaction for agricultural and energy commodity markets. However, the impact of the US federal funds rate on commodity prices is rather limited within the studies of Anzuini et al. (2013) and Frankel and Rose (2010), respectively, whereas the results of Baffes and Savescu (2014) support the negative relationship of interest rates and prices only for specific metals, but state the US dollar exchange rate has a significant effect.

2.2 Co-movement of commodity prices

In general, the global demand, the exchange rates as well as the interest rates affect all commodities simultaneously, which is why commodity prices tend to move in a synchronized way, a phenomenon called co-movement. Hereby, Delle Chiaie et al. (2022) highlight a substantial share of the co-movement can be described by a common factor, which is, in their case, mainly driven by the global economic activity, while according to Vansteenkiste (2009), general macroeconomic fundamentals are the main determinants of the common factor. Byrne et al. (2013) find a negative relation between interest rates, risk and the common factor. Hereby, macroeconomic determinants influence commodity prices directly and indirectly. The interest rate, for example, impacts prices directly by stimulating the current demand, while it further affects them indirectly through the expectations about the future demand, due to the storability of commodities, see Pindyck and Rotemberg (1990).

Besides the simultaneous impact of macroeconomic determinants on commodity prices, the common production as well as the common consumption of commodities leads to further interdependencies between commodity markets. On the one hand, commodities may substitute each other, for example, oil and bio-fuels, which in turn links food prices to the oil price, see Krugman (2008), whereas Baffes et al. (2020) state copper demand is highly correlated to aluminum prices, due to the substitutability of the two metals. On the other hand, commodities may be used collectively in alloys, such as AlSi9Cu3, for example, see Zapp et al. (2002). Moreover, commodities may be related through the co-mining of ores, contributing to the high correlation of prices, see Campbell (1985). In the case of lead, 70% of its production is derived from mixed Lead-Zinc ores, as stated by Nassar et al. (2015) and Shammugam et al. (2019).

However, the empirically observed co-movement of prices on exchanges is larger than what would be explainable by the common production, common consumption and the common factor of commodities, see Pindyck and Rotemberg (1990). Hereby, the authors detect even unrelated commodities co-move, which is why they introduce the concept of excess co-movement. Le Pen and Sévi (2017) reinvestigate the findings of Pindyck and Rotemberg (1990) and reveal the excess co-movement is time-varying and larger in magnitude after 2007. Overall, especially in recent times, the extent of co-movement increased. According to Tang and Xiong (2012), the financialization of commodity markets, especially the fast growing investment in commodity indices after 2004, is a key determinant for this increased co-movement. Moreover, Basak and Pavlova (2016) theoretically analyze how the financialization affects commodity markets, supporting the empirical findings of Tang and Xiong (2012), as their correlations are higher for index futures than those of non-index futures.

Overall, the empirically observed (excess) co-movement between commodity prices calls for jointly modeling commodities. However, the co-production and co-consumption relations imply not only prices, but also supply and demand factors of commodities are related, while these relations cannot be accounted for in a classical, individual commodity market model. Hereby, previous studies only focus on one perspective, either the price determinants of commodities—including microeconomic factors—or the joint behavior of prices. In contrast, our framework incorporates both perspectives and the relations between commodities into one holistic model.

3 Methodological framework

Commodity prices are still determining factors on, as well as determined by, fundamentals. Therefore, we apply individual vector autoregression (VAR) models on all commodities, $i = 1, \ldots, N$, of the analysis, to model the dependencies between the individual supply ($\mathbf{s_i}$), demand ($\mathbf{d_i}$) and price ($\mathbf{p_i}$) variables, which form the vector $\mathbf{x}_{i,t} = (s_{i,t}, d_{i,t}, p_{i,t})'$, for all time periods $t = 1, \ldots, T$:

$$\mathbf{x}_{i,t} = \mathbf{\Phi}_i \mathbf{x}_{i,t-1} + \mathbf{\Psi}_{i,0}\mathbf{e}_t + \mathbf{\Psi}_{i,1}\mathbf{e}_{t-1} + \boldsymbol{\varepsilon}_{i,t} \tag{1}$$

where $\mathbf{\Phi}_i$ is the $k_i \times k_i$ matrix of lagged coefficients, with $\kappa = k_i = 3$, denoting the length of vector $\mathbf{x}_{i,t}$ and the maximum lag length $p = 1$, which is applied for data limitation reasons.[1] To represent the common factor in our framework, we include

[1] The Breusch-Godfrey test shows no autocorrelation for the analyzed commodity data at the 5% significance level, indicating this restriction to lag length one is feasible.

r macroeconomic factors as exogenous variables[2] in the vector $\mathbf{e}_t$, with $\boldsymbol{\Psi}_{i,0}$ and $\boldsymbol{\Psi}_{i,1}$ as $k_i \times r$ matrices of the corresponding coefficients. Further, we assume that the $k_i \times 1$ vectors of idiosyncratic commodity-specific shocks $\boldsymbol{\varepsilon}_{i,t}$ are serially uncorrelated, independent and identically distributed, with mean zero and covariance matrix $\boldsymbol{\Sigma}_{ii}$. Therefore, $\boldsymbol{\varepsilon}_{i,t} \sim iid\,(\mathbf{0}, \boldsymbol{\Sigma}_{ii})$.

While these individual VAR models simultaneously model the dependencies between the commodity-specific supply, demand and price within each commodity market, hereby taking into account the effect of macroeconomic factors, they are unable to reflect the relationships between markets, inter alia the entire co-movement observed on exchanges, as the only connection considered between the commodities is via common macroeconomic information. However, beyond the macroeconomic factors, the commodity markets are interrelated through co-production, co-consumption as well as co-trading, see Sect. 4.2, which is why individual VAR models are not sufficient to represent the complexity of commodity markets. One solution would be the estimation of a single VAR model, including all commodity-specific variables as well as the macroeconomic determinants. Generally, such a model consists of $p\cdot(\kappa\cdot N-1)+(p_{\text{exog}}+1)\cdot r$ parameters, where p denotes the order of the VAR model, N the number of commodities in the analysis, κ the number of variables per commodity and r the number of macroeconomic determinants with p_{exog} the corresponding lag length, see Pesaran et al. (2004). In case of 3 commodities, $\kappa = 3$, $p = 1$ and $r = 3$, this leads to a model of 14 parameters. However, once such an analysis is expanded to 10 or 20 commodities, the number of estimated parameters increases to 35 or 65 already.

As commodity-specific supply and demand data are only available at low frequency, the estimation of these models is infeasible from a statistical point of view. In general, low data frequency in conjunction with many potentially influential variables is a key problem in econometrics. Pesaran et al. (2004) proposed a way to overcome these data limitation issues by connecting several individual VAR models into one global VAR model (GVAR).[3] While the GVAR model was initially constructed for the world economy, we adopt the idea to commodity markets. Therefore, we simultaneously estimate several individual, commodity-specific VAR models consisting of supply, demand and price variables, as well as the macroeconomic determinants and connect these individual models in a GVAR model via a methodology based on the original paper, as well as Dées et al. (2007b) and Dées et al. (2007a) in the following.

We extend the commodity-specific VAR models from Eq. 1 with the $k_i^* \times 1$ vector $\mathbf{x}_{i,t}^* = (s_{i,t}^*, d_{i,t}^*, p_{i,t}^*)'$ of weighted external variables, specific to commodity i:

$$\mathbf{x}_{i,t} = \boldsymbol{\Phi}_i \mathbf{x}_{i,t-1} + \boldsymbol{\Lambda}_{i,0}\mathbf{x}_{i,t}^* + \boldsymbol{\Lambda}_{i,1}\mathbf{x}_{i,t-1}^* + \boldsymbol{\Psi}_{i,0}\mathbf{e}_t + \boldsymbol{\Psi}_{i,1}\mathbf{e}_{t-1} + \boldsymbol{\varepsilon}_{i,t}, \tag{2}$$

[2] Since metal commodity markets are comparably small, we assume exogeneity of all macroeconomic fundamentals and include them as exogenous variables in our models. Moreover, bivariate Granger causality tests confirmed the exogeneity of all macroeconomic variables. While oil and macroeconomic variables are interrelated, the trading and production volumes of the individual metals are comparable small. In particular, we include an economic activity index in the vector of exogenous variables, to account for the impact of global demand on commodity markets, besides the impact of commodity-specific demand within the individual VAR models.

[3] We acknowledge Bayesian VAR models may also be a solution to overcome the problem of data limitations. However, this study focuses on the benefits of adapting the GVAR methodology on commodity markets, which allows for the specific modeling of the connecting channels between markets.

where $\mathbf{\Lambda}_{i,0}$ and $\mathbf{\Lambda}_{i,1}$ are $k_i \times k_i^*$ matrices of coefficients associated with the exogenous, external specific variables, where in our case $k_i^* = k_i$. These external commodity variables are defined as:

$$s_{i,t}^* = \sum_{\iota=1}^{N} w_{i,\iota} s_{\iota,t}, \;\; d_{i,t}^* = \sum_{\iota=1}^{N} w_{i,\iota} d_{\iota,t}, \;\; p_{i,t}^* = \sum_{\iota=1}^{N} w_{i,\iota} p_{\iota,t},$$

with weights $w_{i,i} = 0$ and $\sum_{\iota=1}^{N} w_{i,\iota} = 1$, for $i = 1, \ldots, N$, where the corresponding individual weights $w_{i,\iota}$ may be aggregated to a weight matrix $(w_{i,\iota})_{i,\iota=1,\ldots,N}$. While the initial GVAR model of Pesaran et al. (2004) uses import and export data, the so called trade weights, to link individual economies into one model, our framework incorporates information from common supply, demand and trading activity to link the commodities, see Sect. 4.2.

In order to set up the GVAR model, we define the $(k_i + k_i^*) \times 1$ vector $\mathbf{z}_{i,t} = (\mathbf{x}'_{i,t}, \mathbf{x}^{*\prime}_{i,t})'$ and rewrite Equation 1 for $i = 1, \ldots, N$:

$$\mathbf{A}_i \mathbf{z}_{i,t} = \mathbf{B}_i \mathbf{z}_{i,t-1} + \mathbf{\Psi}_{i,0} \mathbf{e}_t + \mathbf{\Psi}_{i,1} \mathbf{e}_{t-1} + \boldsymbol{\varepsilon}_{i,t}, \tag{3}$$

where $\mathbf{A}_i = (\mathbf{I}_{k_i}, -\mathbf{\Lambda}_{i,0})$, with $\mathbf{I}_{k_i}$ denoting the $k_i \times k_i$ dimensional unit matrix, and $\mathbf{B}_i = (\mathbf{\Phi}_i, \mathbf{\Lambda}_{i,1})$ are $k_i \times (k_i + k_i^*)$ dimensional matrices. Moreover, we require $\mathbf{A}_i$ to have full row rank for $i = 1, \ldots, N$.

By $\mathbf{x}_t = (\mathbf{x}'_{1,t}, \ldots, \mathbf{x}'_{N,t})'$, we denote the $k \times 1$ global vector of all commodity-specific variables, where $k = \sum_{i=1}^{N} k_i$. With the link matrices $\mathbf{W}_i$ of fixed constants, defined in terms of the commodity-specific weights $w_{i,\iota}$, we can write $\mathbf{z}_{i,t} = \mathbf{W}_i \mathbf{x}_t$. Using this in Eq. 3, we get:

$$\mathbf{A}_i \mathbf{W}_i \mathbf{x}_t = \mathbf{B}_i \mathbf{W}_i \mathbf{x}_{t-1} + \mathbf{\Psi}_{i,0} \mathbf{e}_t + \mathbf{\Psi}_{i,1} \mathbf{e}_{t-1} + \boldsymbol{\varepsilon}_{i,t}. \tag{4}$$

Stacking Eq. 4 together for $i = 1, .., N$, we get:

$$\mathbf{G} \mathbf{x}_t = \mathbf{H} \mathbf{x}_{t-1} + \mathbf{\Psi}_0 \mathbf{e}_t + \mathbf{\Psi}_1 \mathbf{e}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{5}$$

with the $k \times k$ dimensional matrices $\mathbf{G} = ((\mathbf{A}_1 \mathbf{W}_1)', \ldots, (\mathbf{A}_N \mathbf{W}_N)')'$, $\mathbf{H} = ((\mathbf{B}_1 \mathbf{W}_1)', \ldots, (\mathbf{B}_N \mathbf{W}_N)')'$, the $k \times r$ dimensional matrices $\mathbf{\Psi}_0 = (\mathbf{\Psi}'_{1,0}, \ldots, \mathbf{\Psi}'_{N,0})'$, $\mathbf{\Psi}_1 = (\mathbf{\Psi}'_{1,1}, \ldots, \mathbf{\Psi}'_{N,1})'$, and the $k \times 1$ vector $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{1,t}, \ldots, \boldsymbol{\varepsilon}'_{N,t})'$. In case of a non-singular matrix $\mathbf{G}$, we define $\mathbf{F} = \mathbf{G}^{-1}\mathbf{H}$, $\mathbf{\Upsilon}_0 = \mathbf{G}^{-1}\mathbf{\Psi}_0$, $\mathbf{\Upsilon}_1 = \mathbf{G}^{-1}\mathbf{\Psi}_1$ and $\boldsymbol{\upsilon}_t = \mathbf{G}^{-1}\boldsymbol{\varepsilon}_t$. Rewriting Eq. 5, we get the GVAR model in its final form:

$$\mathbf{x}_t = \mathbf{F} \mathbf{x}_{t-1} + \mathbf{\Upsilon}_0 \mathbf{e}_t + \mathbf{\Upsilon}_1 \mathbf{e}_{t-1} + \boldsymbol{\upsilon}_t. \tag{6}$$

This enables us to model the markets of all commodities simultaneously, while accounting for the dependencies in the cross-commodity dimension.

In line with Pesaran et al. (2004), we propose to analyze the spillover effects within and between the commodity markets by generalized impulse response functions (GIRF), first proposed by Koop et al. (1996) and further developed in Pesaran and Shin (1998). In contrast to the frequently used orthogonalized impulse response functions, the GIRF analysis needs, due to its invariance property, no hierarchy of the commodities, see Dées et al. (2007b). In general, the GIRF of a shock to the j-th element of $\mathbf{x}_t$, corresponding to the ℓ-th variable of the i-th commodity, is defined as:

$$\begin{aligned}\mathbf{GI}_{x,\varepsilon_{i,\ell}}(n,\ \sqrt{\sigma_{ii,\ell\ell}},\ \mathcal{I}_{t-1}) = \mathbb{E}[\mathbf{x}_{t+n} \mid \varepsilon_{i,\ell,t} = \sqrt{\sigma_{ii,\ell\ell}},\ \mathcal{I}_{t-1}] - \mathbb{E}[\mathbf{x}_{t+n} \mid \mathcal{I}_{t-1}],\\ n = 0, 1, 2, \ldots,\end{aligned} \tag{7}$$

where $\mathcal{I}_{t-1} = (\mathbf{x}_t,\ \mathbf{x}_{t-1},\ \ldots)$ denotes the information set at time $t-1$, including common macroeconomic variables $\mathbf{e}_t$.

Under the assumption of multivariate normal distributed $\boldsymbol{\varepsilon}_t$, we can calculate GIRFs as follows:

$$\begin{aligned}\mathbf{GI}_{x,\varepsilon_{i,\ell}}(n,\ \sqrt{\sigma_{ii,\ell\ell}},\ \mathcal{I}_{t-1}) = \frac{1}{\sqrt{\sigma_{ii,\ell\ell}}}\mathbf{F}^n\mathbf{G}^{-1}\boldsymbol{\Sigma}\boldsymbol{\xi}_j,\\ n = 0, 1, 2, \ldots,\end{aligned} \tag{8}$$

where $\boldsymbol{\Sigma}$ is the $k \times k$ variance-covariance matrix of shocks $\boldsymbol{\varepsilon}_t$, $\sigma_{ii,\ell\ell}$ represents the ii, $\ell\ell$-th element of $\boldsymbol{\Sigma}$, $\boldsymbol{\xi}_j$ denotes the $k \times 1$ selection vector, with $\boldsymbol{\xi}_j = 1$ for the j-th element and $\boldsymbol{\xi}_j = 0$ else. This measures the effect of a one standard error shock to the j-th equation (corresponding to the ℓ-th variable in the i-th commodity) at time t on expected values of $\mathbf{x}$ at time $t+n$. In addition to analyzing commodity-specific effects within a market, the GIRF analysis also reveals spillover effects of a shock on the variables of the other commodity markets.

Besides the spillover effects within and between commodity markets, the impact of shocks to the exogenous variables, e.g., a global demand shock, on commodity markets can be examined via GIRFs. To analyze the effects of a shock in the i-th exogenous variable $\mathbf{e}_{\mathrm{i},t}$ on the commodity markets, a dynamic process for the exogenous variables has to be specified, see Pesaran et al. (2004). Therefore, we assume the vector of exogenous markets follows a first-order[4] autoregression process:

$$\mathbf{e}_t = \boldsymbol{\mu}_e + \boldsymbol{\Phi}_e\mathbf{e}_{t-1} + \boldsymbol{\varepsilon}_{e,t}, \tag{9}$$

where $\boldsymbol{\mu}_e$ denotes the $r \times 1$ vector of intercepts, $\boldsymbol{\Phi}_e$ is the $r \times r$ matrix of lagged coefficients, and $\boldsymbol{\varepsilon}_{e,t}$ is the $r \times 1$ vector of shocks to the exogenous variables. Hereby, we assume $\boldsymbol{\varepsilon}_{e,t}$ to be serially uncorrelated, independent and identically distributed, with mean zero and covariance matrix $\boldsymbol{\Sigma}_e$; therefore, $\boldsymbol{\varepsilon}_{e,t} \sim iid(\mathbf{0}, \boldsymbol{\Sigma}_e)$.

Similar to the GIRFs of a shock to a commodity-specific variable, the GIRF of the effect of a shock to the i-th exogenous variable $\mathbf{e}_{\mathrm{i}}$ on the vector of endogenous variables $\mathbf{x}$ is defined by:

$$\begin{aligned}\mathbf{GI}_{\mathbf{x}:\mathbf{e}_{\mathrm{i}}}(n,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) = \mathbb{E}[\mathbf{x}_{t+n} \mid \boldsymbol{\varepsilon}_{e,t} = \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}] - \mathbb{E}[\mathbf{x}_{t+n} \mid \mathcal{I}_{t-1}],\\ n = 0, 1, 2, \ldots,\end{aligned} \tag{10}$$

[4] The Breusch-Godfrey test shows no autocorrelation for the analyzed commodity data at the 5% significance level, indicating the restriction to lag length one is feasible.

where $\sigma_{e,\mathrm{ii}}$ is the i-th diagonal element of $\boldsymbol{\Sigma}_e$.

Using the GVAR model in its final form in Eq. 6, we derive:

$$\begin{aligned}
&\mathbf{GI}_{\mathbf{x}:\mathbf{e}_\mathrm{i}}(n,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) \\
&= \mathbf{F}\mathbf{GI}_{\mathbf{x}:\mathbf{e}_\mathrm{i}}(n-1,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) \\
&\quad + \boldsymbol{\Upsilon}_0\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(n,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) + \boldsymbol{\Upsilon}_1\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(n-1,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}),
\end{aligned} \tag{11}$$

for $n = 0, 1, 2, \ldots$ with

$$\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(n,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) = \mathbb{E}[\mathbf{e}_{t+n} \mid \boldsymbol{\varepsilon}_{e,t} = \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}] - \mathbb{E}[\mathbf{e}_{t+n} \mid \mathcal{I}_{t-1}]. \tag{12}$$

It holds $\mathbf{GI}_{\mathbf{x}:\mathbf{e}_\mathrm{i}}(n-1,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) = \mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(n-1,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) = 0$, for $n < 1$, and $\mathbf{GI}_{\mathbf{x}:\mathbf{e}_\mathrm{i}}(0,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) = \boldsymbol{\Upsilon}_0\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(0,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1})$. Moreover, for multivariate normal distributed errors $\boldsymbol{\varepsilon}_\mathbf{e}$, the following equation holds:

$$\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(0,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) = \frac{1}{\sqrt{\sigma_{e,\mathrm{ii}}}}\boldsymbol{\Sigma}_\mathbf{e}\boldsymbol{\xi}_\mathrm{i}, \tag{13}$$

where $\boldsymbol{\xi}_\mathrm{i}$ denotes a $r \times 1$ selection vector, with $\boldsymbol{\xi}_\mathrm{i} = 1$ for the i-th element and $\boldsymbol{\xi}_\mathrm{i} = 0$ else. Using Eq. 13 and the VAR model of the exogenous variables in Eq. 9, we obtain:

$$\begin{aligned}
\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(n,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) &= \boldsymbol{\Phi}_e\mathbf{GI}_{\mathbf{e}:\mathbf{e}_\mathrm{i}}(n-1,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) \\
&= \frac{1}{\sqrt{\sigma_{e,\mathrm{ii}}}}\boldsymbol{\Phi}_e^n\boldsymbol{\Sigma}_\mathbf{e}\boldsymbol{\xi}_\mathrm{i}.
\end{aligned} \tag{14}$$

Finally, inserting Eq. 14 in Eq. 11, we obtain:

$$\begin{aligned}
\mathbf{GI}_{\mathbf{x}:\mathbf{e}_\mathrm{i}}(n,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) &= \mathbf{F}\mathbf{GI}_{\mathbf{x}:\mathbf{e}_\mathrm{i}}(n-1,\ \sqrt{\sigma_{e,\mathrm{ii}}},\ \mathcal{I}_{t-1}) \\
&\quad + \frac{1}{\sqrt{\sigma_{e,\mathrm{ii}}}}(\boldsymbol{\Upsilon}_0\boldsymbol{\Phi}_e + \boldsymbol{\Upsilon}_1)\boldsymbol{\Phi}_e^{n-1}\boldsymbol{\Sigma}_\mathbf{e}\boldsymbol{\xi}_\mathrm{i}.
\end{aligned} \tag{15}$$

Further, VAR models may be analyzed via a forecast error variance decomposition. Due to the correlated shocks between commodities in our GVAR model, we apply the alternative approach of generalized forecast error variance decomposition (GFEVD), as proposed in Dées et al. (2007a). Hereby, the GFEVD represents the proportion of the variance of the n-step forecast errors explained by the shocks of variable $j \in \{1, \ldots, k\}$. In particular, the GFEVD, which represents the proportion of the n-step ahead forecast error variance of the h-th element of x_t, accounted for by the innovations in the j-th element of x_t, is defined as:

$$\begin{aligned}
\mathbf{GFEVD}_{\mathbf{x}_{h,t},\varepsilon_{j,t}}(n) &= \frac{\sigma_{jj}^{-1}\sum_{l=0}^{n}(\boldsymbol{\xi}_h'\mathbf{F}^l\mathbf{G}^{-1}\boldsymbol{\Sigma}\boldsymbol{\xi}_j)^2}{\sum_{l=0}^{n}\boldsymbol{\xi}_h'\mathbf{F}^l\mathbf{G}^{-1}\boldsymbol{\Sigma}\mathbf{G}^{-1\prime}\mathbf{F}^{l\prime}\boldsymbol{\xi}_h}, \\
n &= 0, 1, 2, \ldots.
\end{aligned} \tag{16}$$

Since the shocks of variables are correlated, leading to a non-diagonal variance-covariance matrix $\mathbf{\Sigma}$, the elements of the $\mathbf{GFEVD}_{\mathbf{x}_{h,t},\varepsilon_{j,t}}(n)$ across j do not sum to unity, which is why we scale them to guarantee comparability. To summarize, the GVAR methodology allows the consideration of cross-commodity dependencies between markets, while simultaneously incorporating commodity-specific microeconomic and exogenous macroeconomic variables.

4 Empirical application to industrial metal markets

4.1 Data

We analyze the spillover effects, as well as the interdependencies within and beyond the markets of the industrial metals aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn). Therefore, we use their commodity-specific annual attributes supply, demand and price in our VAR models as endogenous variables in the period 1970–2019. Following the idea of Fernandez (2015), we approximate each individual global commodity demand ($\mathbf{d_i}$) by the global, commodity-specific apparent consumption. Therefore, we adjust the commodity-specific US apparent consumption, as provided by U.S. Geological Survey (2020a), by the ratio of reported US GDP and world GDP,[5] drawn from U.S. Bureau of Economic Analysis (2022) and The World Bank (2022).[6] Moreover, we include the worldwide commodity-specific primary production, reported by U.S. Geological Survey (2020b), as supply variable ($\mathbf{s_i}$). The price variable ($\mathbf{p_i}$) is specified as the annual mean of each daily commodity price, while the daily price data of nickel and lead are only provided since July 1993. Therefore, we extend the time series backwards with prices provided in the Mineral Commodity Summaries of the USGS, see U.S. Geological Survey (2013) and Table 18 in the Appendix for more detailed information. The vector of exogenous, macroeconomic variables includes the world gross domestic product, drawn from The World Bank (2022), as proxy for economic activity, the US dollar index, drawn from ICE Futures U.S. (2022), as proxy for the exchange rate, as well as the federal funds rate, drawn from Board of Governors of the Federal Reserve System (U.S.) (2022) as interest rate.

[5] This study proposes a new framework to disentangle single-market effects from inter-market effects, while controlling for macroeconomic factors. Hereby, we intend to analyze the long-term interdependencies between commodity markets in the period from 1970 to 2019. For this period, only the apparent consumption data of the USA is available, provided by U.S. Geological Survey (2020a). Therefore, we approximate the world metal consumption by the US apparent consumption, applying the ratio of reported US GDP and world GDP. However, this approach may underestimate the metal-intense rise of emerging markets in the past 20 years.

[6] As commodity-specific inventory data is unavailable for the required sample period, we rely on the apparent consumption. Hereby, we benefit from the consumption indicating the true consumption of the commodity, in contrast to regular demand, which also includes demand for inventories.

In order to satisfy the central assumption of stationarity in VAR models,[7] we apply the augmented Dickey–Fuller (ADF) test[8] to each of the attributes and calculate log returns, even for interest rates, in case of non-stationary data, based on the five percent significance level. All time series were non-stationary at first, which yields in a final dataset of log return variables from 1971–2019. Descriptive statistics of the resulting stationary variables, as well as the results of the ADF test for the original and log return data are given in Table 19 in Appendix A. For our analysis, we standardize these returns to have zero mean and standard deviation one, but use the original variable names unadjusted, i.e., supply, demand and price.

4.2 Model and weight matrices

4.2.1 Possible linkages in industrial metal markets

In contrast to Pesaran et al. (2004), who use the GVAR model to link individual economies via trade weights, we propose to apply the methodology to commodity markets, estimating the GVAR model several times with different weight matrices, each representing one relationship dimension between industrial metal markets.

First of all, industrial metals are interrelated on their supply side, as they are co-mined together. In the case of lead, 70% of its production is derived from mixed Lead-Zinc ores, as stated by Nassar et al. (2015) and Shammugam et al. (2019).

Second, dependencies between metals also occur on the demand-side of markets. In particular, there are substitution, but also co-consumption links. Baffes et al. (2020) state copper demand is highly correlated to aluminum prices, which originates from the substitutability of copper by aluminum in certain industries, electricity, for example. However, the use statistics of aluminum and copper show their co-consumption in AlSi9Cu3 alloys, used for various automotive applications, see Zapp et al. (2002).

Further, the common trend in prices, observed during the last decades, can no longer be explained via their co-production and co-consumption links only, as the co-movement in commodity prices has significantly increased since the financialization of commodities and the associated increase in index investments. In general, commodity prices tend to move in a synchronized way, as they are simultaneously influenced by macroeconomic determinants. However, Basak and Pavlova (2016) reveal the increasing investments of index funds in commodity markets should further elevate the co-movement. Although Hamilton and Wu (2015) find no direct effect of futures traders positions on prices, the study of Tang and Xiong (2012) empirically detects an increase in the co-movement of commodities, starting in the year 2004, due to the financialization, which is stronger for indexed commodities. Additionally, Zhang et al. (2019) highlight individual commodity prices co-move with a common liquidity factor of the markets, namely the Amihud measure of Amihud (2002). Moreover,

7 Since the results of the Johansen test indicate no cointegration relationship in our data, we estimate vector autoregression models instead of vector error correction models.

8 We thank an anonymous reviewer for the suggestion to use unit root tests with structural breaks. Therefore, we additionally apply the Zivot and Andrews unit root test, which allows a break at an unknown point in either the intercept, the linear trend or in both, see Zivot and Andrews (2002) and get similar results.

Table 1 Co-production of commodities

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.05	0.04	0.24	0.17	0.19
Cu	0.05	0.00	0.02	0.06	0.05	0.06
Ni	0.04	0.02	0.00	0.04	0.06	0.03
Pb	0.24	0.06	0.04	0.00	0.16	0.19
Sn	0.17	0.05	0.06	0.16	0.00	0.13
Zn	0.19	0.06	0.03	0.19	0.13	0.00

This table displays the co-production of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn)

Büyüksahin and Robe (2014) detect the liquidity between spot and futures markets is linked. Therefore, we propose to consider the co-trading behavior on commodity exchanges as further market linking channel.

4.2.2 Weight matrices

In the original study of Pesaran et al. (2004), the authors reflect the interdependencies between individual economies via trade weights. As industrial metal markets are related to each other through their common supply and demand, we propose to estimate the GVAR model several times using different weight matrices. Hereby, we also account for the co-movement between prices due to the investors' behavior. Therefore, the weight matrices in our framework include information on the co-production, co-consumption and co-trading relations between commodities.

First, we use information on the common supply concentration of the commodities and aggregate it as a measure of co-production via:

$$w_{i,\iota} = \sum_{c} \mathrm{prod}_{c,i} \cdot \mathrm{prod}_{c,\iota}, \text{ for } i, \iota = 1, \ldots, N, \; i \neq \iota \tag{17}$$

with $w_{i,\iota}$ denoting the relation between commodity i and commodity ι and $\mathrm{prod}_{i,c}$ denoting the country-specific share of annual world production of country $c = 1, \ldots, C$ for commodity i. Hereby, the production data is the averaged, per-country breakdown of our supply ($\mathbf{s}_i$) variable, in the period from 2010 to 2019, again obtained from U.S. Geological Survey (2020b) (Table 1).

Second, we analyze the sectors in which industrial metals are co-consumed, approximating the economy by the five industries *Automotive/Transportation*, *Chemistry/Pharmaceutics*, *Electrics*, *Construction* and *Mechanical Engineering*, which in summary account for up to 90% of the worldwide demand, see Appendix B for detailed information.

Table 2 displays the proportion of consumption per commodity and industry. We aggregate these industry-specific values to a demand-side information matrix via the

Table 2 Consumption of the commodities

Industry	Al	Cu	Ni	Pb	Sn	Zn
Automotive/Transportation	0.36	0.10	0.32	0.00	0.00	0.63
Chemistry/Pharmaceutics	0.00	0.00	0.00	0.05	0.22	0.08
Electrics	0.15	0.64	0.05	0.83	0.78	0.00
Construction	0.33	0.17	0.32	0.06	0.00	0.29
Mechanical Engineering	0.15	0.09	0.32	0.06	0.00	0.00

This table displays the aggregated consumption of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn), in the industry sectors automotive/transportation, chemistry/pharmaceutics, electrics, construction and mechanical engineering

Table 3 Joint consumption of commodities

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.20	0.27	0.15	0.12	0.33
Cu	0.20	0.00	0.15	0.55	0.50	0.11
Ni	0.28	0.15	0.00	0.08	0.04	0.29
Pb	0.16	0.55	0.08	0.00	0.66	0.02
Sn	0.12	0.50	0.04	0.66	0.00	0.02
Zn	0.33	0.11	0.29	0.02	0.02	0.00

This table displays the demand-side information matrix; based on the common proportion, the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn) are belonging to the considered industry sectors Automotive/Transportation, Chemistry/Pharmaceutics, Electrics, Construction and Mechanical Engineering, according to Eq. 18

following formula:

$$w_{i,\iota} = \sum_h \mathrm{ind}_{h,i} \cdot \mathrm{ind}_{h,\iota}, \text{ for } i, \iota = 1, \ldots, N, \; i \neq \iota \tag{18}$$

where $w_{i,\iota}$ denotes the weight between commodity i and commodity ι, whereas $\mathrm{ind}_{h,i}$ denotes the proportion of consumption of commodity i in industry h = {Automotive/ Transportation, Chemistry/Pharmaceutics, Electrics, Construction, Mechanical Engineering} (Table 3).

Third, to represent the co-trading of investors in commodity markets, we calculate the Pearson correlation coefficient between the daily total volume of traded contracts from the London Metal Exchange (LME), see Thomson Reuters Eikon (2022g), in the period from 2010 to 2019, see Table 4.[9]

[9] In contrast to the observed data of co-production and (approximated) co-consumption, the co-trading information matrix is based on estimated correlations. While the basic idea of Pesaran et al. (2004) is to reduce the number of parameters using the observed trade weights to link the individual country-specific models, Gross (2013) propose a procedure to estimate the weights jointly with the GVAR's parameters. In this line, the estimated correlations of the trading volume matrix will lead to a feasible weight matrix.

Table 4 Futures trading volumes correlation matrix

	Al	Cu	*Ni*	Pb	Sn	Zn
Al	1.00	0.05	−0.15	0.04	0.15	−0.01
Cu	0.05	1.00	0.35	0.37	0.20	0.42
Ni	−0.15	0.35	1.00	0.35	−0.08	0.57
Pb	0.04	0.37	0.35	1.00	0.28	0.66
Sn	0.15	0.20	−0.08	0.28	1.00	0.14
Zn	−0.01	0.42	0.57	0.66	0.14	1.00

This table displays the Pearson correlation matrix between the daily, first Futures trading volumes of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn) from the London Metal Exchange (LME), calculated over the period from 2009 to 2019

Table 5 Supply weight matrix (**S**)

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.08	0.06	0.34	0.25	0.27
Cu	0.21	0.00	0.10	0.26	0.19	0.24
Ni	0.19	0.12	0.00	0.21	0.32	0.16
Pb	0.34	0.09	0.06	0.00	0.23	0.28
Sn	0.30	0.08	0.11	0.28	0.00	0.23
Zn	0.32	0.10	0.05	0.32	0.22	0.00

This table displays the supply-side weight matrix of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn)

To aggregate the individual commodity markets in a GVAR model, we scale these information tables to row sums of 1. The resulting weight matrices supply (**S**), demand (**D**) and trading volume (**T**) are displayed in Tables 5, 6 and 7.[10] However, as co-production, co-consumption and co-trading occur simultaneously in practice, we estimate a fourth, common weight matrix (**C**), which aggregates all three dimensions, see Table 8. Therefore, we construct the common weight matrix by equally weighting the previously calculated, individual weight matrices.

4.3 Empirical results

To analyze the dynamic properties of the GVAR model, we calculate generalized impulse response functions (GIRFs), according to Eq. 8. This methodology investigates direct and indirect effects on the attributes to an innovation of one standard deviation in a certain variable. Our analysis is based on the 68% confidence bounds obtained by a sieve bootstrap procedure with 1000 replications, as proposed in Dées et al. (2007b). Runkle (1987) and Lütkepohl (1990) both point out impulse responses can inflate false negatives, a problem also Galesi and Lombardi (2009) suffer from, in the analysis of their unrestricted GVAR models. Although data limitations, as caused

10 Tables 5, 6, 7 and 8 show rounded values, whereas further calculations in the model use the true values without rounding.

Table 6 Demand weight matrix (**D**)

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.19	0.26	0.14	0.11	0.30
Cu	0.14	0.00	0.10	0.36	0.33	0.08
Ni	0.33	0.18	0.00	0.10	0.05	0.35
Pb	0.11	0.37	0.05	0.00	0.45	0.01
Sn	0.09	0.37	0.03	0.49	0.00	0.01
Zn	0.42	0.15	0.38	0.03	0.02	0.00

This table displays the demand-side weight matrix of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn)

Table 7 Trading weight matrix (**T**)

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.12	0.37	0.11	0.39	0.02
Cu	0.03	0.00	0.25	0.27	0.15	0.30
Ni	0.10	0.23	0.00	0.23	0.05	0.38
Pb	0.03	0.22	0.21	0.00	0.16	0.39
Sn	0.18	0.23	0.10	0.32	0.00	0.17
Zn	0.00	0.23	0.32	0.37	0.08	0.00

This table displays the trading volume weight matrix of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn)

Table 8 Common weight matrix (**C**)

	Al	Cu	Ni	Pb	Sn	Zn
Al	0.00	0.13	0.23	0.20	0.25	0.20
Cu	0.13	0.00	0.15	0.30	0.22	0.20
Ni	0.21	0.18	0.00	0.18	0.14	0.30
Pb	0.16	0.23	0.11	0.00	0.28	0.23
Sn	0.19	0.23	0.08	0.36	0.00	0.14
Zn	0.25	0.16	0.25	0.24	0.11	0.00

This table displays the common weight matrix of the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn)

by a small sample size, could further harm the results, our analysis detects numerous significant responses.

Within this subsection, we first investigate the GIRFs of the individual, commodity-specific VAR models, followed by our main results, the GIRF analysis of the global model. Hereby, we examine the effects of the commodity-specific variables to shocks within the commodity markets as well as the effects of global shocks, i.e., shocks in the economic activity, exchange rates and interest rates, on commodity markets. Subsequently, we underline our findings through a GFEVD analysis, as well as a correlation analysis and conclude with a discussion of our results.

Table 9 GIRF results of the individual VAR models

	Al			Cu			Ni			Pb			Sn			Zn		
	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p
s	+			+	+		+		+	+	+		+		+	+		
d		+		+	+			+		+	+			+			+	+
p			+			+	+		+			+	+		+		+	+

Results of GIRF analysis for the individual, commodity-specific VAR models, showing the response of the column variables to a shock of the row variables supply (s), demand (d) and price (p) of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn), where significant positive (+) or negative (−) effects are displayed, based on the 68%- level

4.3.1 Individual VAR models

First, we examine the spillover effects within the individual industrial metal markets, by analyzing the GIRFs of the commodity-specific VAR models. Therefore, we estimate each industrial metal market separately, with the commodity-specific variables supply, demand and price, via individual VAR(1) models, according to Eq. 1. Hereby, we include the exogenous variables world gross domestic product (GDP), federal funds rate (FFR) and US dollar index (FX), with one lag, to account for the impact of macroeconomic factors on the commodity markets.[11]

To aggregate the GIRF results of each individual commodity market and to facilitate the comparison with the corresponding results of the GVAR model, we present the results of the GIRF analysis in Table 9, where we indicate significant positive, or negative, responses of the column variables to a shock in the row variables, by a (+) or (-) respectively.

Hereby, supply and demand interact positively to each other for copper and lead, while supply and price positively interact in the nickel and tin markets. This is rather counterintuitive, since we would expect an inverse reaction of price (demand) on supply (price) shocks. However, we observe a synchronous behavior between demand and price in the zinc market. As the GIRF methodology investigates direct as well as indirect effects on the attributes to an innovation of one standard deviation in a certain variable, the observed reactions may be caused by unobservable, indirect effects. In contrast, we detect no significant spillover effects in the aluminum market.

[11] The results of the Breusch-Godfrey test, the multivariate ARCH-LM test and the OLS-CUSUM test to each commodity-specific VAR model indicate neither model suffers from autocorrelation, heteroscedasticity nor structural breaks at the 5% significance level, except the nickel market, see Table 28. The Henze-Zirkler test for normality shows the VAR models of aluminum, nickel, lead, tin and zinc have multivariate normal distributed residuals, while the Henze-Zirkler test rejects the null hypothesis of multivariate normality for the copper market. We estimate the VAR models via ordinary least squares, therefore, multivariate normal distributed residuals are, in general, not required. However, we estimate the GIRFs under the assumption of normal errors, based on Eq. 8. We only provide the GIRFs of the individual VAR models as preliminary analysis, to allow for a comparison of the GVAR model with individual commodity market models. As we estimate the GVAR model with one lag, we do not adjust the specifications of the VAR model of the copper market, although the corresponding residuals show a non-normal behavior. Hereby, we keep in mind the true GIRFs may deviate from the presented ones.

Besides the spillover effects within the individual commodity markets, we also investigate the impact of shocks to the exogenous variables to the commodity markets. In particular, we examine how the commodity-specific variables respond to innovations in the economic activity, the exchange rate or the interest rate. Therefore, we first model the exogenous variables, world gross domestic product (GDP), US dollar index (FX) and federal funds rate (FFR), via a VAR(1) model.[12] Subsequently, we derive the impact of a shock to each exogenous variable on the individual commodity markets, using Eq. 15, and display the responses in analogy to the GIRF analysis of shocks within the commodity markets in Table 10.

Overall, the GIRF analysis reveals the shocks to the macroeconomic variables affect each commodity market to a similar extent. Hereby, an increase in the global demand, indicated by a positive shock in the world GDP, leads to significantly rising supply, demand and prices, except for the copper supply. The reduction in copper supply might be explainable via its role as leading indicator of the global economic situation. Hence, the copper production might already have been cut back, although the economy is currently still on the rise. Moreover, in line with Vansteenkiste (2009), a positive shock to the exchange rate, reflecting an appreciation of the dollar, leads to decreasing values in all metal markets, except for the copper supply, which responds positively, again underlining the special position of copper.

In addition, the reactions of the supply side to a contrarian monetary policy, i.e., represented by a positive shock to the interest rate, are mixed. While the supply of lead and zinc decrease, contrary to Frankel (2008), a positive shock in the interest rate leads to an increase in the production volume of tin, probably due to the more profitable extraction of commodities in high interest rates environments. Further, the contrarian monetary policy implies increasing commodity-specific demand and price, which is in contrast to the hypothesized inverse relation of Frankel (2008), who states the cost of capital for holding a commodity should decrease in times of an expansionary monetary policy, while simultaneously the demand for commodities, acting as an alternative asset class, should increase. However, Frankel (2008) can confirm his theory in the empirical analysis of commodity prices only in the period from 1950 to 1979 (2005), whereas the observed relation between interest rates and commodity prices is positive in the period from 1980 (1976) to 2005, underlining the direction of relation between monetary policy and commodity prices changed over time. Hereby, the observed, positive correlation could indicate the central bank reacts to high commodity prices via the interest rate, and thus, prices run ahead of the interest rate.

Overall, we detect the commodity markets react to shocks in the global economy as well as in the individual commodity markets. However, as the aluminum market does not exhibit any spillover effects, one may conclude microeconomic information of supply and demand is already included in the price of aluminum, see Lutzenberger et al. (2017), inducing their consideration is irrelevant and neglectable in modern commodity markets. However, the individual industrial metal market models do not reflect

[12] The results of the Breusch-Godfrey test, the multivariate ARCH-LM test and the OLS-CUSUM test to the VAR model indicate the model does not suffer from autocorrelation, heteroscedasticity or structural breaks at the 1% significance level, see Table 28. Moreover, the Henze-Zirkler test for normality shows the VAR model has multivariate normal distributed residuals.

Table 10 GIRF results of the individual VAR models for shocks in exogenous variables

	Al			Cu			Ni			Pb			Sn			Zn		
	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p
GDP	+	+	+	−	+	+	+	+	+	+	+	+		+	+	+	+	+
FX	−	−	−	+	−	−	−	−		−	−	−		−	−	−	−	−
FFR		+	+		+	+		+	+	−	−	+	+	+		−		+

Results of GIRF analysis for the individual, commodity-specific VAR models, showing the response of the column variables to a shock of the row variables world gross domestic product (GDP), US dollar index (FX) and the federal funds rate (FFR), where significant positive (+) or negative (−) effects are displayed, based on the 68%- level

spillover effects between the commodities yet, which is why we turn our attention to the results of the GVAR models.

4.3.2 Global VAR model

To account for interdependencies between commodity markets, we apply the GVAR model, according to Eq. 6, on the industrial metal markets, whereby we include the impact of macroeconomic factors on the commodity markets via the exogenous variables world gross domestic product (GDP), US dollar index (FX) and federal funds rate (FFR). Hereby, we estimate the GVAR[13] model several times, using the different weight matrices supply (**S**), demand (**D**), trading (**T**) and common (**C**), as outlined in Sect. 4.2.2, for a comparison between the possible linkages of commodity markets.

To aggregate the GIRFs and to provide an holistic overview of the results, we indicate significant positive, or negative, responses of the column variables to a shock in the row variables, by a (+) or (−), in Table 11. Hereby, we differentiate between the models with weight matrices supply (**S**), demand (**D**), trading (**T**) and common (**C**), respectively.

The diagonal of Table 11 shows significant results for all variables and weight matrix combinations, which is rather unsurprising, as it captures the effect of a shock to the response variable itself. Despite the concerns of false negatives within GIRF analyses, we obtain numerous significant GIRFs in the cross-commodity dimension, underlining the importance of jointly modeling commodity markets and making the findings of the framework even more pronounced.

Regarding the differences between the weight matrices, the GVAR model using the demand weight matrix detects more spillover effects, compared to the other models, indicating the relations between commodities may be best modeled by their

[13] We estimate the GVAR models with one lag for the endogenous as well as exogenous variables, due to data limitations. While the results of the Breusch-Godfrey test, the multivariate ARCH-LM test and the OLS-CUSUM test indicate neither model suffers from autocorrelation, heteroscedasticity nor structural breaks, the Henze-Zirkler test implies the residuals of the GVAR model, based on the different weight matrices, are multivariate normal distributed, see Table 28. As the extension of the lag length to validate the stability of the parameters is not feasible from the statistical point of view, we estimate the GVAR model based on a reduced sample period from 1980 to 2019 for a robustness check of the parameters. Hereby, the main findings remain valid even some significant impulse response functions vanish due to the small sample size, indicating the stability of the model.

co-consumption. Since the GVAR models based on the trading and common weight matrices represent less spillover effects, the relations between commodities may be reflected by their co-consumption or co-production, indicating the importance of supply and demand in the (relation between) commodity markets. As the common weight matrix simultaneously represents information on co-production, co-consumption and co-trading with equal weights, the individual effects of the consumption or production behavior are potentially diminished to a certain extent. Therefore, we focus in the following on the results of the GVAR model with the weight matrix demand (**D**), based on information about the co-consumption between commodities.

To start, we compare the results of the individual VAR models to the commodity-specific results of the GVAR model, before we analyze the spillover effects in the cross-commodity dimension in detail. Overall, the spillover effects in the individual commodity markets change, as the GVAR model connects the commodity markets and therefore accounts for unobserved, indirect effects between the commodities, which are not represented in the individual VAR models. Hereby, the significant impact between supply and demand in the copper market, as well as between the zinc demand and price, vanishes once the interdependence between commodities is included, whereas copper demand and price significantly influence each other in the GVAR model, based on the demand weight matrix. However, in line with the findings of the individual VAR models in Table 9, the GVAR analysis also detects no significant responses of aluminum's supply, demand and price to shocks on variables of the same commodity. Moreover, the interdependencies in the nickel, lead and tin markets remain valid, indicating the GVAR models also reflect the spillover effects in the individual commodity markets. Besides these responses in the individual markets, we observe various effects in the cross-commodity dimension. In particular, supply variables mostly affect each other, while the GIRF analysis additionally reveals strong spillover effects between the commodity demand variables, indicating a positive shock in the demand of one commodity leads to increasing demand of another commodity, except for the nickel demand, which responds negatively to a zinc demand shock. Overall, the strong interdependencies between the commodity-specific demand underlines their demand driven relation.

Moreover, there are several spillover effects between supply and demand variables. For example, tin demand affects aluminum supply, while copper demand influences aluminum as well as zinc supply. In addition, the fundamentals influence prices significantly. Hereby, the aluminum (nickel) price responds negatively (positively) to changes in the copper (tin) supply, whereas lead demand affects the copper price.

Further, the GVAR models detect various spillover effects between the commodity prices. Overall, an increase in one commodity's price leads to rising prices of the other commodities, indicating a common behavior in the metals' prices. In particular, aluminum, copper, nickel and zinc prices influence each other. Hereby, shocks to the copper price affect the other commodities, while the copper price reacts only to changes in the zinc price, indicating a strong impact of copper on the other commodity markets. However, there are no spillover effects from lead and tin prices, probably because these metals are the smallest in terms of their trading volume.

Regarding the differences between the commodities, tin, the smallest metal market in terms of the trading volume, is least connected to the other markets, which is

Table 11 GIRF results of the GVAR models

			Al			Cu			Ni			Pb			Sn			Zn		
		W	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p
Al	s	**S**	+						+											
		D	+				+		+									−		
		T	+																	
		C	+						+											
	d	**S**		+			+							+						
		D		+			+													
		T		+			+												+	
		C		+			+												+	
	p	**S**			+	−		+			+									
		D			+				+		+									
		T			+	−														
		C			+						+									
Cu	s	**S**			−	+														
		D			−	+														
		T				+														
		C				+														
	d	**S**	+				+													
		D	+	+			+	−										−	+	
		T	+	+			+													
		C		+			+													
	p	**S**						+												+
		D		−	+		−	+	+		+									+
		T						+												
		C						+												+
Ni	s	**S**							+		+				−					
		D							+											
		T	+						+											
		C							+											
	d	**S**								+										
		D								+										
		T								+										
		C								+										
	p	**S**			+				+		+									
		D							+		+				+	−				
		T			+				+		+				+					
		C							+		+									
Pb	s	**S**							+			+	+					+		
		D							+			+						+		
		T										+								

Table 11 continued

			Al			Cu			Ni			Pb			Sn			Zn		
		W	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p
		C							+			+						+		
	d	**S**		+		+		+		+		+	+						+	+
		D		+		+		+		+		+	+						+	
		T								+		+	+							
		C		+		+				+		+	+						+	
	p	**S**												+			+			
		D												+						
		T			+		+							+			+			
		C												+						
Sn	s	**S**													+		+			
		D									+				+		+			
		T													+					
		C													+					
	d	**S**	+	+			+		+	+						+				
		D	+				+		+							+				
		T							+							+				
		C					+		+							+				
	p	**S**													+		+			
		D													+		+			
		T													+		+			
		C													+		+			
Zn	s	**S**										+						+		
		D										+						+		
		T										+						+		
		C										+						+		
	d	**S**							+		+								+	
		D		+						−			+						+	
		T		+			+												+	
		C																	+	
	p	**S**						+			+									+
		D						+												+
		T						+												+
		C				+		+												+

Results of GIRF analysis for the different weight matrices (W) supply (**S**), demand (**D**), trading volume (**T**) and common (**C**). We analyze the response of the column variables to a shock of the row variables supply (s), demand (d) and price (p) of aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn). Significant positive (+) or negative (−) effects on the 68%- level are displayed

Table 12 GIRF results of the GVAR models to shocks in the exogenous variables

		Al			Cu			Ni			Pb			Sn			Zn		
	W	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p	s	d	p
GDP	**S**	+	+	+	−	+	+	+	+	+	+	+	+			+	+	+	+
	D	+	+	+	−	+	+	+	+	+	+	+	+			+	+	+	+
	T	+	+	+	−	+	+	+	+	+	+	+	+			+	+	+	+
	C	+	+	+	−	+	+	+	+	+	+	+	+			+	+	+	+
FX	**S**	−	−	−	+	−	−	−	−	−	−	−	−		−	−	−	−	−
	D	−	−	−	+	−	−	−	−	−	−	−	−		−	−	−	−	−
	T	−	−	−	+	−	−		−			−	−		−	−	−	−	
	C	−	−	−	+	−	−	−	−	−	−	−	−		−	−	−	−	−
FFR	**S**		+	+	+	+	+		+	+	−	−	+	+	+		−	+	+
	D	+	+	+		+	+	−	+	+	−	−	+	+	+		−	+	+
	T		+	+	+	+	+			+	−	−	+	+	+		−		+
	C		+	+		+	+	−	+	+	−	−	+	+	+		−	+	+

Results of GIRF analysis for the different weight matrices (W) supply (**S**), demand (**D**), trading volume (**T**) and common (**C**). We analyze the response of the column variables to a shock of the row variables world gross domestic product (GDP), US dollar index (FX) and federal funds rate (FFR), where significant positive (+) or negative (−) effects are displayed, based on the 68%- level

reasonable, as it is not co-mined with any of the remaining metals,[14] nor is there a specific, common use case. The lead and nickel markets indicate various significant spillover effects, whereby lead affects and nickel responds to shocks in the other commodity markets. However, the majority of spillover effects is from, or to, the aluminum and copper market. Moreover, these two, most traded, metals also show the strongest interrelation, albeit their link reflected by the weight matrix demand (**D**) is not outstandingly large, see Table 6.

The observed strong spillover effects between these two metals most likely originate from their common applications in the field of electrical conduction, automotive and aerospace industries. Hereby, a shock in copper demand affects aluminum's fundamentals, while the aluminum price responds to copper supply and price shocks, whereas aluminum supply and demand positively influence the copper demand. However, a shock to the supply of one metal does not lead to any significant reactions in the supply of the other metal, as aluminum and copper are not co-mined.

Similar to the GIRF analysis of the individual commodity markets, we also examine the effects of global shocks to the commodity markets modeled by the GVAR framework, based on the different weight matrices supply (**S**), demand (**D**), trading (**T**) and common (**C**). In particular, we examine how the commodity-specific variables respond to innovations in the global economic activity, reflecting the global demand, the exchange rate or the interest rate. Therefore, we use the VAR(1) model of the exogenous variables, world gross domestic product (GDP), US dollar index (FX) and

[14] Actually, tin is not co-mined with the other industrial metals. However, as we reflect the supply weight matrix on the common supply concentration, based on the country-specific production volumes, the weight matrix displays a co-production relation.

federal funds rate (FFR), specified in Sect. 4.3.1, and analyze the impacts of a shock to each exogenous variable on the commodity markets, using the GIRFs derived in Eq. 15. In analogy to the GIRF analysis of shocks within and between the commodity markets, we display the responses of the commodity markets to innovations in the exogenous variables in Table 12.

Overall, similar to the analysis of the individual commodity markets, we observe the shocks to the macroeconomic variables affect each commodity market to a similar extent, across all models. In particular, an increase in the global demand, associated with an expansion of the economic activity, leads to an increase in commodity markets, as production, consumption and prices rise simultaneously, which supports the synchronized pattern of commodity markets and economic activity, see Issler et al. (2014). However, the production of copper declines in response to a global demand increase. Since copper is regarded as a leading indicator of the global economic situation, copper producers may reduce their supply in times of economic booms, to prevent their losses due to the subsequent recession phases.

In addition, a positive shock to the US dollar index, representing an appreciation of the US dollar, leads to decreasing commodity markets. In particular, since the metals are quoted in US dollars, a stronger US dollar implies the metals become more expensive for consumers holding other currencies, see Vansteenkiste (2009), and therefore, the demand and ultimately, the price of the commodities decrease. Moreover, as the profits of the producers raise, see Vansteenkiste (2009), the copper supply increases, and therefore, the copper price declines. However, the production volumes of the other metals reduce, probably caused by indirect effects of the reduction in demand, and price, which are also represented in the GIRF analysis at annual frequency.

Further, a contrarian monetary policy, reflected via a positive interest rate shock, leads to an increase in the production volume of aluminum, copper and tin. This underlines the argument of Akram (2009) and Frankel (2008), who state the extraction of exhaustible commodities will be more profitable in high interest rates environments. In contrast, the production volumes of nickel, lead and zinc decrease in response to a positive interest rate shock, probably again due to indirect effects, also reflected in the GIRF analysis. In particular, both demand and price increase in response to rising interest rates, contrary to Frankel (2008), who argues for rising demand and prices in times of an expansionary monetary policy, as the cost of capital for holding a commodity should decrease and the demand for commodities as an alternative asset class should increase. However, in times of increasing commodity prices, and therefore, a period of increasing inflation, the central banks raise the interest rates. This rise in interest rates dampens the boom in commodity prices, but prices continue to rise in the short-term, which could explain the positive reaction in the metals' markets.

Overall, the GIRF analysis of the global VAR model of the metal markets detects the individual commodity markets are strongly interrelated. Various spillover effects underline innovations in the supply, demand or price of one commodity lead to changes in the other metal markets. Moreover, shocks in the global economy affect all commodity markets simultaneously, where, in particular, a global demand shock leads to increasing commodity prices.

4.3.3 Forecast error variance analysis

We further investigate the interdependencies of the variables through a GFEVD analysis, based on the GVAR model with the demand weight matrix (**D**). However, the results are similar to those of the GVAR models based on the supply (**S**), trading (**T**), or common (**C**) matrix, see Figs. 1, 2, 3 and 4. In Fig. 2, we display the attributes' forecast errors variances for the model based on the co-consumption relation, which are decomposed by aggregated shocks of each endogenous variable as their mean of 1 to 10 years ahead.

In general, the forecast error variances are mainly influenced by each variable itself, in particular, the supply variables' variances are determined by the commodity-specific attributes most, whereas demand and prices are equally driven by them, but to a lesser extent. Hereby, the aluminum and zinc demand are outstanding, as over 50% of their forecast error variance are explained by other commodities' variables.

Turning to a commodity-specific perspective, we observe the forecast error variance of aluminum's supply is particularly influenced by copper, lead and tin demand, whereas copper demand and price, followed by lead and tin demand, describe the forecast error variance of the aluminum demand, underlining the findings of the GIRF analysis, where copper demand and price, as well as lead, tin, and zinc demand significantly affect the aluminum demand. Besides aluminum's fundamentals, the copper market mostly affects the forecast error variance of aluminum's price, further highlighting the strong impact of copper on the aluminum market, see Sect. 4.3.2. However, the strong interdependencies between copper and aluminum are most pronounced in case of the GVAR model based on the demand side weight matrix, as both metals are jointly consumed in the field of electrical conduction, automotive and aerospace industries.

For the copper market, the forecast error variances are mainly influenced by its own, commodity-specific attributes. While supply is equally described by aluminum, nickel, lead and zinc, a large proportion of the forecast error variance of copper's demand is determined by aluminum's attributes, followed by lead and zinc. Hereby, the strong impact of aluminum on the copper demand underlines the strong interrelation between these two metals, probably caused by their co-consumption. While the GIRF analysis reveals the copper price affects the other commodity prices and the copper price itself reacts only to changes in the zinc price, the zinc price hast the most pronounced influence of the external commodities on the copper price' forecast error variance.

Nickel's supply and price forecast error variances are mostly described by aluminum and copper, whereas the forecast error variance of nickel's demand can be explained best by the zinc demand and the lead market. For lead, the forecast error variances of supply and demand are mainly explained by the variables of zinc, apart from the contribution of lead's own variables, underlining the GIRF analysis, which detects lead's fundamentals respond significantly to shocks in the zinc market, probably caused by their strong co-production relation. Moreover, the variance of lead's price is affected by the aluminum, copper and nickel market to a larger extent.

In case of tin, the forecast error variances of supply and price are mostly impacted by nickel, while aluminum mostly explains the forecast error variance of tin's demand. Hereby, tin is explained by the other commodities, but rarely contributes to the forecast

Table 13 Correlation matrix of spot prices

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.84	0.76	0.88	0.83	0.29
Cu	0.84	1.00	0.92	0.68	0.90	−0.18
Ni	0.76	0.92	1.00	0.51	0.85	−0.30
Pb	0.88	0.68	0.51	1.00	0.81	0.50
Sn	0.83	0.90	0.85	0.81	1.00	−0.05
Zn	0.29	−0.18	−0.30	0.50	−0.05	1.00

Correlation matrix of adjusted spot prices, between 2010 and 2019

error variances of the other metals itself, underlining tin is least connected to the other markets, as it is not co-mined with any of the remaining metals, nor is there a specific common use case. Further, zinc's supply and demand variances are mostly related to lead, followed by tin, whereas the forecast error variance of zinc's price is determined by copper, in particular by the copper price, followed by lead. In line with the results of the GIRF analysis, copper and zinc prices help explaining the metal prices' variances, further underlining the strong impact of copper in commodity markets.

4.3.4 Correlation matrices

To highlight our framework's ability to represent the co-movement in commodity prices, we compare the price correlations induced by the GVAR model with the market observed correlations. Therefore, we split our dataset into an expanding in-sample window with data from 1971 to 2009 and an out-of-sample window covering the years 2010 to 2019. For each step in time of the out-of-sample window, we estimate the GVAR model based on the in-sample data and forecast all commodities' annual prices one-step ahead. Subsequently, we calculate Pearson correlation matrices, using the predicted or observed prices, respectively.

The correlation matrices' comparison, presented in Tables 13, 14, 15, 16 and 17, highlights the dependencies between the commodity markets are well modeled by our framework, except for zinc. Hereby, our focus is on the replication's accuracy of the observed co-movement, where the predictive power of the models are not evaluated in further detail. In particular, the correlations observed from the GVAR models based on the different weight matrices supply (**S**), demand (**D**), trading (**T**), or common (**C**), are similar. Apart from the negative relation between zinc and the other metals, which is not reflected, the GVAR framework performs exceptionally well, with differences in the correlations for the predicted and real prices being smaller than 10%, except for the links between copper and lead, as well as nickel and lead.

4.4 Discussion

In general, the literature regards, inter alia, two perspectives on commodity markets. First, the classical fundamental theory, which states a good's price is the result of its supply and demand equilibrium, see Hotelling (1931) and Deaton and Laroque (2003).

Table 14 Correlation matrix of predicted prices based on the GVAR model with supply weight matrix

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.84	0.67	0.88	0.78	0.86
Cu	0.84	1.00	0.88	0.76	0.88	0.62
Ni	0.67	0.88	1.00	0.59	0.78	0.41
Pb	0.88	0.76	0.59	1.00	0.86	0.94
Sn	0.78	0.88	0.78	0.86	1.00	0.71
Zn	0.86	0.62	0.41	0.94	0.71	1.00

Correlation matrix of adjusted spot prices, using the GVAR framework with weight matrix **S**, in an out-of-sample rolling window forecast from 2010 to 2019

Table 15 Correlation matrix of predicted prices based on the GVAR model with demand weight matrix

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.91	0.75	0.88	0.86	0.85
Cu	0.91	1.00	0.88	0.80	0.93	0.65
Ni	0.75	0.88	1.00	0.74	0.91	0.56
Pb	0.88	0.80	0.74	1.00	0.86	0.95
Sn	0.86	0.93	0.91	0.86	1.00	0.69
Zn	0.85	0.65	0.56	0.95	0.69	1.00

Correlation matrix of adjusted spot prices, using the GVAR framework with weight matrix **D**, in an out-of-sample rolling window forecast from 2010 to 2019

Table 16 Correlation matrix of predicted prices based on the GVAR model with trading weight matrix

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.83	0.67	0.83	0.76	0.80
Cu	0.83	1.00	0.95	0.79	0.94	0.77
Ni	0.67	0.95	1.00	0.66	0.88	0.68
Pb	0.83	0.79	0.66	1.00	0.87	0.97
Sn	0.76	0.94	0.88	0.87	1.00	0.82
Zn	0.80	0.77	0.68	0.97	0.82	1.00

Correlation matrix of adjusted spot prices, using the GVAR framework with weight matrix **T**, in an out-of-sample rolling window forecast from 2010 to 2019

Table 17 Correlation matrix of predicted prices based on the GVAR model with common weight matrix

	Al	Cu	Ni	Pb	Sn	Zn
Al	1.00	0.89	0.80	0.89	0.82	0.90
Cu	0.89	1.00	0.95	0.84	0.93	0.83
Ni	0.80	0.95	1.00	0.81	0.93	0.81
Pb	0.89	0.84	0.81	1.00	0.90	0.99
Sn	0.82	0.93	0.93	0.90	1.00	0.87
Zn	0.90	0.83	0.81	0.99	0.87	1.00

Correlation matrix of adjusted spot prices, using the GVAR framework with weight matrix **C**, in an out-of-sample rolling window forecast from 2010 to 2019

Second, the analysis of the empirical observed common patterns in commodity prices, the so-called co-movement in prices, see Pindyck and Rotemberg (1990). While Basak and Pavlova (2016) theoretically combine the two differing, yet valid perspectives on commodity markets, our framework provides the possibility to empirically combine both.

The literature on the impact of microeconomic supply and demand factors on prices is small, probably due to data restrictions. Hereby, most of the previous studies approximate the demand for commodities by economic growth indicators, see, for example, Ahumada and Cornejo (2014),Borensztein and Reinhart (1994),Deaton and Laroque (2003),Helbling et al. (2008),Kilian (2009) and Stuermer (2018). Some of the few studies with commodity-specific supply and demand variables are Thomas et al. (2010) and Chen et al. (2019), which investigate the impact of supply, demand and speculation on the price of oil and copper, respectively, but are hereby unable to account for cross-commodity linkages. In contrast, various studies examine the common pattern in commodity prices, the so-called co-movement, see Byrne et al. (2013),Chen et al. (2014),Le Pen and Sévi (2017),Nicola et al. (2016),Pindyck and Rotemberg (1990),Tang and Xiong (2012),West and Wong (2014) and Zhang et al. (2019), but do hereby not account for the commodity-specific impact of supply and demand.

However, through the application of our framework on the industrial metals markets, we highlight commodity-specific supply and demand still have a significant impact on commodity prices. While previous studies on the co-production, see Jordan (2017) and Nassar et al. (2015) among others, or the co-consumption of metals, see Shammugam et al. (2019), only analyze their effect on prices, our framework allows for a holistic model of commodity markets. Hence, we are able to disentangle single-market effects from inter-market effects, while controlling for macroeconomic drivers. The relevance of the interdependencies between commodity markets is further underlined by our model's ability to represent the actual co-movement between the commodities' prices, in line with Tang and Xiong (2012), see Sect. 4.3.4.

Overall, the GVAR model provides an empirical framework to jointly investigate the co-movement between prices, as well as the impact of commodity-specific supply and demand on prices. Thereby, the GVAR model contributes new insights to the literature, as it disentangles single-market effects from inter-market effects, while controlling for macroeconomic factors. In particular, the numerous significant spillover effects in the cross-commodity dimension underline the importance of jointly modeling commodity markets.

5 Conclusion

In this study, we develop a framework to unite two perspectives on commodity markets, the classical fundamental theory and the empirical observation of (excess) co-movement and detect, by the frameworks' application on industrial metal markets, significant responses of prices to innovations in cross-commodity, microeconomic and price variables.

In a first step, we model each commodity market separately using vector autoregression models with the microeconomic, commodity-specific variables supply, demand

and price, as well as the world gross domestic product, the US dollar index and the federal funds rate, as exogenous, macroeconomic attributes. In a second step, information on co-production, co-consumption and co-trading of the commodities is used to link the individual VAR models into our final global vector autoregression model, allowing us to analyze interdependencies between the markets.

In the empirical application of our framework, we are able to represent the strong co-movement in commodity prices. Additionally, we detect a strong connection between the aluminum and copper market, originating from their joint consumption. Moreover, we reveal the fundamentals are still important, as we observe various spillover effects of supply and demand, both within and across commodity markets, where, in particular, microeconomic variables still influence prices significantly. In addition, we examine shocks to macroeconomic variables affect each commodity market to a similar extent. Especially, an increase in the global demand, associated with an expansion of the economic activity, leads to an increase in commodity markets, as production, consumption and prices rise simultaneously, which supports the synchronized pattern of commodity markets and economic activity.

Further research could extend the framework on other commodity classes, such as agricultural and energy commodities, or even model them jointly with the metal markets in a regional GVAR framework. Moreover, an extension for time-varying parameters might provide deeper inside in the commodity market structure and probably disentangles whether the markets are more or less connected in calm or volatile periods.

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Availability of data and materials The data used in this paper are available upon request.

Code availability The code for this paper is available upon request.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

Appendix A Data description

Data sources for our commodity price series as well as the macroeconomic variables are provided in Table 18.

Further, descriptive statistics of the stationary variables included in our empirical analysis, the results of the ADF test for stationarity of the return data, as well as the results of the Shapiro–Wilk test for normality, are given in Table 19. In our analysis, we further standardize these returns such that they have zero mean and standard deviation one, but use the original variable names unadjusted, i.e., supply, demand and price.

Appendix B Calculation of weight matrix demand (D)

To define a weight matrix based on demand-sided information, we analyze the industries the commodities are consumed in. Hereby, we approximate the world economy by five industries, which in summary account for 75% to over 90% of the demand for the metals considered in the analysis. These industries are *Automotive/Transportation*, *Chemistry/Pharmaceutics*, *Electrics*, *Construction* and *Mechanical Engineering*. We take worldwide consumption data from Brandtzæg (2018) and Leder (2020), hereby implying that the proportion between the industries remains unchanged over the investigated time period.

The consumption of aluminum per industry, provided by Brandtzæg (2018) is given in Table 20. In order to join the different usage of the commodities, we assume that the consumption of aluminum for *Foil*, *Packaging*, *Consumer Goods* and *Other* is zero. The corresponding consumption per industry, displayed in Table 2, is used as input data for the calculation of the weights according to Eq. 18. We note that aluminum is mainly used in the automotive sector as well as for construction, whereas there is no consumption in the chemistry industry.

The worldwide consumption per industry of copper, according to Leder (2020), is displayed in Table 21. We assign these branches, as shown in Table 26, to the five industries and get the corresponding weights. As *Trade and Other* cannot be matched to our five industries in a reasonable way, we assume that its proportion is zero. Similar to aluminum, copper is not used in the *Chemistry/Pharmaceutics* sector, while its majority is utilized for *Electrics* purposes.

As displayed in Table 22, more than half of the worldwide amount of nickel is used for *Stainless Steel*, see Leder (2020), which we equally attribute to the industries *Automotive/Transportation*, *Construction* and *Mechanical Engineering*, see Table 26. We further assume that the consumption of nickel for *Nickel alloys*, *Platings*, *Steel refiner*, *Foundries* and *Other* is zero, to join the different usages of the commodities.

Table 23 displays the consumption of lead per industry, according to Leder (2020), where we are able to assign all of the consuming branches to our five industries, as

Table 18 Data sources

	Name	Ticker	Source	Start	End	Freq
Al	LME-Aluminium 99.7% Cash	[MAL0]	Thomson Reuters Eikon (2022a)	1957	2019	d
Cu	LME-Copper Grade A Cash	[MCU0]	Thomson Reuters Eikon (2022b)	1957	2019	d
Ni	Contract price to US buyers		U.S. Geological Survey (2013)	1970	1979	a
Ni	LME Cash 99.80% purity		U.S. Geological Survey (2013)	1980	1993	a
Ni	LME-Nickel Cash	[MNI0]	Thomson Reuters Eikon (2022d)	1994	2019	d
Pb	Lead primary producer price		U.S. Geological Survey (2013)	1970	1985	a
Pb	Lead North American producer price		U.S. Geological Survey (2013)	1986	1993	a
Pb	LME-Lead Cash	[MPB0]	Thomson Reuters Eikon (2022c)	1994	2019	d
Sn	LME-Tin 99.85% Cash	[MSN0]	Thomson Reuters Eikon (2022f)	1957	2019	d
Zn	LME-SHG Zinc 99.995% Cash	[MZN0]	Thomson Reuters Eikon (2022e)	1957	2019	d
GDP	World gross domestic product		The World Bank (2022)	1960	2019	a
FX	US dollar index		ICE Futures U.S. (2022)	1970	2019	a
FFR	Effective federal funds rate		Board of Governors of the Federal Reserve System (U.S.) (2022)	1955	2019	m

This table displays the covariates, the description of the series (Name), the corresponding ticker (Ticker) and data source (Source), the start (Start) and end (End) year of the series, as well as the frequency (Freq)

Table 19 Descriptive statistics of the commodity-specific variables

		Minimum	5% Quantile	25% Quantile	Median	Mean	75% Quantile	95% Quantile	Maximum	St. Dev.	Skewness	Kurtosis	ADF statistic	SW statistic
Al	s	−0.12	−0.05	0.02	0.04	0.04	0.07	0.11	0.12	0.05	−0.79	1.01	−4.43**	0.95*
	d	−0.31	−0.20	−0.04	0.02	0.02	0.11	0.22	0.27	0.12	−0.29	0.00	−5.93**	0.98
	p	−0.43	−0.25	−0.10	0.01	0.02	0.17	0.29	0.52	0.19	0.03	−0.28	−6.24**	0.99
Cu	s	−0.05	−0.02	0.00	0.02	0.02	0.05	0.08	0.10	0.03	0.28	−0.09	−4.43**	0.98
	d	−0.36	−0.26	−0.03	0.01	0.01	0.08	0.18	0.25	0.12	−0.96	1.81	−7.10**	0.90***
	p	−0.53	−0.30	−0.12	−0.01	0.03	0.15	0.44	0.60	0.23	0.27	−0.05	−6.01**	0.98
Ni	s	−0.23	−0.15	−0.01	0.04	0.03	0.08	0.14	0.31	0.09	−0.19	1.38	−5.44**	0.96
	d	−0.23	−0.20	−0.06	0.01	0.02	0.10	0.18	0.59	0.14	1.02	3.46	−6.46**	0.92***
	p	−0.57	−0.38	−0.15	0.05	0.03	0.18	0.42	1.05	0.28	0.64	1.66	−6.10**	0.96
Pb	s	−0.10	−0.09	−0.03	0.00	0.01	0.04	0.10	0.13	0.05	0.22	−0.32	−6.23**	0.98
	d	−0.30	−0.10	−0.04	0.02	0.02	0.08	0.16	0.28	0.10	−0.26	0.94	−7.32**	0.98
	p	−0.36	−0.31	−0.12	0.04	0.04	0.15	0.47	0.70	0.23	0.62	0.39	−6.08**	0.96
Sn	s	−0.15	−0.10	−0.05	−0.01	0.00	0.05	0.13	0.15	0.07	0.25	−0.75	−5.52**	0.97
	d	−0.48	−0.22	−0.06	0.01	0.00	0.10	0.22	0.27	0.14	−0.85	1.49	−8.05**	0.95*
	p	−0.57	−0.31	−0.09	0.00	0.03	0.16	0.47	0.57	0.22	0.23	0.61	−6.38**	0.97
Zn	s	−0.06	−0.03	0.00	0.02	0.02	0.04	0.07	0.10	0.03	0.03	0.22	−5.38**	0.99
	d	−0.31	−0.17	−0.05	0.02	0.01	0.09	0.16	0.34	0.11	−0.10	0.65	−5.94**	0.98
	p	−0.55	−0.29	−0.12	0.03	0.04	0.19	0.40	0.86	0.26	0.77	1.62	−5.46**	0.95*
Macro	FX	−0.20	−0.16	−0.08	0.01	−0.00	0.07	0.12	0.15	0.09	−0.30	−0.90	−5.35**	0.97
	GDP	−0.06	−0.01	0.03	0.07	0.07	0.11	0.16	0.20	0.06	−0.01	−0.64	−2.43*	0.98
	FFR	−3.28	−0.80	−0.24	−0.01	−0.02	0.32	0.80	0.88	0.66	−2.39	9.87	−5.91**	0.80***

This table displays the descriptive statistics of the stationary, commodity-specific variables supply (s), demand (d) and price (p) for the commodities aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn), as well as for the macroeconomic variables US dollar index (FX), world gross domestic product (GDP) and federal funds rate (FFR). Moreover, the results of the test statistics of the augmented Dickey–Fuller (ADF) test and the Shapiro–Wilk (SW) test, with corresponding significance level (0.1% (***), 1% (**), 5% (*) and 10% (.)), are reported

Table 20 Aluminum consumption

Industry	%
Automotive/Transportation	0.26
Construction industry	0.24
Mechanical and Plant Engineering	0.11
Electrical Engineering	0.11
Foil	0.08
Packaging	0.08
Consumer goods	0.06
Other	0.06

This table displays the proportion of aluminum (Al) consumption per industry

Table 21 Copper consumption

Industry	%
Cables and electrics	0.57
Construction industry	0.15
Automotive	0.09
Mechanical Engineering	0.08
Trade	0.05
Other	0.06

This table displays the proportion of copper (Cu) consumption per industry

Table 22 Nickel consumption

Industry	%
Stainless steel (Automotive, Construction, Mechanical Engineering)	0.57
Electrical Engineering	0.03
Nickel alloys	0.13
Platings	0.11
Steel refiner	0.09
Foundries	0.06
Other	0.01

This table displays the proportion of nickel (Ni) consumption per industry

displayed in Table 26. The majority of lead is used in the *Electrics* sector, as well as in *Construction*, *Mechanical Engineering* and *Chemistry/Pharmaceutics*, but none in the *Automotive/Transportation* industry.

In Table 24, we display the demand for tin per industry, where we neglect the consumption for *Brass bronze*, *Float glass*, *Packaging (tinplate)* as well as *Other*, since no direct assignment of these usages to the five considered industries is possible. Hereby, the main use of tin is in *Electrics*, followed by the *Chemistry/Pharmaceutics* sector.

Table 23 Lead consumption

Industry	%
Electrical Engineering (Lead-acid batteries)	0.74
Construction (Roof, Facade)	0.06
Plant construction (Radiation Protection, Anodes)	0.06
Chemistry (Pigments)	0.05
Other (Alloys, Cable Sheath, Glass)	0.09

This table displays the proportion of lead (Pb) consumption per industry

Table 24 Tin consumption

Industry	%
Electronics industry (solder)	0.52
Chemical industry (PVC stabilizer)	0.15
Brass bronze	0.06
Float glass	0.02
Packaging (tinplate)	0.16
Other	0.09

This table displays the proportion of tin (Sn) consumption per industry

Table 25 Zinc consumption

Industry	%
Automotive Engineering (Galvanizing)	0.50
Construction (Zinc, Brass Products)	0.23
Chemistry / Pharmaceutics	0.06
Other (Zinc casting alloys)	0.21

This table displays the proportion of zinc (Zn) consumption per industry

Finally, we consider the consumption of zinc by industries, displayed in Table 25. Since the point *Other (Zinc casting alloys)* is rather unspecific, we neglect it for further calculations. The assigned branches are displayed in Table 26. Zinc is mainly used in the *Automotive/Transportation* sector, whereas there is no significant application for *Electrics* and *Mechanical Engineering*, according to Leder (2020). There is also only few consumption in the industries *Chemistry/Pharmaceutics* and *Construction*.

Table 26 Commodity—industry mapping

	Automotive/ Transportation	Chemistry/ Pharmaceutics	Electrics	Construction	Mechanical Engineering
Al	Automotive/ Transportation	–	Electrical Engineering	Building Industry	Mechanical and Plant Engineering
Cu	Automotive	–	Cables and Electrics	Building Industry	Mechanical Engineering
Ni	Stainless Steel (automotive, construction, mechanical engineering)	–	Electrical engineering	Stainless Steel (automotive, construction, mechanical engineering)	Stainless steel (automotive, construction, mechanical engineering)
Pb	–	Chemistry	Electrical Engineering & Other	Construction	Plant Construction
Sn	–	Chemical Industry (PVC stabilizer)	Electronics industry (solder)	–	–
Zn	Automotive Engineering	Chemistry / Pharmaceutics	–	Construction	

This table displays the mapping of the industry data for aluminum (Al), copper (Cu), nickel (Ni), lead (Pb), tin (Sn) and zinc (Zn) to the five industry sectors Automotive/Transportation, Chemistry/Pharmaceutics, Electrics, Construction and Mechanical Engineering

Appendix C Test results

See Tables 27, 28 and 29.

Table 27 Test results for autocorrelation, heteroscedasticity, structural breaks and normality

		DW						ARCH		CUSUM		HZ	
		Supply		Demand		Price							
		Stat.	*p*	Stat.	*p*	Stat.	*p*	Stat.	*p*	Stat.	*p*	Stat.	*p*
Individual VAR	Al	1.96	0.43	1.88	0.34	2.17	0.70	43.51	0.18	0.88	0.42	0.59	0.64
	Cu	2.05	0.56	2.02	0.53	1.90	0.37	26.96	0.86	0.90	0.39	0.94	0.04
	Ni	1.74	0.18	1.88	0.34	1.99	0.48	18.79	0.99	0.58	0.90	0.72	0.29
	Pb	2.04	0.57	1.76	0.22	2.04	0.57	32.48	0.64	0.80	0.55	0.60	0.60
	Sn	2.18	0.73	2.05	0.58	1.95	0.45	37.72	0.39	0.90	0.39	0.80	0.16
	Zn	1.97	0.46	1.79	0.25	1.80	0.25	30.11	0.74	0.83	0.50	0.63	0.52
S	Al	2.15	0.69	1.92	0.40	2.21	0.76	40.63	0.27	0.48	0.98	1.00	0.35
	Cu	2.23	0.77	2.01	0.51	1.91	0.39	35.15	0.51	0.68	0.74	1.00	0.35
	Ni	1.86	0.33	1.88	0.34	2.22	0.76	32.12	0.65	0.57	0.90	1.00	0.35
	Pb	1.96	0.50	1.77	0.28	2.24	0.81	52.35	0.04	0.61	0.85	1.00	0.35
	Sn	2.01	0.52	2.28	0.81	1.98	0.47	21.04	0.98	0.55	0.92	1.00	0.35
	Zn	1.98	0.44	1.90	0.34	1.53	0.06	27.57	0.84	0.75	0.62	1.00	0.35
D	Al	2.00	0.49	2.01	0.50	2.20	0.72	32.86	0.62	0.42	0.99	1.00	0.15
	Cu	2.20	0.74	2.05	0.57	1.90	0.37	41.32	0.25	0.71	0.70	1.00	0.15
	Ni	1.95	0.42	1.84	0.30	2.31	0.83	20.21	0.98	0.69	0.72	1.00	0.15
	Pb	1.94	0.44	1.73	0.21	2.24	0.79	41.94	0.23	0.57	0.91	1.00	0.15
	Sn	2.04	0.55	2.24	0.78	1.99	0.49	18.05	0.99	0.57	0.90	1.00	0.15
	Zn	1.97	0.47	1.78	0.24	1.70	0.17	15.63	1.00	0.69	0.73	1.00	0.15
T	Al	2.06	0.58	2.16	0.69	2.20	0.73	38.56	0.35	0.47	0.98	1.00	0.54
	Cu	2.20	0.74	2.09	0.61	2.07	0.59	31.22	0.70	0.64	0.80	1.00	0.54
	Ni	1.90	0.37	1.86	0.32	2.22	0.76	24.84	0.92	0.77	0.59	1.00	0.54
	Pb	2.08	0.64	1.88	0.39	2.13	0.70	49.08	0.07	0.69	0.73	1.00	0.54
	Sn	1.93	0.41	2.37	0.88	1.96	0.45	20.86	0.98	0.61	0.85	1.00	0.54
	Zn	2.00	0.46	1.81	0.23	1.53	0.06	24.11	0.93	0.91	0.38	1.00	0.54
C	Al	2.01	0.51	1.94	0.41	2.23	0.76	27.66	0.84	0.36	1.00	1.00	0.22
	Cu	2.30	0.83	1.96	0.44	1.91	0.38	42.37	0.22	0.68	0.75	1.00	0.22
	Ni	1.96	0.43	1.90	0.36	2.37	0.87	28.55	0.81	0.64	0.81	1.00	0.22
	Pb	1.96	0.49	1.87	0.38	2.33	0.87	50.31	0.06	0.51	0.96	1.00	0.22
	Sn	1.94	0.43	2.26	0.79	2.02	0.52	24.51	0.93	0.60	0.86	1.00	0.22
	Zn	2.01	0.47	1.85	0.28	1.66	0.12	26.59	0.87	0.78	0.58	1.00	0.22

This table displays the results of the Durbin-Watson (DW) test for autocorrelation, the multivariate ARCH-LM (ARCH) test for heteroscedasticity, the OLS-CUSUM (CUSUM) test for structural breaks and the Henze-Zirkler (HZ) test for normality. Hereby, the Durbin-Watson test is applied on each, individual regression equation of the VAR model, corresponding to the commodity-specific supply, demand and price, whereas the multivariate ARCH-LM test and the OLS-CUSUM test are applied on the commodity-specific VAR models, and the Henze-Zirkler test is applied on the final residuals. In particular, we report the test results for the individual VAR models, the GVAR models based on the weight matrices supply (**S**), demand (**D**), trading (**T**) and common (**C**)

Table 28 Test results for autocorrelation, heteroscedasticity, structural breaks and normality

		BG		ARCH		CUSUM		HZ	
		Stat	*p*	Stat	*p*	Stat	*p*	Stat	*p*
individual VAR	Al	1.14	0.31	43.51	0.18	0.88	0.42	0.59	0.64
	Cu	0.95	0.56	26.96	0.86	0.90	0.39	0.94	0.04
	Ni	1.89	0.01	18.79	0.99	0.58	0.90	0.72	0.29
	Pb	1.09	0.37	32.48	0.64	0.80	0.55	0.60	0.60
	Sn	1.02	0.46	37.72	0.39	0.90	0.39	0.80	0.16
	Zn	1.26	0.19	30.11	0.74	0.83	0.50	0.63	0.52
S	Al	1.36	0.15	40.63	0.27	0.48	0.98	1.00	0.35
	Cu	1.14	0.33	35.15	0.51	0.68	0.74	1.00	0.35
	Ni	1.22	0.25	32.12	0.65	0.57	0.90	1.00	0.35
	Pb	1.49	0.09	52.35	0.04	0.61	0.85	1.00	0.35
	Sn	0.90	0.64	21.04	0.98	0.55	0.92	1.00	0.35
	Zn	1.41	0.12	27.57	0.84	0.75	0.62	1.00	0.35
D	Al	1.11	0.36	32.86	0.62	0.42	0.99	1.00	0.15
	Cu	0.81	0.75	41.32	0.25	0.71	0.70	1.00	0.15
	Ni	1.51	0.09	20.21	0.98	0.69	0.72	1.00	0.15
	Pb	0.84	0.72	41.94	0.23	0.57	0.91	1.00	0.15
	Sn	0.88	0.67	18.05	0.99	0.57	0.90	1.00	0.15
	Zn	0.92	0.60	15.63	1.00	0.69	0.73	1.00	0.15
T	Al	1.00	0.50	38.56	0.35	0.47	0.98	1.00	0.54
	Cu	1.00	0.50	31.22	0.70	0.64	0.80	1.00	0.54
	Ni	1.56	0.07	24.84	0.92	0.77	0.59	1.00	0.54
	Pb	1.11	0.36	49.08	0.07	0.69	0.73	1.00	0.54
	Sn	0.81	0.76	20.86	0.98	0.61	0.85	1.00	0.54
	Zn	0.98	0.53	24.11	0.93	0.91	0.38	1.00	0.54
C	Al	1.14	0.33	27.66	0.84	0.36	1.00	1.00	0.22
	Cu	1.07	0.41	42.37	0.22	0.68	0.75	1.00	0.22
	Ni	1.40	0.13	28.55	0.81	0.64	0.81	1.00	0.22
	Pb	1.28	0.20	50.31	0.06	0.51	0.96	1.00	0.22
	Sn	0.81	0.76	24.51	0.93	0.60	0.86	1.00	0.22
	Zn	1.14	0.33	26.59	0.87	0.78	0.58	1.00	0.22

This table displays the results of the Breusch-Godfrey (BG) test for autocorrelation, the multivariate ARCH-LM (ARCH) test for heteroscedasticity, the OLS-CUSUM (CUSUM) test for structural breaks and the Henze-Zirkler (HZ) test for normality. Hereby, the Breusch-Godfrey test, the multivariate ARCH-LM test and the OLS-CUSUM test are applied on the commodity-specific VAR models, and the Henze-Zirkler test is applied on the final residuals of the GVAR model. In particular, we report the test results for the individual VAR models, the GVAR models based on the weight matrices supply (**S**), demand (**D**), trading (**T**) and common (**C**)

Table 29 Test results for autocorrelation, heteroscedasticity, structural breaks and normality

BG		ARCH		CUSUM		HZ	
Stat	*p*	Stat	*p*	Stat	*p*	Stat	*p*
1.10	0.35	18.54	0.99	0.57	0.90	0.83	0.13

This table displays the results of the Breusch-Godfrey (BG) test with the small sample correction of Edgerton and Shukur (1999) for autocorrelation, the multivariate ARCH-LM (ARCH) test for heteroscedasticity, the OLS-CUSUM (CUSUM) test for structural breaks and the Henze-Zirkler (HZ) test for normality. Hereby, the Breusch-Godfrey (BG) test, the multivariate ARCH-LM test and the OLS-CUSUM test and the Henze-Zirkler test are applied on the final residuals of the VAR model for the exogenous variables world gross domestic product (GDP), the US dollar index (FX), as well as the federal funds rate (FFR)

Appendix D Figures

See Figs. 1, 2, 3 and 4.

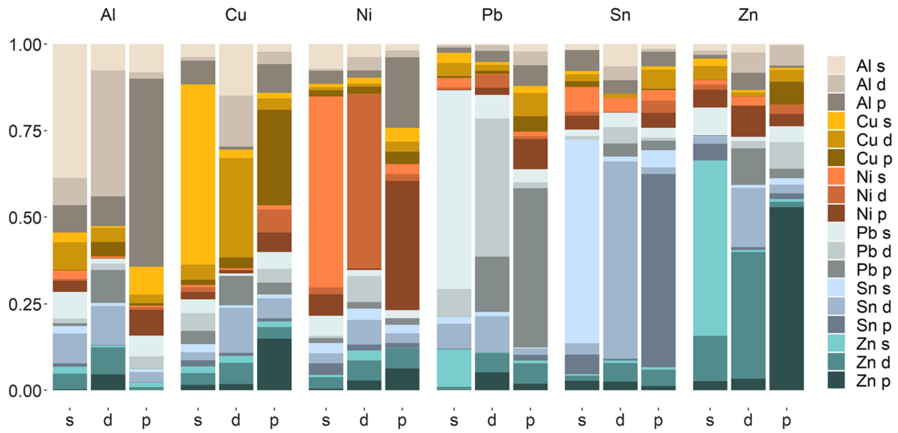

Fig. 1 Aggregated GFEVD plots for weight matrix supply (**S**). Scaled and aggregated GFEVD of the GVAR with weight matrix supply by the mean of 1 to 10 steps ahead per attribute, decomposed by the shocks of each endogenous variable

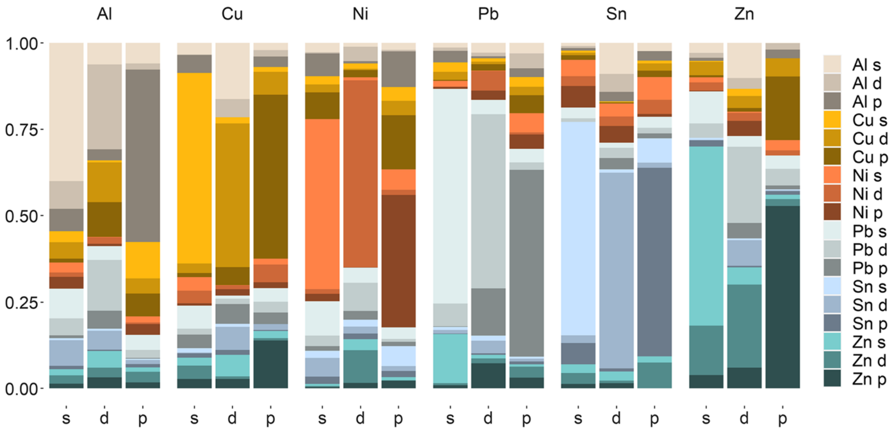

Fig. 2 Aggregated GFEVD plots for weight matrix demand (**D**). Scaled and aggregated GFEVD of the GVAR with weight matrix demand by the mean of 1 to 10 steps ahead per attribute, decomposed by the shocks of each endogenous variable

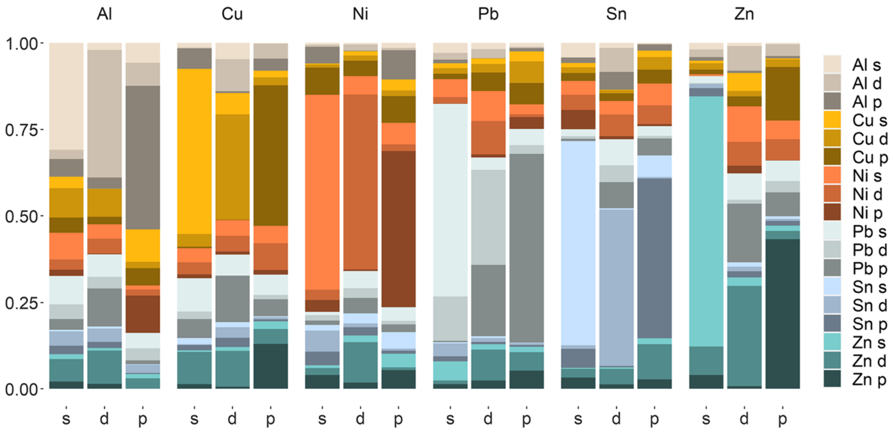

Fig. 3 Aggregated GFEVD plots for weight matrix trading (**T**). Scaled and aggregated GFEVD of the GVAR with weight matrix trading by the mean of 1 to 10 steps ahead per attribute, decomposed by the shocks of each endogenous variable

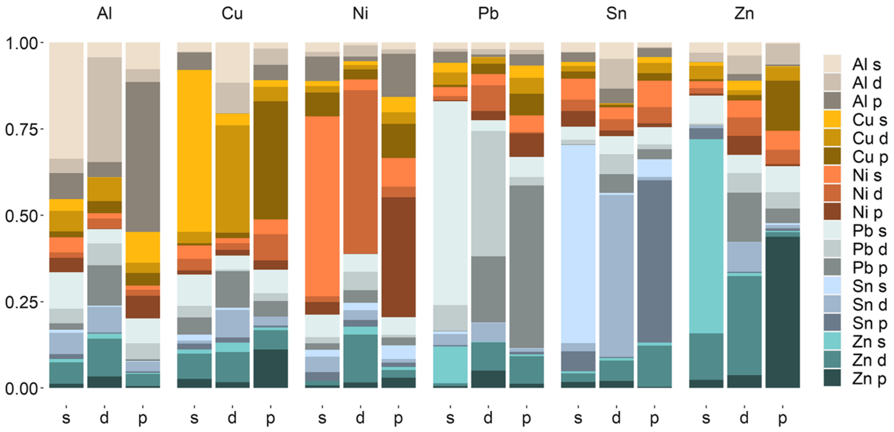

Fig. 4 Aggregated GFEVD plots for weight matrix common (**C**). Scaled and aggregated GFEVD of the GVAR with weight matrix common by the mean of 1 to 10 steps ahead per attribute, decomposed by the shocks of each endogenous variable

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